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Contents

Executive Summary ... 6

1. Introduction ... 9

2. Theoretical framework ... 10

2.1 Regional specialisation, related and unrelated diversification ... 10

2.2 Cognitive proximity, relatedness and regional branching ... 11

2.3 Network space and regional diversification ... 13

2.3.1 Network analysis and the study of relatedness ... 13

2.3.2 Relatedness in the occupational space ... 14

2.3.3 Relatedness in the trademark space ... 15

3. Data and methods ... 16

3.1 Data sources ... 16

3.1.1 Occupation data ... 16

3.1.2 Trademarks ... 17

3.1.3 Data period ... 18

3.1.4 NUTS Regions ... 18

3.2 Typology to classify occupations, trademarks and regions ... 19

3.2.1 Cultural and creative occupations (CCOs) ... 19

3.2.2 Trademarks related to cultural and creative activities ... 23

3.2.3 Regions by degree of urbanisation ... 24

3.3 Analysis framework: specialisation, co-occurrence and relatedness density ... 26

4. Results ... 28

4.1 Occupational diversification opportunities for the European Union ... 28

4.2 Occupational diversification opportunities for non-urban and urban regions ... 31

4.3 Trademark diversification opportunities for the European Union ... 36

4.4 Trademarks diversification opportunities for non-urban and urban regions ... 38

5. Case studies for the IN SITU Lab regions ... 42

5.1 Diversification opportunities in occupations for the IN SITU Lab regions ... 43

5.2 Trademarks related to CCI in the IN SITU Lab regions 56

6. Final remarks **61**

References **64**

Appendices **70**

Appendix A – List of Nice classes and full description 70

Appendix B – Descriptive analysis of trademarks related to CCI 73

Appendix C – Treemap by occupation of the IN SITU Lab regions 76

List of Tables

Table 1: List of ISCO-08 codes (3 and 4-digit) associated with cultural and creative occupations 21

Table 2: List of Nice classes related to Cultural and Creative Industries 24

Table 3: Countries and numbers of NUTS regions by degree of urbanisation 25

Table 4: Cultural and Creative Occupations by ISCO 45

List of Figures

Figure 1: Occupation space for the European Union (all regions) 30

Figure 2: Occupation space for non-urban regions in the European Union 31

Figure 3: Occupation-space for urban regions in the European Union 33

Figure 4: Eigencentrality histogram for occupations in non-urban and urban regions 34

Figure 5: Eigencentrality for CCOs in non-urban and urban regions 35

Figure 6: Trademark space for the European Union (2019) 37

Figure 7: Trademark space for non-urban regions in the European Union 39

Figure 8: Trademark space for urban regions in the European Union 40

Figure 9: Eigencentrality histogram for trademarks in non-urban and urban regions........................ 41

Figure 10: Eigencentralitry by trademark classes related to CCI in non-urban and urban regions...... 42

Figure 11: Comparative heatmap of occupational relatedness of the IN SITU Lab regions................ 44

Figure 12: Occupation space and specialisation degree for PT20 (Autonomous Region of the Azores, Portugal).. 46

Figure 13: Occupation space and specialisation degree for LV00 (includes Valmiera County, Latvia) 48

Figure 14: Occupation space and specialisation degree for IS00 (includes West Region, Iceland)...... 49

Figure 15: Occupation space and specialisation degree for IE04 (includes Western Coastal Periphery, Ireland).. 51

Figure 16: Occupation space and specialisation degree for FI19 (includes Länsi-Suomi region, Finland) 52

Figure 17: Occupation space and specialisation degree for HR03 (includes Šibenik-Knin County, Croatia).. 53

Figure 18: Relatedness density for Cultural and Creative Occupation by IN SITU Lab region............. 55

Figure 19: Total trademark applications by IN SITU Lab region and type 57

Figure 20: Distribution of trademark applications by IN SITU Lab region and type (2019)................. 58

Figure 21: Distribution of trademark applications related to CCI by Nice class and IN SITU Lab region (2019) 60

Executive Summary

Empirical studies carried out over the last decade have convincingly shown that new activities are more likely to emerge and develop in a region when they are related to the existing structure in that place, since these represent capacities from which local companies and actors can develop new activities (Boschma, 2017). The knowledge base and competencies established in a region will determine the future paths that the region can follow, that is, path dependence matters (Neffke *et al.,* 2011). In this sense, the relatedness between activities is an important driver of industrial dynamics at regional level, as the more related two activities are, the easier it will be to jointly share and leverage relevant knowledge and capabilities.

Occupations can provide complementary insight into local capabilities (Neffke & Henning, 2013). Cognitive proximity among workers allows knowledge to spread more effectively, with corresponding benefits for the regional economy (Boschma, 2005). Another element that leverages the understanding of regional capacity is the market categories revealed by trademarks. This intellectual property is relevant for capturing non-technological regional specialisations (Castaldi & Mendonça, 2022) and can capture specific markets where local companies are active.

In Deliverable 1.1, we discussed the limitations of an industry perspective on CCIs, which fails to recognise the contribution of cultural and creative activities across the whole economy. Taking those insights into account, the **objective of Deliverable 1.2** is to shed light on the disparity in **diversification opportunities** across non-urban regions in Europe by applying the relatedness approach from Evolutionary Economic Geography, starting not from industries but from occupations and markets.

We **aim to comprehensively identify possibilities for consolidation and emergence of new specialisations in cultural and creative activities**. To do so, Deliverable 1.2 is composed of two tasks drawn up jointly in this report:

In **Task 1.3** we focus on **occupations** and, using official data from Eurostat, we calculate in what occupations each European region is specialised, highlighting **cultural and creative occupations** (these results are displayed in Sections 4.1 and 4.2). We study relatedness by visualising in different network graphs the similarity among occupations, evaluating the network structure through a measure of network centrality and comparing the networks of urban and non-urban regions.

In **Task 1.4** we move our focus from occupations to **markets** where cultural and creative products and services are offered (results are discussed in Sections 4.3 and 4.4). In Deliverable 1.1, Task 1.2, we learned that the trademark is the most suitable measure for examining intellectual properties and soft innovation in non-urban regions, so in Deliverable 1.2 we rely on these special characteristics of trademarks and use such data to capture markets and market relatedness. Since there is no clear definition of **trademarks related to cultural and creative activities**, we suggest an innovative way of

capturing them. With this, we study the structure of trademark networks in urban and non-urban regions and calculate similar indicators to those in Task 1.3.

In **addition**, to deepen the connections with the other Work Packages and Tasks of the IN SITU project, we have also drawn an illustration of the **opportunities for specialisation in the regions where the IN SITU Labs** are located (these results are given in Section 5). We calculated indicators for occupations to assess whether regions specialise in cultural and creative occupations and possible paths for new specializations. Additionally, we also we provide a vision in qualitative terms of CCI-related trademarks found in the IN SITU Lab regions.

From the development of Task 1.3 and Task 1.4, we can summarise the results found in this report as follows:

1. The occupation-space revealed to us that cultural and creative workers in the non-urban network space provide many possibilities to diversify into different activities. CCOs are surrounded by a broad range of occupations – from managers and professionals to clerical support and elementary occupations – with a high relatedness among CCOs and other occupations.
2. CCOs have a more significant potential to influence the occupation network in non-urban regions compared to CCOs in urban regions. This means that CCOs in non-urban regions provide greater diversification possibilities compared to the same occupation in an urban region, therefore playing an essential role in the diversification dynamics of non-urban regions.
3. The trademark-space reveals that trademark classes related to the CCI appear as relevant intermediate links connecting different branches, related and non-related CCI trademarks. In this sense, in non-urban regions CCI-related trademarks have the potential to promote diversification along several paths, more diverse than the results found for urban regions.
4. The influence of CCI-related trademarks over other nodes in the trademark-space for urban regions is greater than in non-urban regions (as opposed to occupational-space).

In turn, based on the complementary task of evaluating the non-urban regions where the IN SITU Labs belong, we can summarise that:

5. Creative and cultural workers across the six non-urban regions face somewhat different situations. While part of the higher density scores for the case of Iceland and Latvia may be affected by the data available from Eurostat, in some regions CCOs are very strongly connected to other occupations, such as in Šibenik-Knin (Croatia) and Länsi-Suomi (Finland).
6. There is a low number of trademark applications – including CCI-related trademarks – in some of those non-urban regions, particularly in the Autonomous Region of the Azores (Portugal), Iceland and Šibenik-Knin (Croatia), indicating that trademarks are still being

underused and the potential linked to this form of intellectual protection is not being fully tapped.

While we rely on methodologies frequently used in the relevant literature and, therefore, our approach is in line with the state of the art, the approaches are still exploratory and need further validation for different regional levels. The main issues in this sense have to do with the granularity of the data both in terms of occupations as well as in terms of geography.

Leveraging established theories and frameworks on novel datasets has provided a fresh perspective that can inform research and policy alike. While many publications have concluded that non-urban regions may not have many diversification opportunities, our analyses show that this deserves closer attention. Non-urban regions may be able to develop and take advantage of diversification opportunities, especially if occupations and trademarks with greater potential are identified and supported by local policy interventions.

1. Introduction

Studying the dynamics of regional development is essential in order to understand how regions are able to adapt over time and generate enough opportunities. Research has highlighted how this process might be easier for large and diversified urban regions than for small and specialised non-urban regions. Non-urban regions are more likely to depend on specific industries or economic activities and might find it challenging to reinvent themselves (Diemer *et al*., 2022; Pinheiro *et al*., 2022a; Rodríguez-Pose, 2018).

Evolutionary economic geography (EEG) has offered insights into the mechanisms behind the above evidence. Examining how economic activities and structures evolve over time in geographical space, EEG emphasises the importance of path dependence and the role of the local context in shaping economic development (Balland & Boschma, 2021a; Boschma, 2017; Hidalgo, 2021). One of the basic tenets of EEG is that, to assess the development trajectory of a region, it is critical to study the activities present in the region since those represent capabilities from which local firms and actors can develop new activities. The concept of relatedness, capturing the degree of similarity or overlap between capabilities in different economic activities within a region, is very important in this context since the more related two activities are, the easier it is to share and jointly leverage relevant knowledge and capabilities.

Taking EEG as the conceptual and methodological bedrock for our analysis, the analyses in this report use relatedness to study diversification opportunities of cultural and creative activities in non-urban regions. In Deliverable 1.1 (Task 1.1) we discussed the limitations of an industry perspective on CCIs, which fails to recognise the contribution of cultural and creative activities across the whole economy. Taking those insights into account, we propose to apply the relatedness approach starting not from industries but from occupations and markets (Feser, 2003).

This report (Deliverable 1.2) involves two Tasks that complement the vision of regional specialisation. In Task 1.3 we focus on occupations and, leveraging official data from Eurostat, we calculate what occupations each European region is specialised in. The measure of specialisation in different occupations in EU regions is the starting point to compute relatedness across occupations and thus to identify complementarities among occupations. We study relatedness by visualising in different network graphs the similarity among occupations, evaluating the network structure through a measure of network centrality and comparing the networks of urban and non-urban regions. In our analysis, we single out the position and diversification opportunities for creative and cultural occupations (CCOs) in European regions.

In Task 1.4 we shift our focus from occupations to markets where cultural and creative products and services are offered. We take the lessons learned from Deliverable 1.1, Task 1.2, which says that the trademark is the most suitable measure for intellectual properties and soft (or nontechnological) innovation in non-urban regions and use trademark data to capture markets and market relatedness. After identifying trademarks connected to the creative and cultural output, we study the structure of trademark networks in urban and non-urban regions and calculate similar indicators to those in Task 1.3.

As an additional task, to contribute to shaping the scenario where the IN SITU Labs are located, we combine our data with the information collected in Work Package 3. With this, we aim to provide a tailored analysis of the diversification opportunities in the six IN SITU Lab regions.

This report is organised in the following way. Section 2 brings a theoretical review of key points, covering how relatedness influences regional specialisation; the relevance of cognitive proximity in the regional branching process; and how network analysis helps to investigate the relatedness among occupations and market activities. In Section 3 we present the methodological procedures, including data sources; typologies employed to classify cultural and creative occupations, trademarks related to CCI and urbanisation degree; and closing with the conceptualisation of specialisation, co-occurrence and relatedness density. Results are displayed in Section 4, showing first the finds regarding diversification opportunities in terms of occupations in the European Union, urban and non-urban regions; and after that, the finds about the diversification opportunities in terms of classes of trademarks. Section 5, we deeply analyse the IN SITU Lab regions, assessing their specialisation in cultural and creative occupations and bringing a qualitative analysis of the trademarks related to CCI filled by these regions. To finalise the report, Section 6 show final remarks and policy implication that we can take from the previous finds.

2. Theoretical framework

2.1 Regional specialisation, related and unrelated diversification

In the last decade, there has been a growing literature discussing the role of the capabilities of regions and how they lay the foundations for developing new activities. Local capabilities can give birth to new activities by providing a pool of local resources, such as similar knowledge, skills and institutions. However, at the same time, they also set limits to what can be achieved in this diversification process. If a region does not possess the capabilities required for a new activity, developing it will be much more challenging and riskier. Therefore, one expects regions to diversify into new activities related to existing local activities to reinforce local capabilities. By contrast, unrelated diversification requires a complete transformation of local capabilities, accompanied by high transition costs and high risks of failure, and, thus, is less likely to happen (Balland & Boschma, 2021a; Boschma, 2017; Hidalgo, 2021).

Even though relatedness has been found to play a significant role in the region's diversification process (Boschma, 2017; Hidalgo, 2021), there are significant regional and development heterogeneities, which may lead us to under or overestimate its effect. Recently, scholars have set out to investigate better inter- and intra-regional disparities in the diversification possibilities of regions and the factors that influence them. Galetti, Tessarin & Morceiro (2021)'s study of Brazilian regions revealed that the entry of a new skill-related industry is more likely in large regions and depends less on relatedness in advanced and middle-income regions. Skill-relatedness plays a role in preventing exit from small regions and enhancing employment growth in larger regions (Galetti, Tessarin & Morceiro, 2021). Pinheiro *et al.* (2022) found that diversification opportunities in more complex technologies and industries tend to be higher in high-income than in low-income regions. Countries focusing on related diversification tend to have robust economic performances (Coniglio *et al.*, 2018, 2021). Pinheiro *et al.* (2022b) showed that related diversification is more frequent for countries at low levels of development but becomes less frequent as countries climb the complexity ladder. Petralia *et al.* (2017) pointed out that countries also climb the ladder of technological development by building up new capabilities gradually; at early stages of development, the diversification depends more heavily on related capabilities, and at later stages, countries can develop new technologies less related to their previous knowledge bases.

A common point in most of these studies is that they focus on regional diversification, mainly analysing product and industry diversification or technological diversification. To offer a more comprehensive picture of regions' diversification potential, we propose to broaden this view and including other measures, such as occupation and trademark data. Such an effort is also needed to capture better capabilities in peripheral regions which rely less on technological innovation and high-tech industrial activities (Castaldi & Drivas, 2023; Tessarin & Azzoni, 2022).

Additionally, occupational and trademark data allow us to capture the many ways in which creative and cultural activities are embedded in regional economies beyond an industry perspective.

The focus on occupations and occupational capabilities points to a complement to diversification in understanding regional performance, for instance, in terms of product differentiation. If a region lacks occupations that require creativity, it will be more difficult for such a region to move beyond production of commodities that face harsh price competition.

2.2 Cognitive proximity, relatedness and regional branching

It is already well recognised in the literature that knowledge is neither equally accessible nor equally relevant to economic agents (Nooteboom, 2000). For knowledge to be transmitted and absorbed, scholars have highlighted the importance of alternative forms of proximity between the actors who share this knowledge (Cortinovis et al., 2017). One main element for transmitting knowledge in an economy is cognitive proximity (Boschma, 2005).

In this sense, the more related the knowledge bases and skills of different actors are, the easier it will be to exchange and internalise ideas, skills and knowledge. On the other hand, when the cognitive distance is significant, and the actors do not have common knowledge that allows them to understand what is being exchanged (i.e., they "don't speak the same language"), knowledge spillovers are less likely to occur (Breschi *et al.,* 2003). Nevertheless, we must remember that unrelated diversification is still important to avoid economic lock-in (Pinheiro *et al.,* 2022b) and to generate breakthrough innovations (Castaldi *et al.,* 2015), since innovation happens by the combination of seemingly unrelated ideas ex ante that prove to have substantial utility ex post.

Besides cognitive proximity, other dimensions of proximity also support spillovers of knowledge, for instance organisational, social and institutional proximity (Boschma, 2005). According to Fitjar & Rodríguez-Pose (2011) the innovative capacity of peripheral regions is strongly enhanced by these other types of proximity, especially cognitive and organisational.

Cognitive proximity is essential between industries, technologies, institutions, workers, etc. In the labour market, workers in occupations with related sets of knowledge facilitate spillovers through continuous social and work interactions (Nooteboom, 2000), enhancing the processes of learning, recombination, creation and diffusion of new types of knowledge (Neffke & Henning, 2013). This occurs through processes of learning by doing and interacting and through the interplay of tacit and technical knowledge (Muneepeerakul *et al.,* 2013). By sharing related skills, workers optimise cognitive distance and knowledge exchange, reinforcing the recombination process through which the regional economic structure is transformed over time (Galetti, Tessarin & Morceiro*,* 2021).

In other words, workers who share similar skills tend to optimise their cognitive distance and increase learning and knowledge spillovers. In particular, the flow of tacit knowledge tends to be geographically localised and generates externalities for local industries. Industries that employ workers with similar skills have a greater degree of relatedness. Consequently, they are better positioned to learn from each other, increase their absorptive capacity, optimise cognitive distance, and exchange and recombine related knowledge (Cohen & Levinthal, 1990; Nooteboom, 2000).

As a result, the transformation of regional economies over time is influenced by the existing variety of occupational specialisations in the process of path-dependent branching, in which new professions emerge from those already present in local economies.

Several studies have sought to identify the links between occupations and structural change in countries or regions. Farinha *et al.* (2019) identified that in U.S. cities, there are different dimensions of relationships (similarity, complementarity and local synergies), which, on the one hand, increase the chances of a new job entering a city and, on the other hand, decrease the probability of an existing job disappearing. The authors also found that proximity between occupations (local synergies between job classes) has the strongest effect on avoiding the loss of occupational specialisation (Farinha et al., 2019). Tessarin et al. (2020) found that the proximity between industries that have workers with similar productive and technological skills produces a positive impact, in particular, on productivity and investment in fixed capital of those industries. Galetti, Tessarin & Morceiro (2022b) also spotted that occupational relatedness is associated with regional ramifications in a developing country such as Brazil. They showed that the relationship between relatedness and regional branching depends on the type of occupational relatedness and regional characteristics.

The regional branching process is also evident in producing new technologies (Balland *et al.,* 2019; Boschma *et al.,* 2015; Kogler *et al.,* 2013; Petralia *et al.,* 2017). Relying essentially on patent data, studies show that regions are more likely to generate new technological advantages in fields related to their existing knowledge base. In an effort to expand this analysis, Drivas (2022) showed that the regional branching process also applies to trademark activities. Following the principle of relatedness, Drivas (2022) showed that it is more likely that a region presents a new specialisation in a trademark class closely related to classes of trademark in which the region already specialises. Castaldi & Drivas (2023) expanded on this original idea and conceptualised market relatedness as an additional channel through which regions can branch to new specialisations.

2.3 Network space and regional diversification

2.3.1 Network analysis and the study of relatedness

Many researchers use network analysis to understand the links between economic activities (products, industries, technologies or workers). The seminal arguments that support this discussion come from Hausmann & Klinger (2006), Hidalgo *et al.* (2007) and Hidalgo & Hausmann (2009). Their analysis argues that when two products or services share most of the same necessary inputs or production capabilities, countries that export one will also tend to export the other. Hidalgo *et al.* (2007) investigated how the productive structure of countries changes towards the more sophisticated production of goods. The authors start from the premise that the production of different types of products requires different types of capacities, so the capacities that a country possesses determine which goods it is able to produce and what effort is needed to switch to producing goods that require other types of capacity.

Based on this approach, other studies have emerged to understand the relationship between technologies (Balland & Boschma, 2021b; Drivas *et al*. 2023), industries (Cicerone *et al.,* 2020; Innocenti & Lazzeretti, 2019; Janssen & Frenken, 2019; Neffke & Henning, 2008), occupations (Muneepeerakul *et al.,* 2013; Farinha et al., 2019; Davies & Maré, 2021; Galetti, Tessarin & Morceiro, 2021; Tessarin *et al.,* 2023) and scientific domains (Balland & Boschma 2022), using network-space.

These studies consider the proximity of links based on the probability of two variables co-existing with a revealed comparative advantage. For example, occupations with a revealed comparative advantage at the same time in the same region have greater proximity. Likewise, occupations that do not share many capabilities are less likely to co-occur, and then the proximity between them will be low. For example, the proximity between physicians and nurses is expected to be high, as regions tend to co-specialise in those two occupations; unlike an aeronautical engineer and a shoemaker, where regional co-specialisation is likely not to be there.

On the one hand, there are central nodes, those nodes that have several connections linked to them, meaning that they have a strong relatedness with other participants (present in the same cluster). On the other hand, nodes in sparsely populated clusters, i.e., with few links, have less proximity to other ones and, therefore, less relatedness that would allow them to co-occur with other nodes.

A network usually also contains links situated in an intermediate position. These cross-links are not necessarily important from an economic point of view, but they are certainly interesting from the point of view of cross-specialisation (Janssen & Frenken 2019). Regions with several cross-links are in a favourable position, as they can integrate knowledge from two parties that do not typically collaborate.

Taking the occupation space as an example, we can say that regions with a revealed comparative advantage in groups of occupations centrally positioned in networks will show higher levels of potential diversification than those whose revealed comparative advantage is in occupations positioned in the periphery of the network. The reason is that these central occupations offer greater possibilities for learning and knowledge sharing. At the same time, regions with occupations in the intermediate links are also in a favourable position since these intermediate occupations facilitate the exchange of knowledge and techniques necessary for different occupations that do not communicate with each other directly.

In this sense, the relatedness framework and the conceptualisation of economic activities as networks are helpful tools for assessing the possibilities of diversification and regional branching applied to various contexts. Next, we explain how the concepts outlined can be applied to occupations and trademarks and why these two data sources are particularly useful when it comes to capturing creative and cultural activities.

2.3.2 Relatedness in the occupational space

Occupations provide complementary insight into local capabilities (Muneepeerakul *et al*., 2013; Brachert, 2016; Farinha *et al.,* 2019; Neffke & Henning, 2013; Tessarin & Azzoni, 2022), especially with the increasing importance of human capital and skills (Acemoglu & Restrepo, 2018). Scholars have been applying occupation data from linked employer-employee data or national labour force surveys to study the diversification of regions in individual countries, e.g., Fitjar & Timmermans (2017) on Norwegian regions, Farinha *et al*. (2019) on U.S, cities, and Galetti, Tessarin & Morceiro (2021; 2022) on Brazilian regions. These studies all confirm the importance of relatedness in the entry of new occupations in regions.

Based strongly on the notion of cognitive proximity (Boschma, 2005), relatedness allows knowledge to spread more effectively, with corresponding benefits for the regional economy. The degree of relatedness increases with the similarity between occupations through a branching process in which, on the one hand, new occupations grow from existing ones and, on the other, unrelated occupations shrink through endogenous changes at the local level (Farinha *et al.,* 2019; Frenken & Boschma, 2007).

As occupational diversification trajectories are built on the basis of the current occupational structure, they follow a process of path dependency (Frenken & Boschma, 2007). It is more associated with related diversification but also increases the variety of the set of occupations to a certain extent because the new occupations are similar, but not the same, as the existing ones.

Occupational relatedness is based on the similarity of worker's skills and the complementary demand for workers. In this sense, occupations are employed together to enhance learning in specific tasks based on skills that can overlap and substitute for each other to some extent (Farinha *et al.,* 2019; Galetti, Tessarin & Morceiro, 2020; Muneepeerakul *et al*., 2013). Occupations are related if they perform interdependent tasks and complement each other in such a way that what a worker knows is enhanced by what their co-workers also know (Neffke & Henning, 2008).

We discussed in Deliverable 1.1 - Task 1.1 (Tessarin *et al.,* 2023a) how using industry data to capture these activities has important limitations for the specific case of creative and cultural activities. Many creative and cultural workers are employed across the economy, also beyond CCIs. Hence, focusing on occupations allows us to better account for the many ways creative and cultural activities might spur diversification opportunities.

2.3.3 Relatedness in the trademark space

Another way to capture creative and cultural activities beyond industries is to do so through the actual products (goods and services) being developed and offered in the market. Drivas (2022) has suggested that a market focus allows the capture of regional specialisations beyond technology only. Regions can be market leaders in specific markets even without technology leadership. This insight is particularly salient for creative and cultural products, which rely much more on soft innovation and symbolic knowledge bases than on technology (Castaldi, 2018). In Deliverable 1.1 - Task 1.2 (Castaldi *et al.*, 2023) we also provided evidence that collective trademarks can be important metrics for capturing trademarks related to cultural and historical assets, especially relevant in non-urban regions.

Trademarks have emerged as data that bear relevance for capturing non-technological regional specializations (Castaldi & Mendonça, 2022). They have specific advantages for revealing soft innovation (Stoneman, 2010) as they are symbols identifying meanings and market categories (Mendonça, 2014).

In the context of intellectual property rights, trademarks are used by economic actors to distinguish their goods and services in the marketplaces and refer to commercialised products (Castaldi, 2020). They are relevant in all sectors, serving to protect innovations at different stages of development (Seip *et al.,* 2018) and as an alternative to patents when the latter are not an option or because the type of innovation is not technological (Flikkema *et al*., 2014; Mendonça *et al.,* 2004).

Block *et al.* (2015) pointed out several reasons that lead firms to use trademarks. Generally speaking, these reasons are associated with: i) the protection of the origin of the good, ii) a marketing strategy to ensure differentiation in terms of quality and reputation, and iii) using trademarks as an exchange asset, which allows the brand to become a valued, monetised and tradeable asset.

Trademark filings are associated with specific market classes: when a company files for a trademark, they need to indicate the specific markets where the trademark will be used. These market classes can then be used to construct a trademark space or market space, following the same general principle of relatedness discussed above. Two markets can be considered related when regions are more likely to co-specialise in those two markets, suggesting that they both rely on similar underlying market capabilities or exploit similar knowledge bases (Castaldi & Drivas, 2023).

In a sense, the trademark space bears strong similarities with the product space originally studied by Hidalgo *et al.* (2007). The product space was captured with export data and relied on export product categories. Export data has a focus on goods and manufacturing, hence, it is less suitable for application to more intangible activities like services. Trademark data has the advantage of covering both goods and services, which is particularly relevant for creative and cultural activities.

3. Data and methods

3.1 Data sources

In this report, we combined information on occupations and trademarks from different databases to study cultural and creative occupations and trademarks related to cultural and creative activities. In this way, we intend to evaluate the scenario across non-urban European regions and their possibilities for diversification.

Part of the methodology used in this report was previously developed for Deliverable 1.1 (Tessarin *et al.*, 2023a), which made up the initial part of this project – it includes the identification of cultural and creative occupations and the division of NUTS regions into urban and non-urban. In the following sections, we return to these concepts and the methodology employed and add the methodology for identifying trademarks related to cultural and creative activities.

3.1.1 Occupation data

Data on occupations comes from the Labour Force Survey (LFS), from Eurostat, a national household survey conducted by European countries to produce official national statistics following the same statistical regulation. This database collects information on individuals indicating occupation (by ISCO-

08) and place of work (by NUTS level 2), among many other variables. We had access to the LFS microdata in the scope of the IN SITU project, so we could leverage disaggregated information from occupations and NUTS regions to conduct this study.

LFS microdata provides occupation information at the 3-digit level at ISCO-08 (available from 2011 onwards), which covers 130 exclusive codes and regional desegregation by NUTS level 2.

We cleaned the database, removing information without comparable codes for ISCO occupation and workers without occupational or regional identification. We also dropped workers from regions outside European Union countries, thus out of scope for our report. In the end, proportionally to the total, little information was lost in the process of cleaning and organising data. After this process, we dropped only 4% of the workers.

In total, our dataset covers 15.7 million workers between the period 2011 to 2019, about 1.6 million workers per year.

As LFS is a national household sample survey conducted by European countries, verifying whether the regional distribution of employment is similar to that reported by the Eurostat statistics based on administrative records is essential. Concerned about this same issue, Tessarin *et al.* (2023) worked on a verification of LFS regional employment distribution to see whether the national surveys are well-balanced and represent the large and small regions well. They found a high Pearson correlation index between a country's regional employment distribution based on the LFS and the Eurostat regional employment, above 90% for most EU countries. In addition, the authors performed additional tests with other variables that also showed a very high correlation – for instance, the correlation of the manufacturing share in total regional employment for all regions was 99% (Tessarin *et al.,* 2023). Therefore, their results ensure the validity of data from LFS at the subnational level.

3.1.2 Trademarks

Trademark data comes from the European Union Intellectual Property Office – EUIPO Trademark database, and we accessed from the ISI-Trademark Data Collection (ISI-TM).[1] It provides detailed information on trademarks filed at the EUIPO and the USPTO (Neuhäusler *et al*., 2021).

We selected the EUIPO trademark applications and focused on those filed by applicants with addresses in one of the European regions. We also excluded filings from Andorra, as there is no information for this region in the other database. We also excluded incomplete occurrences, for instance, when there was no "applicant_ID", because it is impossible to allocate a region in this case.

[1] We are especially grateful to Peter Neuhäusler, from Fraunhofer Institute for Systems and Innovation Research (ISI), for his help in making the geocoded dataset available.

After cleaning and processing the data, we dropped 5.5% of the dataset since applications had no NUTS code or other missing information.

Notice that the EUIPO filings are different from trademarks filed at national trademark offices: these are not easily available for all countries. Flikkema, De Man & Castaldi (2014) found that trademarks filed at the EUIPO were more likely to refer to innovation than national trademark filings. In this sense, our focus on EUIPO filings makes the trademark-based innovation metrics more valid than metrics based on national filings.

3.1.3 Data period

For the purpose of this report, we consider an average between 2018 and 2019. Firstly, we chose not to include 2020 and 2021 due to the various external shocks resulting from the Covid-19 pandemic, which affected regions, especially occupations with distinct magnitudes, throughout that period.

3.1.4 NUTS Regions

As we are working with different databases, we had to choose a regional level of analysis that would fit the data availability across all sources.

We also made a concordance table between NUTS 2 region codes and all their variations (in names or codes) and changes over the years. Sometimes, a country requires changing the regional breakdown, then the European Commission amends the classification. For instance, from NUTS 2016 to NUTS 2021, at the NUTS level 2, several regions had names changed in Spain; Hungary had one region discontinued and three new ones created; and Norway had seven regions rearranged into six, one had been through a large revamp, and a new one was created. In 2011, the NUTS 1 code of Greece was changed from GR to EL, consequently changing the codes of all NUTS 2 and 3 levels and, in addition, another four regions were reclassified. These and all other amendments over the analysed period were included in the concordance table so we do not miss data from the restructured regions.

LFS provides information for 32 European countries at 1- and 2-digit NUTS regions. We chose to work with the most disaggregated version at the 2-digit NUTS level to be able to identify the degree of urbanisation. However, five countries do not have the granularity of data by region or occupation necessary to develop our research, so they were dropped. Bulgaria, Malta, Poland and Slovenia have no 3-digit occupation information, while the Netherlands do not provide subnational information despite having more than one NUTS region (only country-level information). The United Kingdom is included in the analysis but only provides regions at the 1-digit NUTS level, which means 12 NUTS regions.

As for trademarks, we have information at the NUTS 3 level. Therefore, we had to consolidate them into the NUTS 2 level to be able to create a dataset that matched the same level of analysis as occupations.

3.2 Typology to classify occupations, trademarks and regions

3.2.1 Cultural and creative occupations (CCOs)

Several studies within economic geography and geography of innovation have used industry-based definitions of creative and cultural activities to measure their role in regional development (Innocenti & Lazzeretti 2019; Lee 2020; Lee & Drever 2013; Protogerou *et al.* 2017; Stam *et al.* 2008). More recently, one has seen a shift from defining creative and cultural activities based on industrial classifications towards defining them based on occupations. The key advantage of using occupations is that one can map the contribution of these activities across the whole economy. Many creative workers are not employed in creative industries but rather in industries that complement occupations based on other skills and talent (Cruz & Teixeira 2012).

By now, many studies have adopted the occupation-based approach (Bakhshi *et al.,* 2013; Boschma & Fritsch, 2009; Markusen *et al.,* 2008; OECD, 2022a; Rodríguez-Pose & Lee, 2020; Tessarin *et al*., 2023a). In this case, the emphasis is more on what workers do than where they work (Feser, 2003; Markusen *et al.,* 2008).

A seminal contribution of Florida (2002, 2004) uses data from the United States and the American classification of occupation (Standard Occupational Classification) to assess the creative class and its contribution to regional growth and innovation. Lee & Rodríguez-Pose (2014) captured creative jobs across different industries and found that they contributed to product and process innovation in non-creative industries in the UK. Wojan *et al.* (2007) also evaluated the share of workers in creative occupations in U.S. counties and found that those occupations help explain the economic dynamism of regions, given that these workers are more likely to move to places with greater amenities and more opportunities for interaction.

Bakhshi et al. (2013) proposed a way of measuring the cultural and creative industries based on the share of cultural and creative occupations, including some types of jobs related to information and communication technologies, and identifying others based on the skills characteristic of creative and cultural occupations. Rodríguez-Pose & Lee (2020) tested whether the presence of creative occupations and STEM occupations (named *hipsters* and *geeks*, respectively) correlated with the level of innovation in American cities, as measured by innovation. The authors found that although the presence of geek workers is a more relevant driver of innovation, a combination of geeks and hipsters was most beneficial for innovation across cities.

In a critical review of Rodríguez-Pose & Lee (2020), Wojan (2022) also found a direct effect of creative workers on innovation using a measure for inventive class. In addition, Wojan (2022) also suggests evaluating the job composition effect on invention, as not all workers can necessarily contribute to patenting – in this case, the author proposes using employment in inventive occupations to normalise innovation results (instead of per capita values).

Overall, it has become evident that occupation-based definitions allow for better capturing of the actual contribution of creative and cultural activities, while industry-based definitions tend to underestimate it grossly (Eurostat, 2018; OECD, 2022b). We follow these insights and leverage the occupation-based perspective in this report.

Nevertheless, we are aware that this approach also has limitations. First, the national labour force surveys only include paid employment and do not always capture secondary or non-formal work, which is highly relevant in the context of cultural and creative activities (OECD, 2022a). A second challenge is the availability of data at a useful level of granularity in occupational classification (Higgs & Cunningham, 2008). The best scenario would be achieving ISCO (International Standard Classification of Occupations) classification at four-digit disaggregation, but such information is rare and unavailable in several countries (OECD, 2022b; Stam *et al*., 2008). A third issue relates to selecting occupational categories that count as creative and cultural. There is no widely accepted list (Boschma & Fritsch 2009). Some nuances to the ISCO code list define what creative occupations are, and these also vary slightly in some countries (Markusen *et al.*, 2008). The OECD (2022b) report provides some examples of mismatching. For example, some countries include information technology consultancy services and software developers in their definition of creative and cultural occupations (CCOs), whereas others only include video game software developers. Other countries include amusement parks, cultural education, sport, tourism and gastronomy, whereas others exclude them. A few countries include social science and humanities research and development; some countries have a specific category for circus professionals. These cross-country differences typically reflect variations in national policy priorities and data availability (Pires *et al.*, 2014).

Despite the challenges above, one can identify a group of workers that is widely recognised as performing cultural and creative occupations. At the European level, work has been done to define a common framework for cultural and creative occupations over the past two decades, culminating in harmonised statistics organised by Eurostat (Eurostat, 2018). The attractive feature of this framework is that it combines all individuals working in cultural and creative industries plus all individuals in cultural and creative occupations outside cultural and creative industries.

The Eurostat Guidelines (Eurostat, 2018) argue that occupations are fully and partly related to cultural and creative activities. Partly related occupations include occupations that may perform cultural and creative activities but may also be active in other industries performing any other tasks. To identify more precisely whether such occupations are effectively engaged in creative tasks, it is necessary to know the industry in which the worker is allocated (this means a crossover between classifications ISCO-NACE) (OECD, 2022a). However, this is not easy as this information is scarcely available in national statistics (Stam *et al.,* 2008). That is why, in most studies, this cross-section of occupations-industry is not included in the exercise.

In light of these arguments, the limitations and benefits of using occupations, we have selected a typology to identify occupations considered cultural and creative. Table 2 presents the occupations classified by national statistical offices and compiled by Eurostat for standardisation purposes as fully related to cultural and creative occupations.

Because the data received from the LFS was only available at ISCO-08 at the 3-digit level, we had to consider all occupations within the class at 3-digits. Here, we point to the ISCO code with an asterisk (*) to indicate the occupations not universally classified as cultural and creative in Table 2. The others that do not have the (*) indicate occupations commonly accepted as cultural and creative occupations (Eurostat, 2018; OECD, 2022a).

It is worth remembering, as already pointed out earlier, that some divergences exist between national statistical offices, with some extra codes being considered in specific countries (OECD, 2022a). However, due to the scarcity of data on 4-digit occupations, most studies follow the same strategy and adopt the complete composition of 3-digit ISCO codes to compute cultural and creative occupations.

This report considers the following nine ISCO-08 codes as CCOs: 216, 235, 262, 264, 265, 343, 352, 441 and 731. Overall, in 2019, this set of occupations represented 5.22% of the total occupations in the 27 European countries considered in this report, as we will see further below.

Table 1: List of ISCO-08 codes (3 and 4-digit) associated with cultural and creative occupations

ISCO-08 code	Cultural and Creative Occupations
216	Architects, planners, surveyors and designers
2161	Building architects
2162	Landscape architects
2163	Product and garment designers
2164	Town and traffic planners
2165	Cartographers and surveyors
2166	Graphic and multimedia designers
235	Other teaching professionals
2351*	Education methods specialists
2352*	Special needs teachers
2353	Other language teachers
2354	Other music teachers
2355	Other arts teachers
2356*	Information technology trainers
2359*	Teaching professionals not elsewhere classified
262	Librarians, archivists and curators
2621	Archivists and curators

ISCO-08 code	Cultural and Creative Occupations
2622	Librarians and related information professionals
264	Authors, journalists and linguists
2641	Authors and related writers
2642	Journalists
2643	Translators, interpreters and other linguists
265	Creative and performing artists
2651	Visual artists
2652	Musicians, singers and composers
2653	Dancers and choreographers
2654	Film, stage and related directors and producers
2655	Actors
2656	Announcers on radio, television and other media
2659	Creative and performing artists not elsewhere classified
343	Artistic, cultural and culinary associate professionals
3431	Photographers
3432	Interior designers and decorators
3433	Gallery, museum and library technicians
3434*	Chefs
3435	Other artistic and cultural associate professionals
352	Telecommunications and broadcasting technicians
3521	Broadcasting and audiovisual technicians
3522*	Telecommunications engineering technicians
441	Other clerical support workers
4411	Library clerks
4412*	Mail carriers and sorting clerks
4413*	Coding, proof-reading and related clerks
4414*	Scribes and related workers
4415*	Filing and copying clerks
4416*	Personnel clerks
4419*	Clerical support workers not elsewhere classified
731	Handicraft workers
7311	Precision-instrument makers and repairers
7312	Musical instrument makers and tuners
7313	Jewellery and precious-metal workers
7314	Potters and related workers
7315	Glassmakers, cutters, grinders and finishers
7316	Sign writers, decorative painters, engravers and etchers
7317	Handicraft workers in wood, basketry and related materials
7318	Handicraft workers in textile, leather and related materials
7319	Handicraft workers not elsewhere classified

Source: Authors, based on Eurostat.

For the purpose of this report, cultural and creative workers are defined as all individuals working under the ISCO-08 codes described above, regardless of which industry the worker is allocated – inside or outside cultural and creative industries.

3.2.2 Trademarks related to cultural and creative activities

Trademarks are classified by class according to the Nice Classification, which assigns goods to classes 1 to 34, and services to classes 35 to 45. Each class contains a set of terms providing general information about the type of goods or services to be protected by the trademark application. Some definitions are narrower, while others encompass a wide range of goods or services in the same class. For example, class 35 denotes "Advertising; business management; business administration; office functions", while class 42 is a broader one, covering "Scientific and technological services and research and design relating thereto; industrial analysis and industrial research services; design and development of computer hardware and software".

Since trademarks refer to goods or services, there is no ready-made definition to classify trademarks linked to cultural or creative activities. To identify that, we rely on the work of Zolas, Lybbert & Bhattacharyya (2017), who connected trademark classes to industrial classifications. According to the authors, trademark data does not talk to economic data, which makes it impractical to analyse it in conjunction with other economic data. To eliminate this barrier, they proposed a concordance table through an algorithmic approach called 'algorithmic links with probabilities' (ALP) matching to explicitly link trademarks and economic data via standard, widely used product and industry classification systems, such as Harmonized System (HS) for products and the International Standardised Industrial Classification (ISIC) for industries (Zolas *et al*., 2017).

This ALP matching approach has been used similarly to connect patents to economic data (Lybbert & Zolas, 2014). It enables researchers to map trademarks directly into industry categories in order to create measures of trademarks-use intensity by the probability of such industry code being covered by such trademark class. Our interest is to link trademarks to cultural and creative activities. To this end, we carried out the following procedure:

a. **first,** we identified which industries are classified as a CCI by the Eurostat Classification;
b. **second,** supported by the ALP matching approach probability list, we examined the compatibility between the ISIC Rev. 4 and the Nice class to identify which trademarks are related to creative industries defined in the previous step. As a result, we obtained 11 Nice classes linked to CCIs;
c. **third,** we double-checked the description of the 11 classes indicated as likely to fit the CCI codes. In this step, we chose to exclude class 36 "Insurance; financial affairs; monetary affairs; real estate affairs" because it refers in a very complementary way to practically all activities, not just cultural and creative ones. We also chose to keep class 9 because,

although its probability is low compared to the others, the description of the activities in this class is directly related to the implementation or operation of CCI activities.

After concluding these steps, we found a list of 10 trademark classes likely to be related to cultural and creative industries. Table 2 displays the final list.

Table 2: List of Nice classes related to Cultural and Creative Industries

Nice Class	Trademark type	Nice description	Probability
9	TM related to CCI	Scientific, research, navigation, photographic, cinematographic, audiovisual, optical, and measuring apparatus and instruments; instruments for recording sound, images or data.	0.0460
15	TM related to CCI	Musical instruments; stands for musical instruments.	0.9540
16	TM related to CCI	Paper and cardboard; photographs; drawing materials; plastic for wrapping and packaging.	0.4543
28	TM related to CCI	Games, toys; video game apparatus; gymnastic and sporting articles; decorations for Christmas trees.	0.3897
35	TM related to CCI	Advertising; business management; office functions.	1.0000
38	TM related to CCI	Telecommunications.	1.0000
39	TM related to CCI	Transport and storage of goods; travel arrangement.	0.9646
40	TM related to CCI	Treatment of materials.	0.8295
41	TM related to CCI	Education; training; entertainment; sporting and cultural activities.	0.8869
42	TM related to CCI	Scientific and technological services and research and design; industrial research services; design and development of computer hardware and software.	0.2560

Source: Authors, based on Zolas, Lybbert & Bhattacharyya (2017). Note: the trademark description was shortened. For the full description, see Appendix A.

3.2.3 Regions by degree of urbanisation

Another crucial step for the analysis consists of classifying the NUTS 2 regions by levels of urbanisation, to be able to identify non-urban and urban areas. For this, we again chose to work with the Eurostat criteria.

The division of regions by degree of urbanisation is based on the classification developed by Eurostat to provide standardised territorial typologies for all countries of the European Union. The methodology classifies Local Administrative Units (LAU) based on a combination of criteria of geographical contiguity and minimum population in an area (Eurostat, 2021). As a result, the areas are assigned to three degrees of urbanisation:

1. **Cities** (densely populated areas): where at least 50% of the population lives in urban centres – urban centres have a population density of at least 1,500 inhabitants per km² and collectively a minimum population of 50,000 inhabitants.
2. **Suburbs** (intermediate density areas): where at least 50% of the population lives in urban clusters and less than 50% lives in urban centres – urban cluster means areas with a population density of at least 300 inhabitants per km² and a minimum population of 5,000 inhabitants.
3. **Rural** (thinly populated areas): where at least 50% of the population lives in rural areas – it covers all other areas not identified as urban centres or as urban clusters.

This territorial typology is only available for NUTS 3 regions and there is no typology at NUTS 2 digits. However, the LFS occupation data used in this work covers regions at NUTS level 2. Therefore, it was necessary to aggregate the NUTS 3 areas to the NUTS 2 regional level to perform this work.

In the "History of NUTS" file[2], the 3-digit NUTS regions are classified as predominantly urban, intermediate and rural. We use the distribution of employed persons in each NUTS 3 to classify NUTS 2 regions as predominantly urban or non-urban. In other words, a region is "**predominantly urban**" when the majority proportion of employed people work in an area classified as urban; and a "**non-urban region**" comprises the regions in which the proportion of non-urban jobs is greater than 50%.

Table 3 indicates the total number of regions by the degree of urbanisation according to this methodology.

Table 3: Countries and numbers of NUTS regions by degree of urbanisation

Country	Urban regions	Non-urban regions
AT	1	8
BE	1	10
BG	3	4
CH	0	7
CY	1	0
CZ	1	7
DE	10	33
DK	1	4

[2] Available here: https://ec.europa.eu/eurostat/web/nuts/history

Country	Urban regions	Non-urban regions
EE	0	1
EL	1	12
ES	15	11
FI	1	4
FR	6	23
HR	0	2
HU	1	7
IE	1	2
IS	0	1
IT	4	20
LI	0	1
LT	1	1
LU	0	1
LV	0	1
MT	1	0
NL	8	4
NO	1	7
PL	5	14
PT	3	6
RO	1	7
SE	2	6
SI	0	2
SK	1	3
UK	8	7
Total	**78**	**216**

Source: Authors, based on Eurostat and LFS.

In total, there are 294 regions in the European Union. Note that for the analysis of trademarks, all regions have been included; in the case of occupations, the regions of five countries have been excluded (BG, NL, MT, PL and SI) due to the absence of ISCO 3-digit occupation data.

One of the concerns about this regional reclassification exercise is that it may be capturing large urban agglomerations consistent with the identification of global cities as urban regions and everything else as non-urban. However, given the unavailability of NUTS 3 data for the analysis, we believe that this may be the best that can be achieved at the moment.

3.3 Analysis framework: specialisation, co-occurrence and relatedness density

We constructed measures of regional specialisation, relatedness and relatedness density using both occupation and trademark data. Below, we will explain the construction of indicators using occupations. However, we can interpret it similarly for constructing indicators based on trademarks – instead of ISCO codes, we replace them with the Nice classes.

In this way, first, we constructed the indicator of specialisation that has become standard in the relatedness literature based on Balassa index (Balland & Boschma, 2022; Castaldi & Drivas, 2023; Cortinovis *et al.,* 2017). The indicator identifies whether region has a revealed comparative advantage (RCA) in a particular occupation during a period *t* (Tessarin *et al.,* 2023b). A higher RCA implies that a region is relatively more active in an ISCO category compared to the entire set of regions. Similar specialisation indicators were calculated for trademarks using Nice classes.

Second, we estimate the relatedness by examining the probability of two occupations co-occurring in the same region. We calculate the probability that a region specialises in an occupation *a*, given that it also specialises in an occupation *b*. Occupational relatedness in a period is a standardised measure of the frequency of two occupations appearing in the same region with RCA (Juhász *et al.,* 2021). High relatedness values indicate that two occupations are more frequently combined, while low relatedness values suggest that the occupation pairs are relatively independent (Tessarin *et al.,* 2023b). For example, a relatedness of 0.6 between a pair of occupations means that there is at least a 60% chance that a region with an RCA in occupation *a* also has an RCA in occupation *b*.

As we have 130 ISCO codes for occupations in total in our dataset, we obtain a 130x130 matrix of proximities for occupation. As for trademarks, we have 45 Nice class; then, we obtain a 45x45 matrix of proximities for trademarks.

Third, after calculating the relatedness based on co-occurrence for occupations and trademarks, we created the occupation space and a trademark space, which is a representation of links and nodes based on the proximity between the occupations or trademarks.

Additionally, to evaluate how important one node is within the network, we calculated the eigenvector centrality (or eigencentrality). This measure indicates how relevant a node is, based on how important the node in contact with it is (Hansen *et al*., 2020; Hausmann & Klinger, 2006; Hidalgo *et al.,* 2007). In other words, the eigenvector centrality reveals which nodes are better connected to important nodes in the network. The higher the eigencentrality score, the greater the level of influence within the network (Cicerone *et al.*, 2020). We understand that this measure of centrality is better than others (such as degree centrality, betweenness or closeness centrality) because it shows not only how many connections that node has but also how well-connected the other central nodes linked to it are (Hansen *et al.,* 2020).

4. Results

In this section, we present a qualitative analysis of the position of non-urban and urban regions in the occupation and trademark space. To fulfil this objective, we elaborated a representation of the network space, highlighting occupations and trademarks related to cultural and creative activities.

Section 4.1 presents the results on cultural and creative occupations for the European Union scenario. In Section 4.2, we introduce the findings on opportunities for occupational diversification by contrasting non-urban and urban regions. In Section 4.3, we start by presenting the diversification opportunities in terms of classes of trademarks, firstly for the European Union and then, in Section 4.4, we move on to the results for non-urban and urban regions.

4.1 Occupational diversification opportunities for the European Union

Cultural and creative occupations contribute to introducing new ideas, products and brands to the market, as introduced in Deliverable 1.1 (Tessarin *et al.* 2023a). Such occupations can be found in all industries – not just cultural and creative industries per se – stimulating innovation and adding value at different stages of development (Bakhshi *et al.,* 2013; Wojan *et al.,* 2007). Cultural and creative workers play a key role in bringing new ways of doing things, imagining and designing new products or services, and finding creative solutions (Boschma, 2005; Grillitsch & Nilsson, 2015; Rodríguez-Pose & Lee, 2020).

The evolutionary economic geography (Balland *et al.,* 2019; Boschma, 2017; Hidalgo *et al.,* 2018; Neffke *et al.,* 2011) argues that regions tend to diversify into activities similar to those they already produce. Local capabilities provide opportunities but set also limits this diversification process in regions. The more related a new activity is to local activities, the lower the costs and risks to develop it in a region. In this way, previous capacities help define regions' future diversification possibilities.

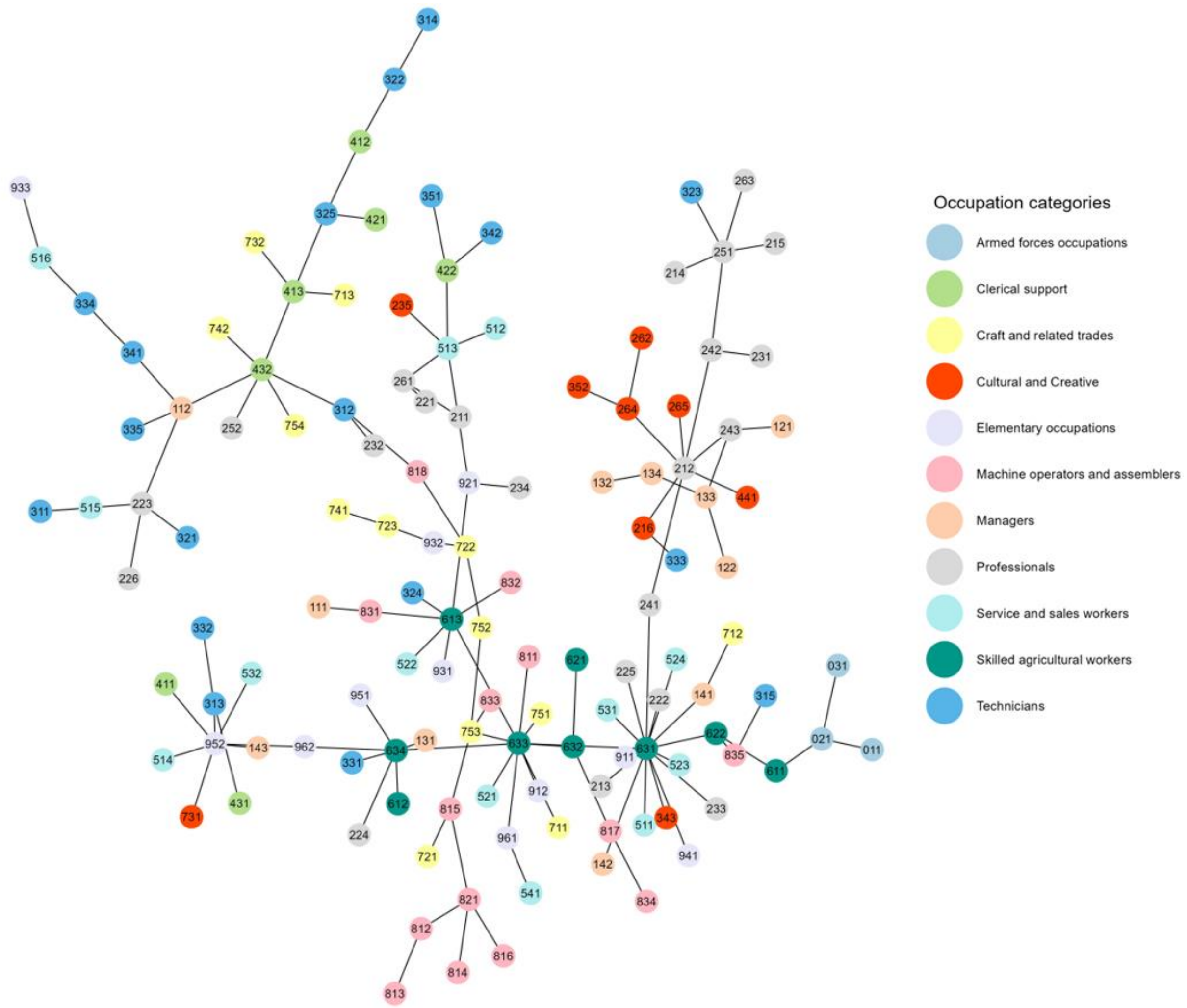
We employed network analysis to investigate the diversification opportunities of cultural and creative activities in the EU regions. As presented in Section 3.3, a network provides valuable tools for describing the structure of interactions, as it connects two occupations that appear together in the same region. When two occupations are linked, there are indications that they have characteristics (skills, knowledge and tasks) that they share and contribute to each other's existence. In this way, it is possible to identify diversification possibilities based on the position and connections of occupations in the occupational space.

Next, we present the occupation space elaborated from the 130 ISCO occupations (Figure 1) for the entire EU. We are using data from LFS to calculate an average between the years of 2018 and 2019 to avoid sporadic shocks in a specific occupation-year. We followed Hidalgo *et al.* (2007) and applied a max spanning tree (MST) network[3] based on Pedersen (2022). Each node in the network represents an ISCO 3-digit occupation. To facilitate the visualisation, we categorised the occupations by colours representing the ISCO major group (at 1-digit level) that each 3-digit ISCO minor group belongs to.

Besides the 10 major groups at 1-digit ISCO classification (see the label in the network), we have added one more occupation group called cultural and creative to address the focus of this report.

[3] The network was visualised using "ggraph" package and "lgl" layout in the R software (Pedersen, 2022).

Figure 1: Occupation space for the European Union (all regions)



Source: Authors, based on LFS.

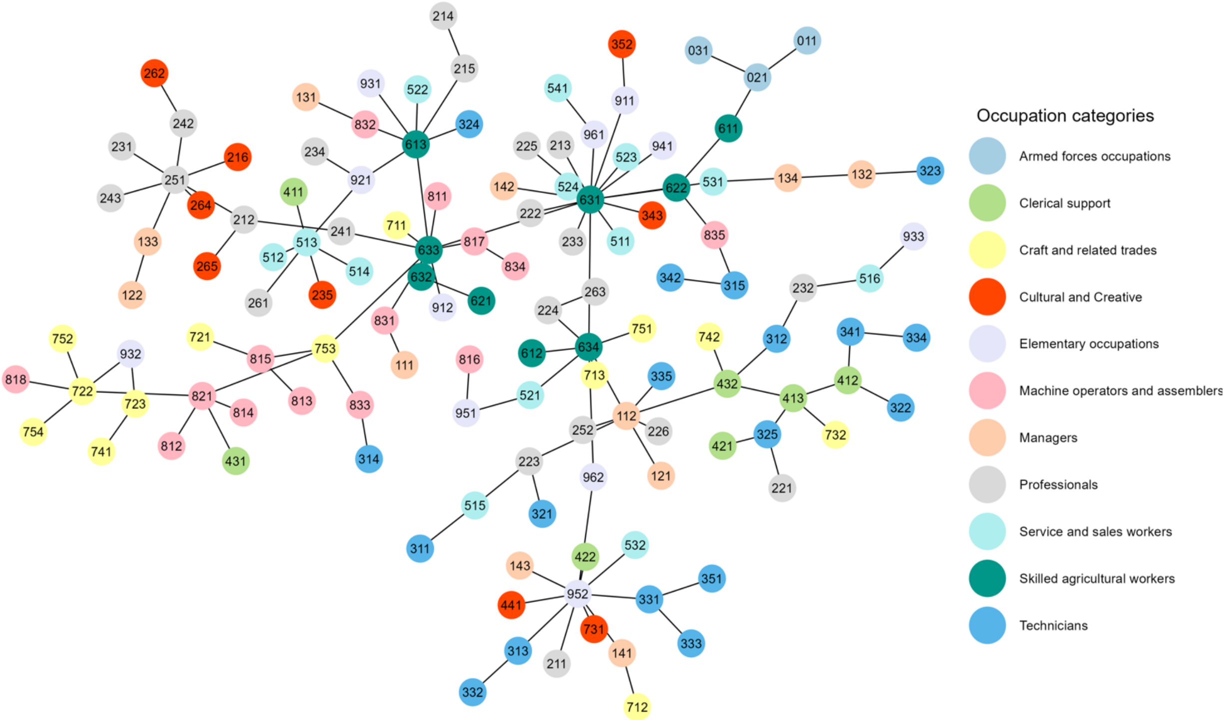
We can observe several clusters of nodes mixing distinct colours. In general, Professionals (grey) and Technicians (bright blue) are well distributed among clusters, but they are not central nodes, which may indicate that they co-occur with many other occupations and play a role in supporting all those other occupations. We can also find a branch (located in the top left corner) where the network is not very dense, i.e., with few occupations co-occurring together. In this case, green, yellow and blue nodes, representing, respectively, Clerical support; Craft and related trades; and Technician, are linked to only one or two other occupations, indicating few possibilities for related diversification.

Now looking specially at red nodes, which represent the cultural and creative workers, we can take a few insights. First, CCOs are not central nodes in the network; second, a group of CCOs are part of a cluster with sophisticated occupations, including Professionals and Managers occupations (on the right branch of the network); third, CCOs are also present individually in other three clusters where they are linked to different types of occupations (namely, Service and sales workers; Elementary occupations; and Skilled agricultural workers). In this sense, we understand that for the European Union as a whole, CCOs are quite diverse in terms of co-occurrence with other occupation types, which can offer numerous opportunities for diversification since they are present in highly populated clusters of the network (and not at the edges of the network, where diversification opportunities tend to be scarcer).

4.2 Occupational diversification opportunities for non-urban and urban regions

In this section, we focus on the differences between non-urban and urban regions. Figure 2 shows the network for non-urban regions, while Figure 3 is a visualisation for urban regions in the European Union. Both networks have specific characteristics.

Figure 2: Occupation space for non-urban regions in the European Union



Source: Authors, based on LFS.

In the occupation space for non-urban regions, on one side, we can see clusters with a smaller variety of occupations. For example, we notice a less dense branch with mainly yellow and pink nodes (on the left) representing Machine operators and assemblers; and Craft and related trades. In this case, the diversification possibilities for related occupations are more restricted for these two groups.

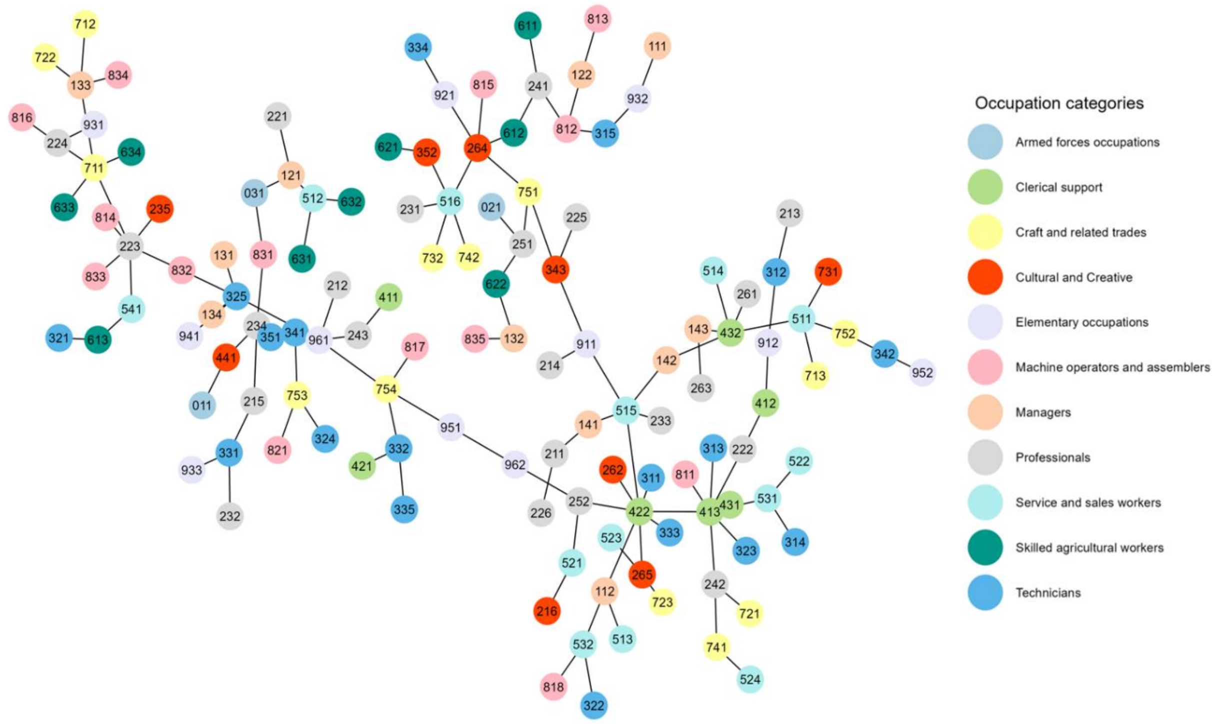
On the other side, we can visualise many dense clusters. Additionally, we also see cultural and creative workers distributed in three of them. First, on the left top side, there is a cluster involving mainly CCOs; Professionals; and Managers, similar to the previous figure for all EU regions, but in this case, the cluster is made up of fewer nodes. Second, we can also see cultural and creative workers present in two dense clusters (one at the top and one at the bottom centre of the network) involving different types of occupations in each of the nodes. One cluster mix involves Skilled agricultural workers; Professionals; Service and sales workers; and Elementary workers, besides two Cultural and creative occupations. The second cluster comprises Technicians; Managers; Clerical support; Elementary occupations; together with Cultural and Creative occupations.

Regarding cultural and creative workers in the non-urban occupational network space, we can say that there are many possibilities to diversify into different activities that demand occupations in a broad range – from managers and professionals to clerical support and elementary occupations. As other types of occupations more densely populate the clusters in which CCOs are present with a high degree of relatedness, it is easier to diversify towards these types of occupations, taking advantage of the similarities that the pair of occupations possess, which can also lead to the diversification of other occupations that are also surrounding the same cluster.

Figure 3 illustrates the occupation-network for urban regions in the EU. In this case, occupations form more branches than highly concentrated nodes. Besides, all these branches are very diversified in terms of occupation types since the colour of nodes is quite mixed along all the branches.

Cultural and creative workers in the urban regions are also very spread out along the occupation-space. A relevant difference compared to the previous network, which portrays the proximity of occupations in non-urban regions, is that some red nodes are in central positions (for example, see occupations 264 and 343). In this instance, such central occupations have the capacity to promote diversification in a more varied way, given that their presence often co-occurs with a variety of other occupations to which they are directly linked.

Figure 3: Occupation-space for urban regions in the European Union



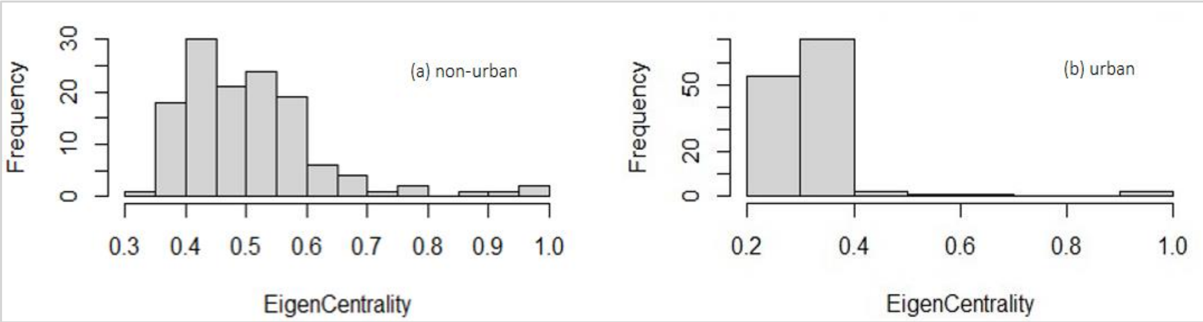
Source: Authors, based on LFS.

Based on the eigenvector centrality (Figure 4) we can see that the frequency of occupations in non-urban regions (chart a) is much more well-distributed than for urban regions (chart b). More than 85% of the occupations in the urban network have a similar eigencentrality, ranging from 0.2 to 0.4 (given that there are 130 occupations, and it is possible to identify around 50 occupations in the first bar and 70 in the second). In non-urban regions, the highest frequency of occupations occurs in the higher eigencentrality range, from 0.35 to 1.0.

This means that the various occupations with high eigencentrality located in non-urban regions have a more significant influence on the network than other occupations, so their links lead to other occupations. The existence of occupations with high eigencentrality is positive for diversification, as they can form a dense cluster with several other connected occupations. Therefore, diversification options are greater as the network has denser clusters.

In turn, urban regions have occupations with low and similar degrees of eigencentrality (Figure 4 – b), which means that less dense and sparse clusters will guide the diversification process. This configuration of the urban network might sound counterintuitive, as cities concentrate large volumes of workers, and one might expect denser clusters. However, we should bear in mind that occupation space captures related occupations. A characteristic of large cities is the great diversity of occupations that are not always highly related.

Figure 4: Eigencentrality histogram for occupations in non-urban and urban regions

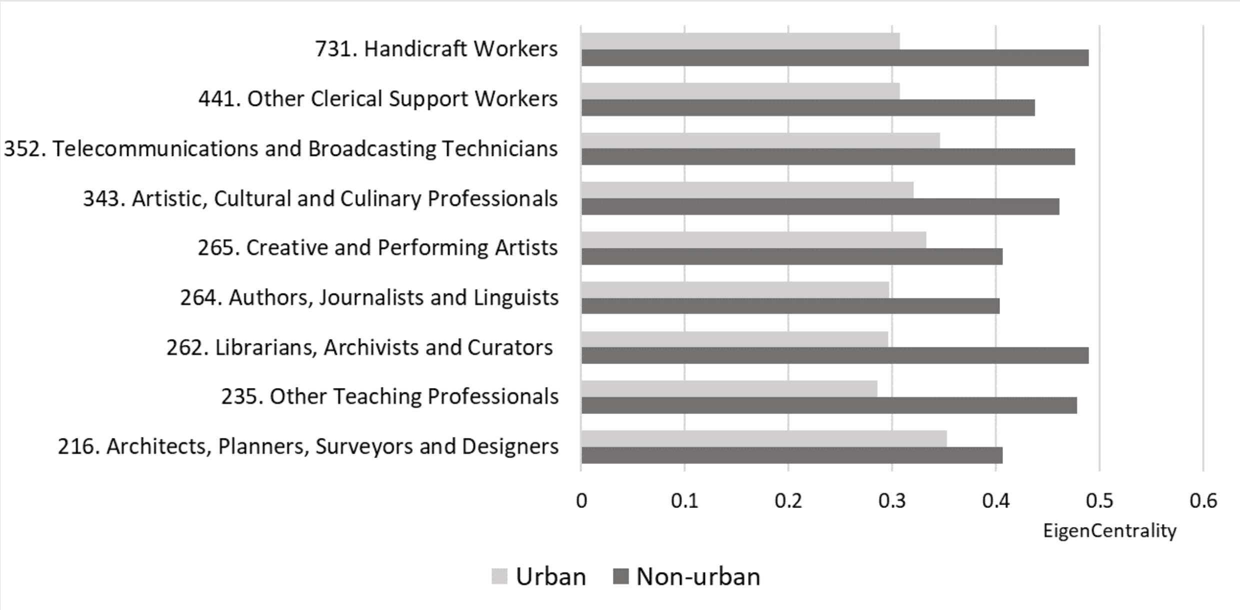


Source: Authors. Note: (a) non-urban regions; (b) urban regions.

Figure 4 (a and b) shows the eigencentrality of all 130 occupations for urban and non-urban regions. We are now interested in knowing the eigencentrality of only the CCOs (Figure 5) in order to understand whether they play a different role in the network of urban and non-urban regions. The higher the eigencentrality of an occupation, the greater the possibilities for diversification. Thus, even if a CCO is located on the network's periphery, if it has a higher eigencentrality, it still has greater possibilities for diversification than smaller eigencentralities.

The eigencentrality in non-urban regions is higher than in urban regions for all CCOs (Figure 5). On average, eigencentrality ranges from 0.4 to 0.5 in the CCOs of non-urban regions, while in urban regions, the CCOs have an average eigencentrality value of 0.3.

Figure 5: Eigencentrality for CCOs in non-urban and urban regions



Source: Authors, based on LFS.

Therefore, although CCOs are not located at the centre of the network in non-urban regions, they have a more significant potential to influence the network when compared to CCOs in urban regions. In this way, CCOs in non-urban regions have greater diversification possibilities compared to the same occupation in an urban region.

Handcraft workers (731); telecommunications and broadcasting technicians (352); artistic, cultural and culinary professionals (343); librarians, archivists and curators (262); and other teaching professional (235) have the highest eigencentrality values. It suggests those CCOs have the highest potential to promote new specialisation paths in non-urban regions.

Comparing the position of these CCOs in Figure 2 (occupation network for non-urban regions), clusters in which these CCOs are present have high proximity to professional workers, managers, services and sales workers, and technicians. Following the principle of relatedness, in non-urban areas such occupations and CCOs tend to either support each other and stimulate diversification.[4]

4.3 Trademark diversification opportunities for the European Union

In this section, we explore market diversification opportunities in terms of trademarks based on the analytical framework explained in Section 3.

In the network structure, two interconnected trademarks indicate their characteristics (technologies, utility, destination, etc.) that contribute to each other's existence. Therefore, diversification paths are more likely to occur in the direction of trademark classes that are close together in the network than in the direction of those that are not connected. As well as being more likely, they are less costly and risky than large leaps (unrelated diversification).

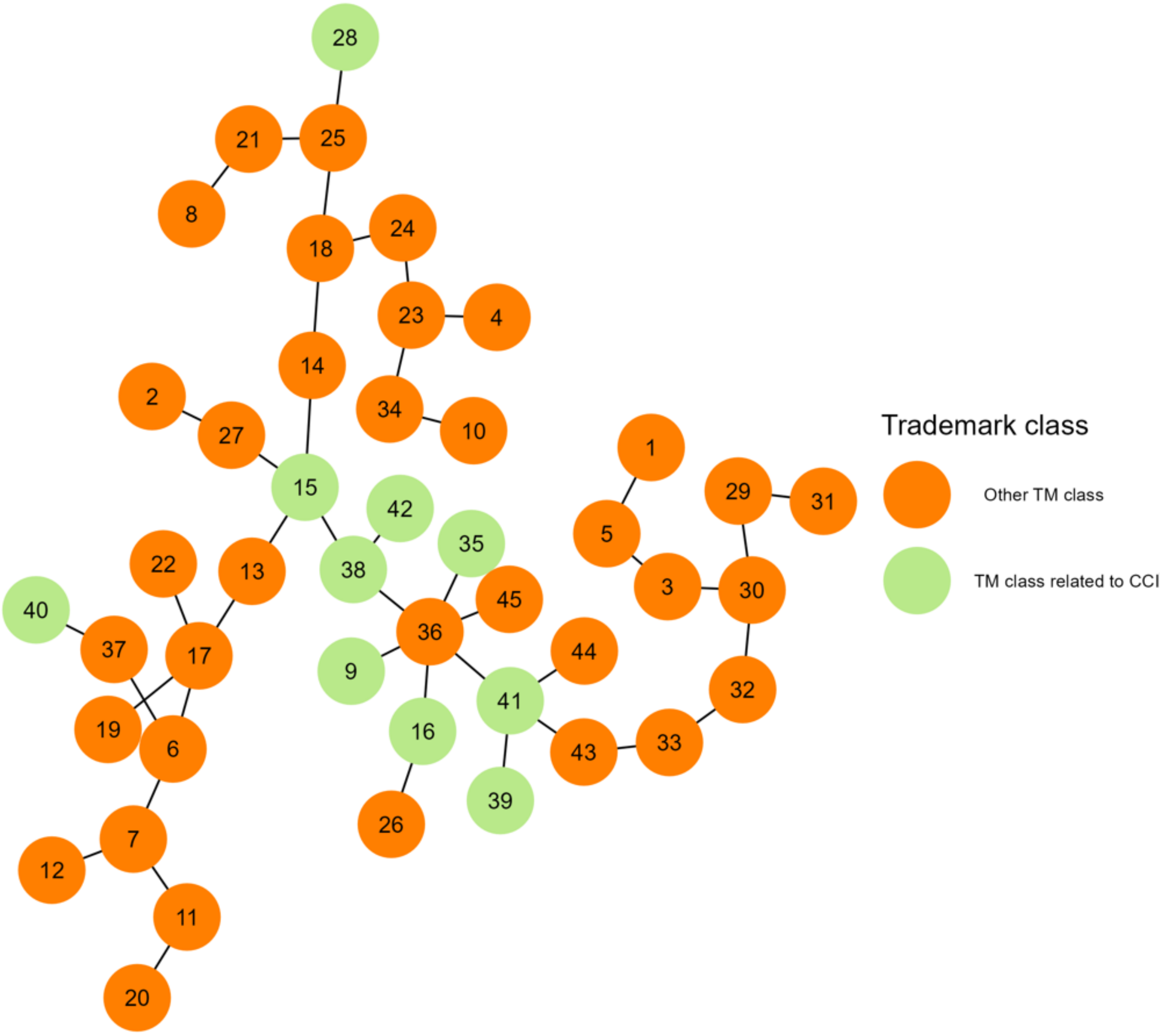
Figure 6 presents the trademark space constructed from the 45 Nice classes for the entire EU. Since we verified that the total amount of trademarks per year is relatively stable, in this case, we do not need to calculate an average period as we did for occupations. As for trademarks, we are using data from the EUIPO for the year 2019.

Here, we also applied a maximum spanning tree (MST) to build the network[5], following the Hidalgo *et al.* (2007) approach. Each node in the network represents a Nice class, and there are two colours, which represent trademark classes related to CCI and all the other classes.

[4] Understanding whether CCOs lead to diversification in professional occupations or vice versa requires research to specifically study diversification dynamics on a case-by-case study. In Section 5 we analyse the cases of the six IN SITU Lab regions.

[5] The network was visualised using "ggraph" package and "lgl" layout in the R software using Pedersen (2022).

Figure 6: Trademark space for the European Union (2019)



Source: Authors, based on EUIPO.

The visualisation of the network is neater since the total number of Nice classes is lower than the total number of ISCO codes (45 versus 130, respectively). The first observation we have of the network for the entire EU is that most of the trademark classes related to CCIs (green colour) form a cluster around class 36 - Financial affairs and real estate affairs. Only classes 28 and 40 are located further away from this cluster. Therefore, specialisation in a trademark class related to CCIs is more likely to promote diversification into other market classes that are still related to CCIs.

Secondly, we noticed some trademark classes related to CCIs operating as leading nodes within the network, i.e., operating as facilitators to connect different classes of trademarks. For example, classes 15 - Musical instruments and stands for musical instruments; 38 - Telecommunications; and 41 -

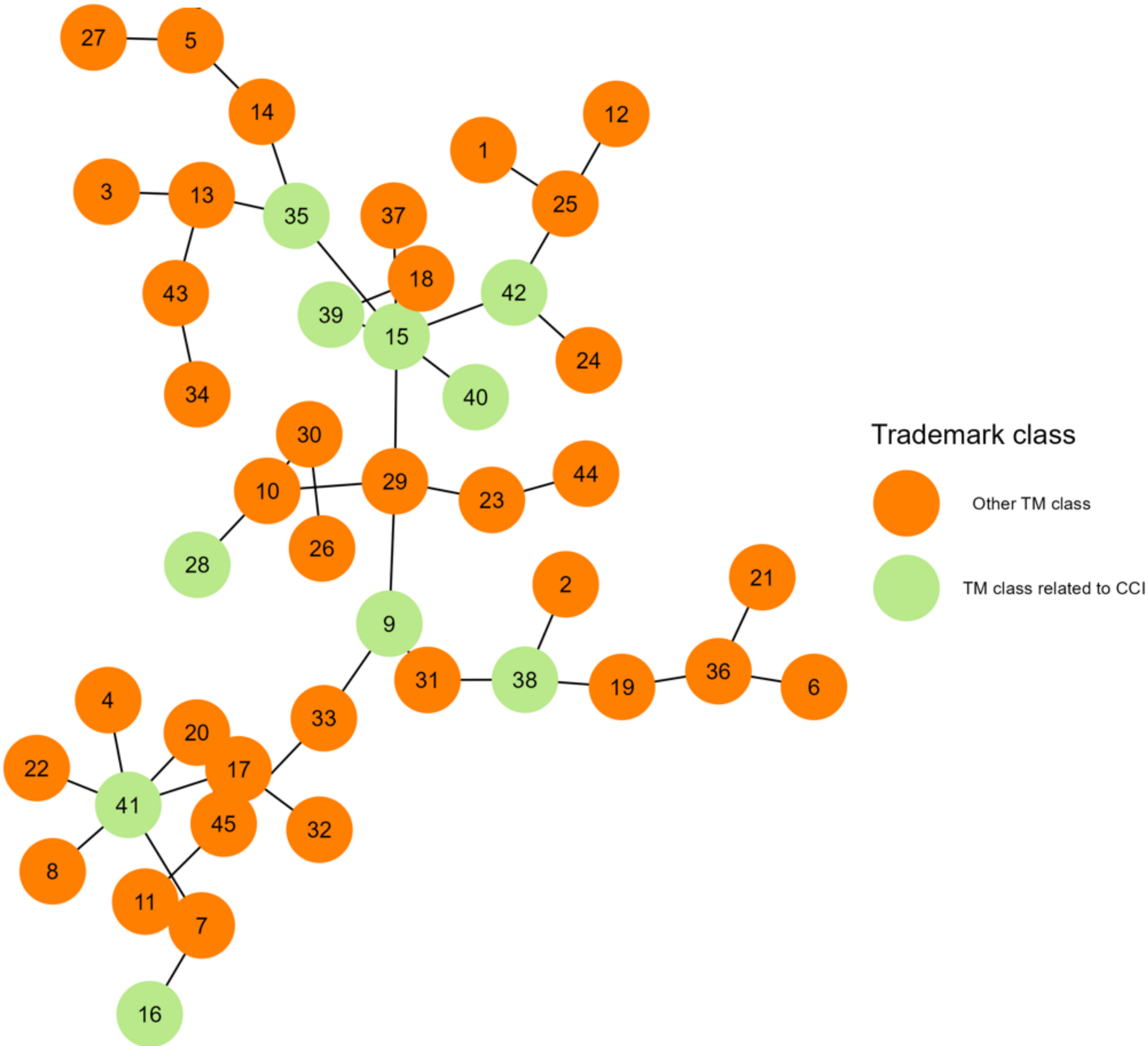
Education, training, entertainment, sporting and cultural activities. This suggests that such trademark classes are important for the process of diversification, as they connect links that would not otherwise be connected.

4.4 Trademarks diversification opportunities for non-urban and urban regions

Figure 7 presents the trademark space for non-urban regions only. For non-urban regions, the trademark space is different in terms of both the position of nodes and the links between them. There is a cluster of non-CCI classes around class 41 - Education; training; entertainment; sporting and cultural activities, which is classified as related to CCI. Class 41 connects directly with six classes of other trademarks associated with goods (which are: 4 - Industrial oils, lubricants, candles; 22 - Ropes and string, nets, sails, padding; 8 - Hand tools and implements, hand-operated; 7 - Machines tools, power-operated tools; 17 - Unprocessed and semi-processed rubber and substitutes materials, plastics and resins; and 20 - Furniture, containers, not of metal, for storage or transport). Thus, the diversification opportunities arising from the trademark class 41 point to other markets unrelated to CCIs.

Figure 7 also shows that trademark classes related to CCIs appear as relevant intermediate links connecting different branches, especially classes 9, 15 and 35. Class 9, in particular, which essentially includes equipment for scientific research, photographic, audio-visual, instruments for recording sound, images or data, is in a very important position as it connects practically all the branches of the network. Class 15, which covers musical instruments, also forms a cluster populated by trademarks related to CCI, which, at a second level of relatedness, connect to other trademarks consolidated in at least three other branches. Class 35, which involves advertising and business management, also connects two other branches of trademarks not related to CCIs.

Figure 7: Trademark space for non-urban regions in the European Union

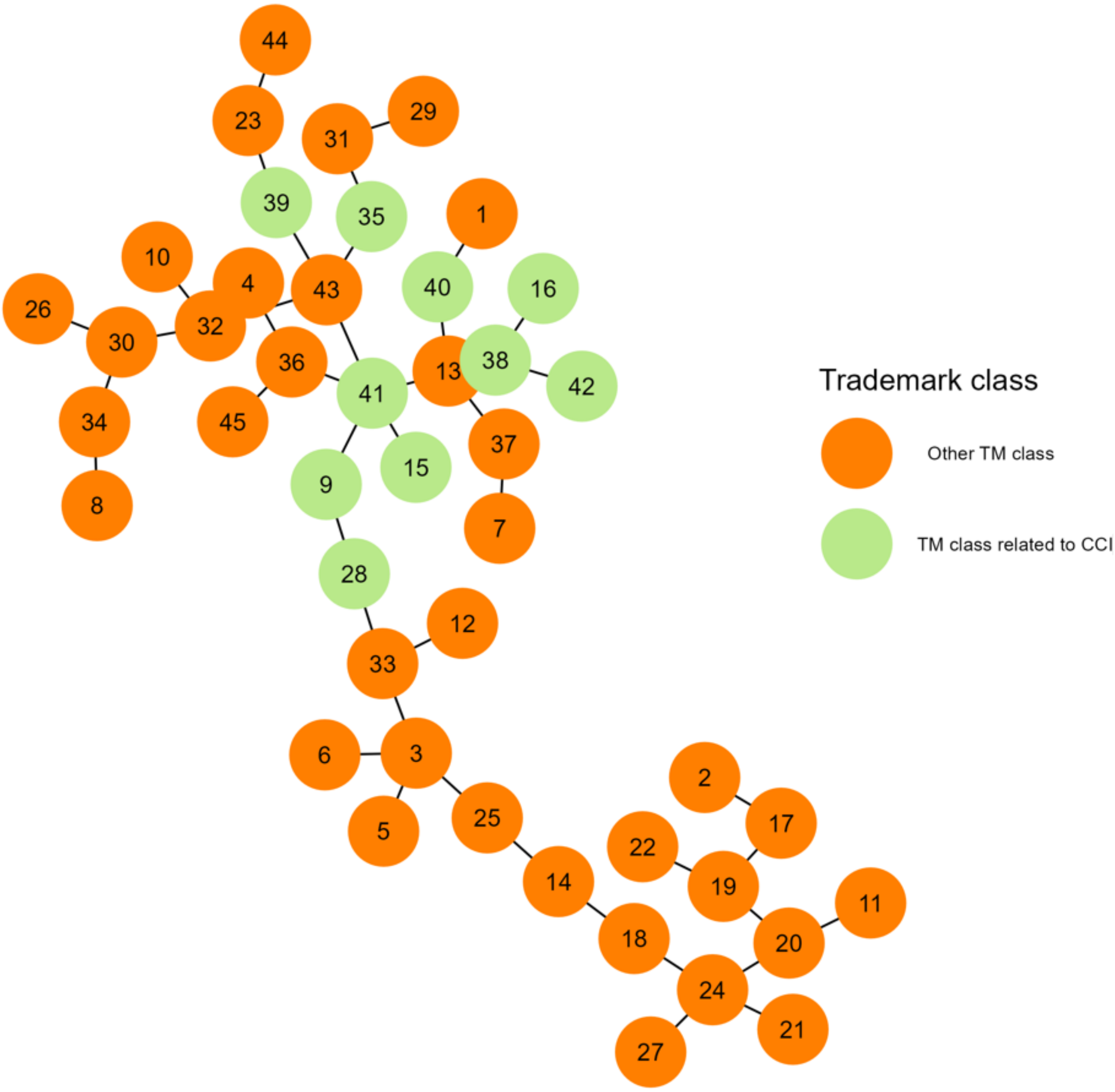


Source: Authors, based on EUIPO.

Therefore, in addition to the cluster located at the bottom left of Figure 7, which indicates diversification paths towards goods not related to CCIs, the cluster made up of class 15 is more strongly related to trademarks covering services. Thus, we can say that CCI-related trademarks have the potential to promote diversification along several paths in non-urban regions.

In Figure 8 we present the trademark space for urban regions only.

Figure 8: Trademark space for urban regions in the European Union



Source: Authors, based on EUIPO.

It is interesting to notice how the trademark space changes shape when we consider only the trademarks filed in urban regions. We can see that other trademark classes not related to the CCIs are strongly related to each other. Although there are not many central nodes in this network, they form a chain in which practically all of them function as intermediary channels, enabling diversification into other markets.

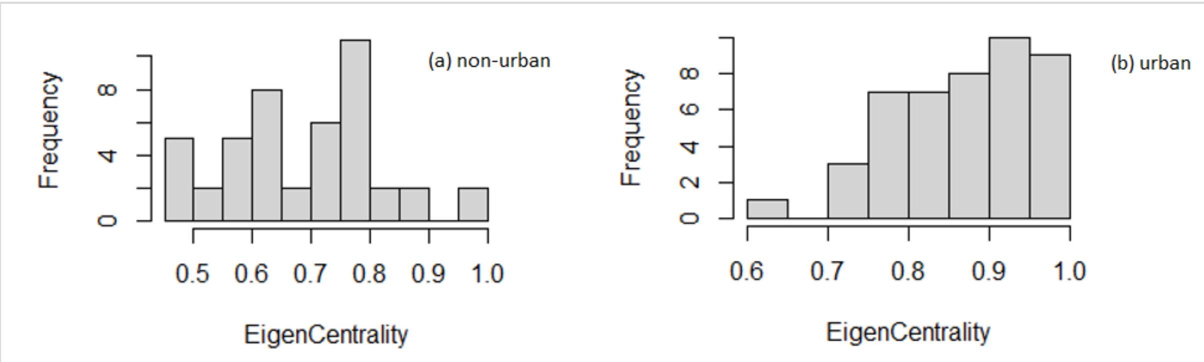
As for trademarks related to CCIs, class 41 - Education, entertainment and cultural activities has a central position with greater proximity to other non-CCI trademarks and also to other trademarks related to CCIs. Thus, diversification opportunities tend to occur in markets related to services for providing food, drink and accommodation (43); explosives and fireworks (13); and financial affairs and real estate affairs (36), in addition to other CCI-related markets.

Having evaluated the proximity network of the classes of trademarks, we wish to assess the importance of these links in the network and the frequency of their distribution. To do this, we examined the eigencentrality of the links in the network (Figure 9).

The graph on the left shows the distribution of the eigencentrality measure of the trademark classes in non-urban regions. In contrast, the chart on the right shows the results for urban regions. We can see that the distribution is more dispersed in the case of non-urban regions and more concentrated in high eigencentrality values in urban regions.

As for the frequency of trademarks classed in non-urban regions, we can see that although quite dispersed, there is a higher frequency of trademarks with eigencentrality between 0.7 and 0.8. This means that there are some trademarks (about a third of the total) that have a strong influence on the network as a whole.

Figure 9: Eigencentrality histogram for trademarks in non-urban and urban regions



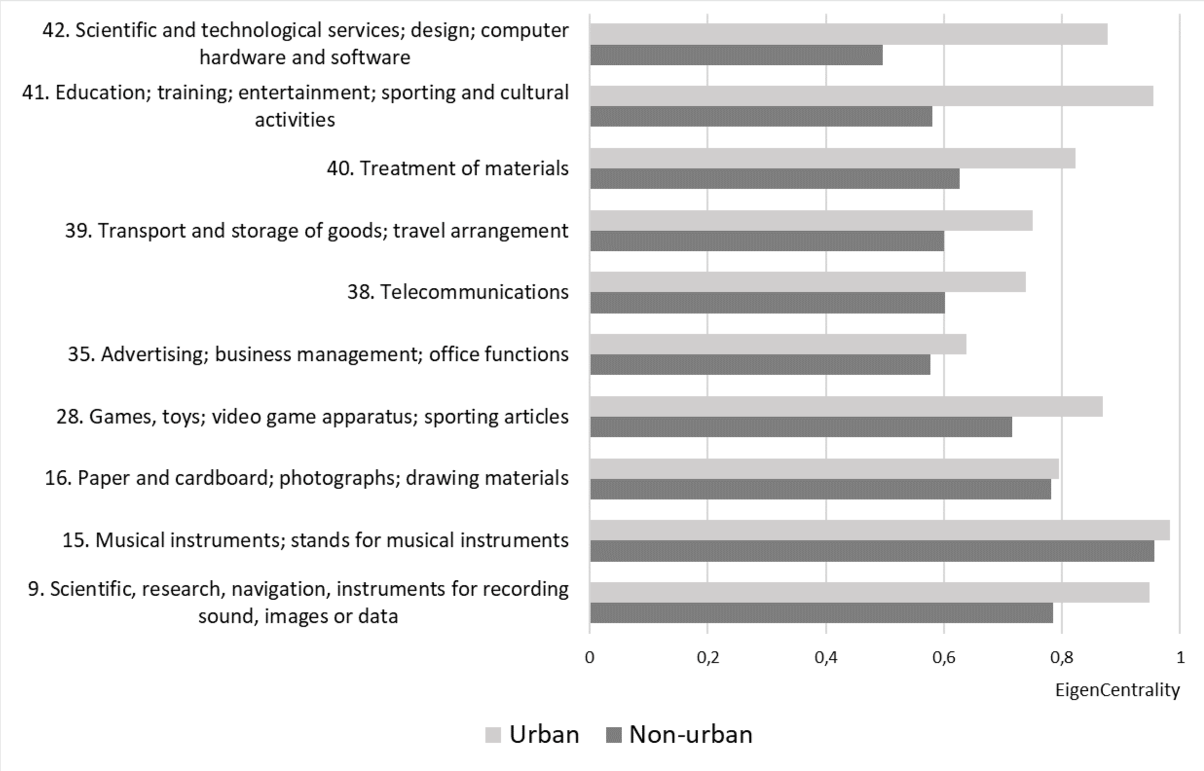
Source: Authors. Note: (a) non-urban regions; (b) urban regions.

When analysing the classes of trademarks related to CCI in depth, comparing them between non-urban and urban regions, we found that the eigencentrality for such trademark classes is higher in urban regions (Figure 10). This result suggests a strong influence over other nodes in the network of urban regions, greater than in non-urban regions.

The ability to stimulate diversification from CCI-related trademarks in urban regions to other nearby trademark classes is more uneven than in non-urban regions, especially in classes 41- Education and cultural activities; 42 - Scientific and technological services; and 40 - Treatment of material.

In the classes involving 15 - Musical instruments; and 16 - Paper and cardboard, photographs and drawing material; the ability to influence diversification is similar for both types of regions.

Figure 10: Eigencentralitry by trademark classes related to CCI in non-urban and urban regions



Source: Authors.

5. Case studies for the IN SITU Lab regions

After identifying the scenario of urban and non-urban regions, both in terms of occupations and trademarks, we will try to move forward in understanding the regions in which the IN SITU Labs are located. Six non-urban areas of the EU have been selected to host IN SITU Labs, located in Portugal, Ireland, Iceland, Finland, Latvia and Croatia.

As an additional task within the scope of this report, in Section 5.1, we selected the NUTS 2 regions where each of the IN SITU Labs belongs and calculated indicators for occupations to assess whether regions specialise in cultural and creative occupations. In Section 5.2, we aim to contribute with an illustrative scenario for trademarks related to CCI in such regions, bringing a qualitative analysis of this type of trademark in the Labs' regions.

5.1 Diversification opportunities in occupations for the IN SITU Lab regions

To introduce a characterisation of the regions we bring the comparative heatmap of occupational relatedness of the IN SITU Lab regions including all the existing occupations in the region.

Figure 11 presents the relatedness index of all 130 ISCO occupations calculated using the average value between 2018-2019. To create the heatmap we used the package elaborated by Zhao *et al.* (2021) on R software. We have placed the nine CCOs at the top of Figure 11 for easier identification.

The heatmap allows us to comparatively identify the level of relatedness of the CCOs in the general context of the structure of occupations in each region. Besides, by bringing the regions side by side in a graphic visualisation, it also compares the level of relatedness between the Lab regions.

The stronger colours indicate a higher proportion of occupational relatedness in an occupation compared to the other occupations in each region. Thus, we can see that Iceland (IS00) stands out, where CCOs have very high levels of relatedness compared to other occupations in the country. In the regions of Portugal (PT20) and Latvia (LV00), on the other hand, CCOs have a very low level of relatedness compared to the other occupations.

Figure 11: Comparative heatmap of occupational relatedness of the IN SITU Lab regions

Source: Authors based on LFS.

Next, we present the networks with the occupation space for each of the six Lab regions. We have identified the CCO and non-CCO occupations which each Lab region has a comparative advantage. To do so, we use the EconGeo package on R software (Balland, 2023).

The colours in the network indicate the type of occupation and whether the region has a revealed comparative advantage (RCA) in that occupation. The orange node refers to a specialised region (RCA > 1) in a CCO, and the yellow if the region is not specialised (RCA < 1) in that CCO. For the other occupations, blue captures specialisation (RCA > 1) and grey the opposite (RCA < 1).

To simplify the visualization of the networks, Table 4 shows the code and description of the nine occupations classified as cultural and creative.

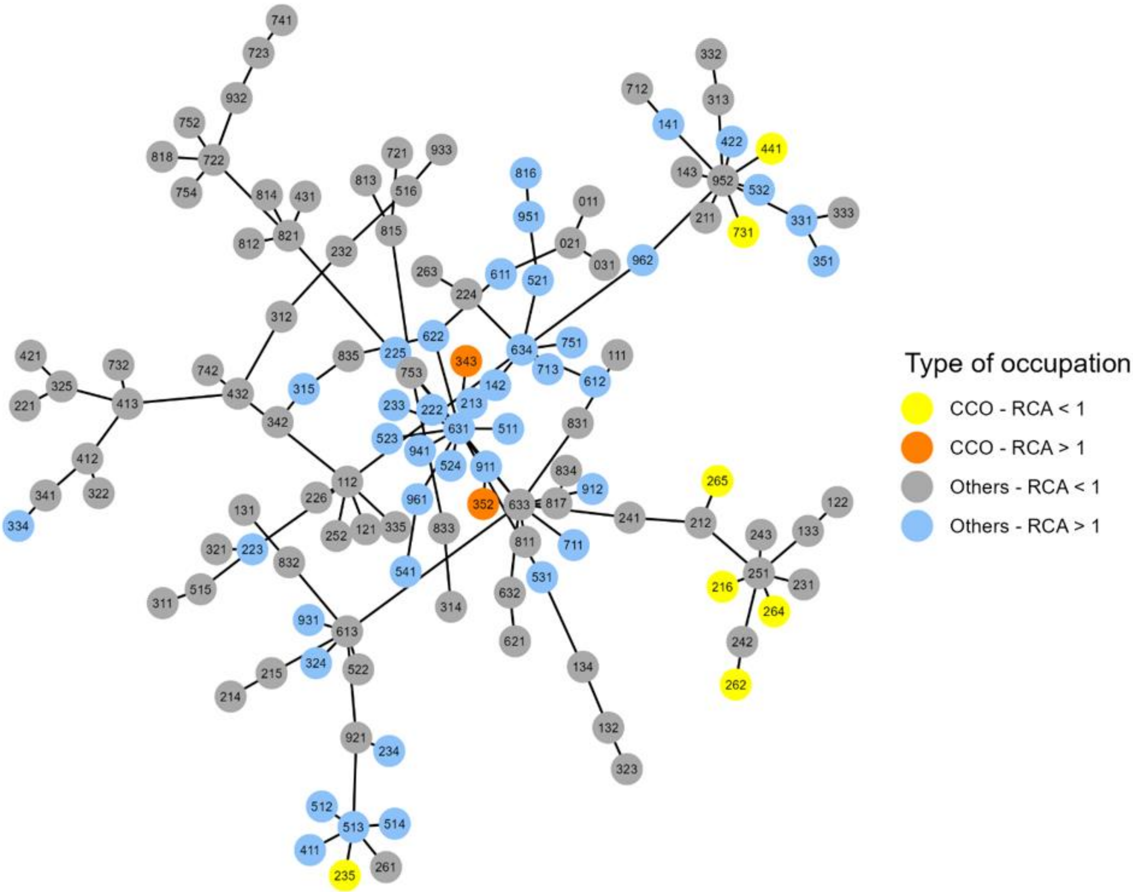
Table 4: Cultural and Creative Occupations by ISCO

ISCO-08	Cultural and creative occupations
216	Architects, planners, surveyors and designers
235	Other teaching professionals
262	Librarians, archivists and curators
264	Authors, journalists and linguists
265	Creative and performing artists
343	Artistic, cultural and culinary associate professionals
352	Telecommunications and broadcasting technicians
441	Other clerical support workers
731	Handicraft workers

Source: Authors, based on Eurostat.

Following the principle of relatedness, a region that already specialises in one occupation tends to promote diversification into nearby occupations that share the same skills and knowledge but in which the region is not yet specialised. Thus, the greater the number of occupations a region specialises in, the wider the range of diversification options, given that there will be different types of knowledge and skills already present in the region.

Figure 12: Occupation space and specialisation degree for PT20 (Autonomous Region of the Azores, Portugal)



Source: Authors.

Figure 12 shows the occupational space for the Autonomous Region of the Azores (PT20). We can see that the region specialises in two CCOs, 343 - Artistic, cultural and culinary associate professionals; and 352 - Telecommunications and broadcasting technicians. These two CCOs are located in the same cluster (in the central region of the network), which has many connections with other occupations in which the region specialises (blue colour). This means that these two occupations could become even more specialised. In addition, there are also some branches that the region does not specialise in from this central cluster, which may represent non-CCO occupations with high diversification potential.

Among the other seven CCO occupations that the Autonomous Region of the Azores has yet to specialise in, occupation 235 has the greatest potential to become specialised, as it is in a cluster (in the south of the network) where most occupations have a comparative advantage.

The other CCO occupations are close to non-specialised occupations, making it more difficult for the region to specialise in them.

The findings of report D3.1 within the IN SITU Project scope (Rainey & Collins, 2023) elucidate the cultural and creative dimension of the Lab regions[6], striving to recognise the most frequent CCI companies and jobs there. Their results (Section 5.5, D3.1) show that the Azores region has a substantial number of companies in the cultural education and recreation industry (more than 500 enterprises). We can consider that this sector is one of those that potentially employs other teaching professionals, one of the occupations that we have indicated has a high potential for specialisation.

In addition, another sector that stands out in the cultural and creative industries is film, television, music and radio businesses, which are considerable contributors to the CCIs sector with more than 300 enterprises. This industry is strongly related to the professionals that we pointed out that the region specialises in (telecommunications and broadcasting technicians).

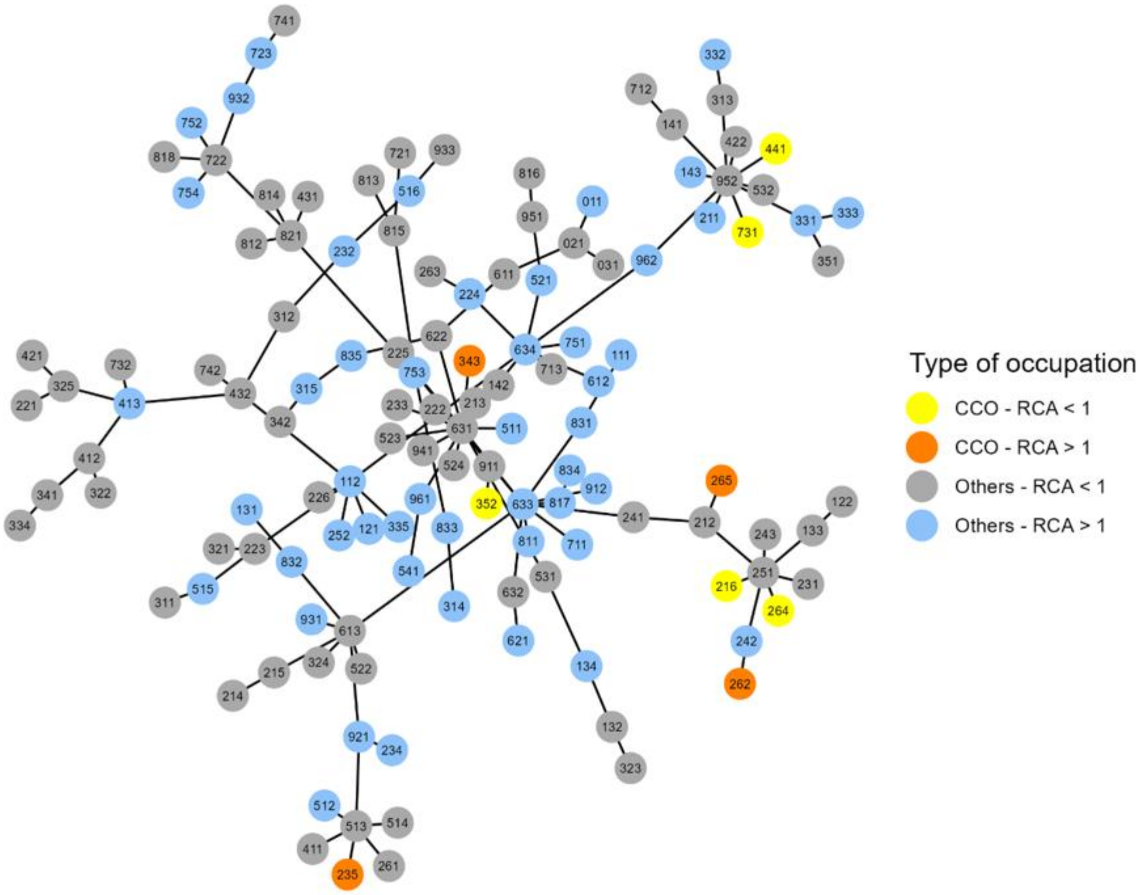
Figure 13 shows the occupation space for the Latvia region (LV00), which includes the Valmiera County region. In this case, the region specialises in four of the nine CCOs, namely: 235 - Other teaching professionals; 262 - Librarians, archivists and curators; 265 - Creative and performing artists; and 343 - Artistic, cultural and culinary associate professionals. According to Rainey & Collins (2023), Valmiera County has a significant presence in cultural education and recreation with 143 enterprises, highlighting the emphasis on cultural preservation and promotion to the public.

However, the CCOs in which the Latvia region specialises are located in clusters surrounded by other occupations in which it does not specialise (grey colours). The high proximity to these other occupations suggests the most accessible paths for diversification, for example, towards occupations 631, 513, 212 and 251, which also represent central nodes of clusters. From these more central occupations, various other occupational specialisations can be achieved due to the ease of sharing existing skills, techniques and knowledge.

Remembering that Valmiera County also has a tradition of craft manufacturing, it can promote occupational specialisation based on this industry, which covers, especially, textiles and footwear (29 companies); artisans working with glass, ceramics, stone and metals (18 companies); and perfumes, jewellery, instruments and games (13 companies), as per the D3.1 report.

[6] Report D3.1 is not a public report for reasons of privacy of the information collected from local actors. We are only quoting information from public data that can be shared and helps with the purpose of this Section.

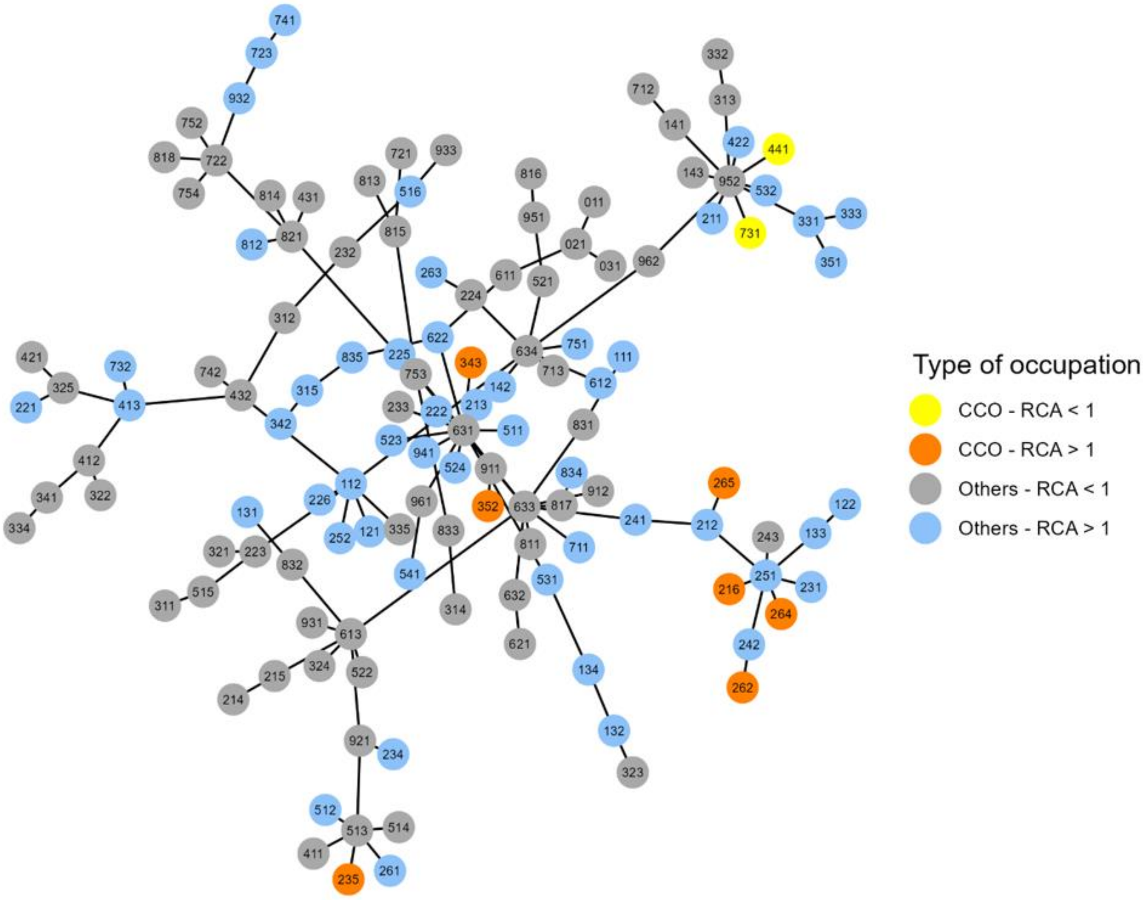
Figure 13: Occupation space and specialisation degree for LV00 (includes Valmiera County, Latvia)



Source: Authors.

Figure 14 shows the occupation space for Iceland (IS00), which includes the West Region, where the IN SITU Lab is located.

Figure 14: Occupation space and specialisation degree for IS00 (includes West Region, Iceland)



Source: Authors.

Iceland has a revealed comparative advantage in practically all CCOs except for 441 and 731 (other clerical support workers; and handicraft workers, respectively). The two occupations in which the region does not yet specialise are part of the same cluster, which is surrounded by other occupations in which the region already specialises. Thus, these two CCOs have the potential to become specialised in the future, along with some other non-CCI occupations present in the same cluster, such as occupation 952.

Report D3.1 states that in the craft sector, the West Region in particular, encapsulates a range of small companies with less than 10 employees in general, including printing; textiles and footwear; and manufacturing involving materials such as glass, ceramics, stone and metals; electronics manufacturing; and perfumes, jewellery, instruments and games. In this sense, the possible areas for specialising in handicraft workers are diverse.

We notice a highly specialised cluster (located in the bottom right corner), including four CCOs with RCA > 1. In this example, there is only one occupation, 243, in which the region has not yet developed specialisation. As this occupation is surrounded by others in which the region already specialises, there is strong potential for it to diversify and specialise in this occupation as well. The same goes for occupation 513 in the cluster located south of the network.

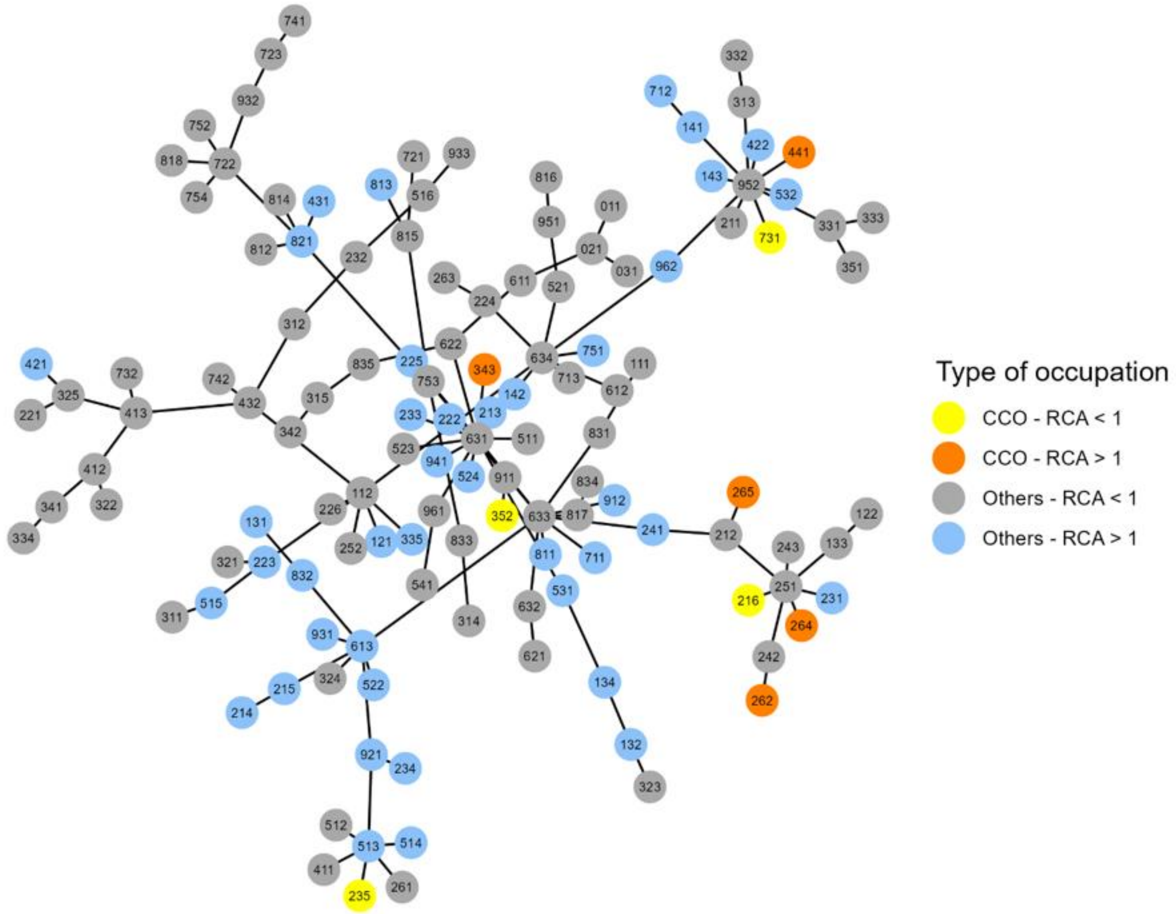
Looking at the D3.1 report, it is interesting to note that it mentions that the preservation of traditional crafts is growing along with the contemporary creative and cultural industries (Rainey & Collins, 2023). They also say that there is a diversity of enterprises in different cultural and creative industries, which have the potential to create job opportunities for the local population. It, therefore, makes sense for the region to be specialised in several CCOs, as we find in Figure 14.

Figure 15 shows the occupational specialisation of the region comprising the Western Coastal Periphery (IE04) in Ireland. We can see that this region specialises in five CCOs, and there are still many other occupations in which the region can develop revealed comparative advantage.

In this case, the occupations that comprise the cluster in the bottom right-hand corner are still areas where the country can diversify and specialise. There are CCOs in which the region specialises in this cluster, but it is still possible to develop a specialisation in CCO number 216 and other CCOs such as 251, 242 and 212. In these latter three occupations, the Irish region is not yet specialised. Still, they are directly linked to occupations in which the region already has well-established capabilities (i.e., specialisation), thus facilitating diversification towards this group of occupations.

According to the D3.1 report, the cultural and creative industries in the Western Coastal periphery of Ireland encompass a variety of areas, including software and media, architecture, design and photography, publishing, film and television, and traditional manufacturing crafts. In the creative sectors there are more than 100 enterprises, while in the cultural sector they found more than 40 enterprises.

Figure 15: Occupation space and specialisation degree for IE04 (includes Western Coastal Periphery, Ireland)



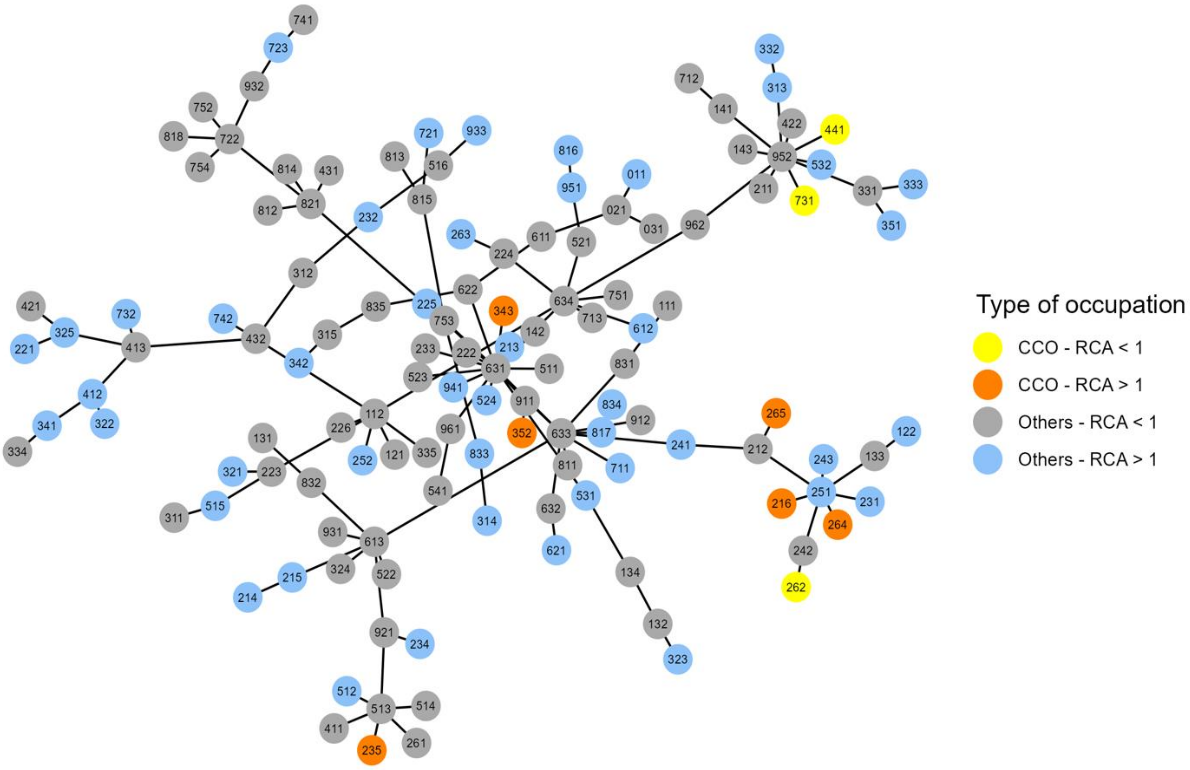
Source: Authors.

In Finland, the region hosting the IN SITU Lab is Länsi-Suomi (FI19), as shown in Figure 16. This region specialises in six of the nine CCOs.

CCOs 343 and 352 (artistic, cultural and culinary associate professionals; and telecommunications and broadcasting technicians, respectively), in which the region specialises, are part of the cluster located in the centre of the figure. In this cluster, there are still many occupations in grey, meaning the region is not yet specialised. Therefore, it represents several possibilities for diversification since, in addition to the CCOs with RCA > 1, there are some other occupations that the region also specialises in (blue colour, such as 941, 213 and 524) and can provide the prerequisite skills to develop a specialisation in the occupations that are linked but do not yet have RCA > 1. The same goes for the lower-right cluster, in which there are three CCOs with RCA > 1, and five other occupations with RCA > 1, but three occupations (212, 242 and 133) do not yet specialise.

We have seen that the Finish region where the IN SITU Lab is located has a remarkable number of companies operating in the software publishing, computer and information technology sector, with 51 companies (Rainey & Collins, 2023). According to the D3.1 report, a striking feature of the creative and cultural sectors in Rauma and Eurajoki is the role they play in preserving local heritage and, at the same time, adapting to modern demands. The architecture, design and photography sector is an excellent example of this combination, with 88 companies offering services that showcase the unique regional style and aesthetics to a global audience.

Figure 16: Occupation space and specialisation degree for FI19 (includes Länsi-Suomi region, Finland)

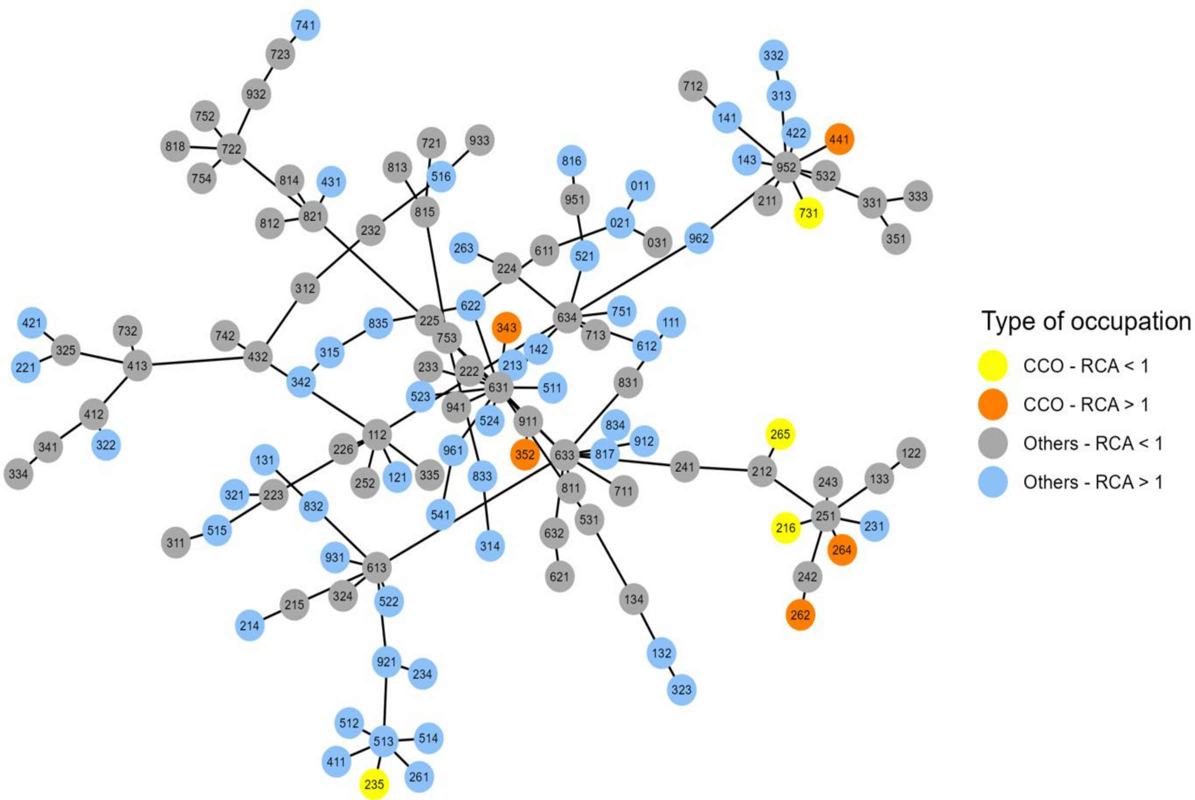


Source: Authors.

The occupation space for the HR03 region in Croatia, which includes Šibenik-Knin County, is shown in Figure 17.

Of the nine CCOs, the Croatian region specialises in five of them. As with the previous example of the Finnish region, in this case, one of the diversification options based on the CCOs in which the region already specialises points to the central cluster. In this cluster, there are also several other occupations in grey, which are, therefore, potential areas for diversification along the lines of the region's previous skills.

Figure 17: Occupation space and specialisation degree for HR03 (includes Šibenik-Knin County, Croatia)



Source: Authors.

Other possibilities for diversification can be seen in the two clusters on the right (top and bottom), in which the region shows specialisation in some CCOs. However, there is still room to develop others. For example, in the direction of occupations 242, 251 and 212, as well as CCOs 216 and 265, which do not yet appear as specialised. Report D3.1 indicates that in the region there are 91 architecture, design and photography companies that allow the local aesthetic to be celebrated and preserved, contributing to the regional brand. In addition, the cultural industries in Šibenik-Knin County reflect the rich history of the area and the commitment to cultural preservation and education, with a significant number of cultural education and recreation companies (99 in total) that emphasise the importance of culture and education (Rainey & Collins, 2023)

In the top cluster on the right of the network, we can also mention opportunities for diversifying occupations in which the region does not yet have an RCA > 1, such as 952, 712, 211 and 532, along with CCO 731.

Another important creative sector in Šibenik-Knin County includes the craft industries. They combine traditional skills with contemporary design and innovation. With 51 companies focused on the manufacture of perfumes, jewellery, instruments and games, the county showcases its creative talent and craftsmanship (Rainey & Collins, 2023), which can become areas of occupational specialisation for the region.

All these networks above show us that there are some safer and less risky diversification opportunities following the strategy of diversifying into nearby links that the region already has related capacities.

We will now try to identify which CCOs have the highest degree of proximity to the local production structure, i.e., which are most likely to become specialised in the region.

To link occupational relatedness with the economic structure of the regions, we calculated the occupational relatedness density following Hidalgo *et al.* (2007). Since relatedness density represents the distance between an occupation and the existing occupational structure in a region, we can indicate the most probable path for diversification based on the existing resources in each region. The values of relatedness density ranges between 0 and 1 (or 0 and 100 as in the graph below), with higher values indicating a higher proportion of related occupations in which the region is already specialised. This measure is shown in Figure 18.

The webs (or radar) compare the relatedness density (RD) measure between the cultural and creative occupations (CCO) for each of the Lab regions (Figure 18). The nine CCO categories are positioned at the edges of the webs. The occupations written in red highlight the CCOs in which each region is not yet specialised, in a way, are the most relevant for future diversification opportunities. The higher the relatedness density of a CCO, the greater the chance that this occupation will become part of specialisation in the region or further increase its specialisation if the region already specialises in this occupation.

Figure 18: Relatedness density for Cultural and Creative Occupation by IN SITU Lab region

Source: Authors.

Note: PT20 (Autonomous Region of the Azores, Portugal); LV00 (includes Valmiera County, Latvia); IS00 (includes West Region, Iceland); IE04 (includes Western Coastal Periphery, Ireland); FI19 (includes Länsi-Suomi region, Finland); HR03 (includes Šibenik-Knin County, Croatia)

Some observations can be made from Figure 18.

Firstly, the IN SITU Lab region in Portugal is the region with the lowest RD in all the CCOs. This suggests that the CCOs are poorly related to the region's occupation structure. Comparing this information with Figure 15 of the occupation space of PT20, in which we find that the region specialises in only two CCOs, we can say that diversification towards cultural and creative occupations still requires a lot of public policy effort for this Portuguese region.

Secondly, the IN SITU Lab regions of Croatia and Iceland have the highest RD indicators in most of the CCOs. In Iceland specifically, only CCO 731 has a low RD, one of the two CCOs in which the region is not specialised (as shown in Figure 13). For the Croatian region, there are four CCOs in which the region is not yet specialised (see Figure 19). Given the high RD of all CCOs in this region, we can say that the diversification path towards these occupations has a high probability of occurring, given that the region has other occupations that require similar characteristics already present there.

Thirdly, in the Finnish Lab region, although not all CCOs have high RD, in four of them (namely 216, 262, 264 and 265), the RD is relatively high, and in one of these occupations, 216, the region is not yet specialised. Therefore, diversification into this occupation is less costly and more likely to occur.

Fourthly, both the Irish and Latvian Lab regions don't have very high RD in CCOs, nor are they specialised in several CCOs (more specifically, the Irish region is not specialised in four CCOs while the Latvian region is not specialised in 5 of them, as shown in Figures 18 and 16, respectively). The higher the occupation's score on relatedness density, the closer, on average, it is to the existing set of occupations. Still, it is harder for those regions to become specialised in those CCOs.

To get a better idea of the participation of an individual occupation in the occupational structure of each region, we have drawn up treemaps using the package elaborated by Tennekes (2023) on R software. These figures are presented in Appendix C (Figures C.1 to C.6). They show the percentage participation in relation to the total not only of the CCOs but of each of the 130 occupations in the region. If the percentage share of an occupation is low but it has a high RD and several links to other specialised occupations, this indicates that there is room for this occupation to grow in the regional context.

It is worth mentioning that regional agencies and public policies can facilitate the process of related diversification, accelerating some of the trends portrayed in this section.

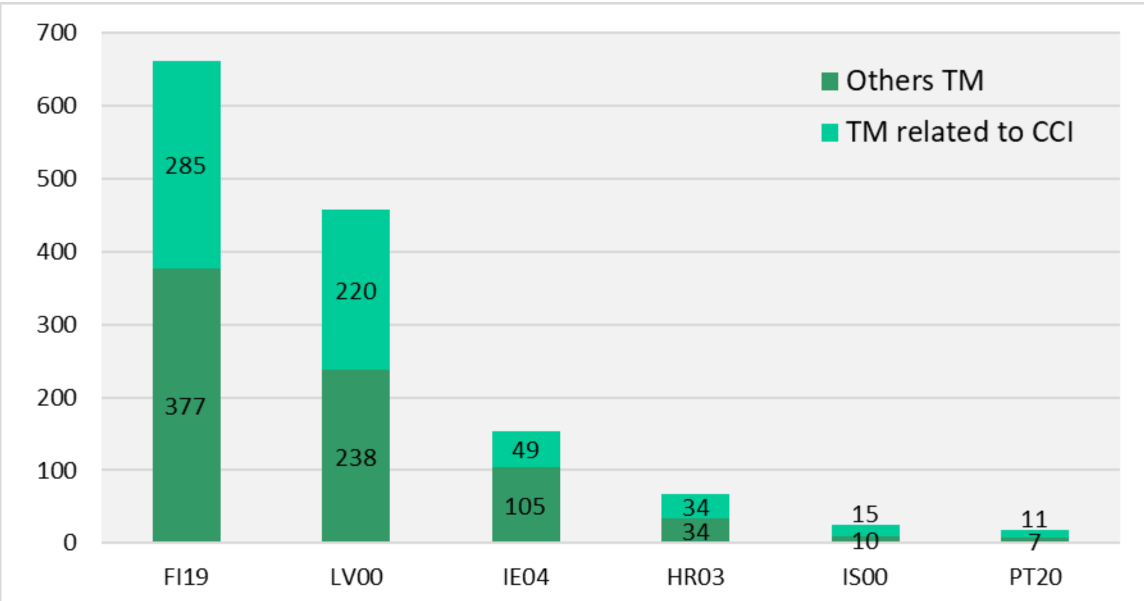
5.2 Trademarks related to CCI in the IN SITU Lab regions

This work is the first to our knowledge to identify and measure CCI-related trademarks. Leveraging our innovative approach, we also sought to broaden our knowledge of the regional characteristics of the regions hosting IN SITU Labs and to illustrate the participation of trademark classes related to CCIs in each region. The following figures will support us in this task.

As this is the first effort to measure this specific type of trademark, we present in Appendix B (Figures B.1 to B.4) a characterisation of the results found using the EUIPO dataset for the European Union as a whole.

Figure 19 shows the trademark applications in 2019 for each of the IN SITU Lab regions, subdivided by CCI-related trademarks and other trademarks. On the one hand, the regions of Finland and Latvia are the most relevant regarding trademark applications, while the regions of Iceland and Portugal have few applications.

Figure 19: Total trademark applications by IN SITU Lab region and type

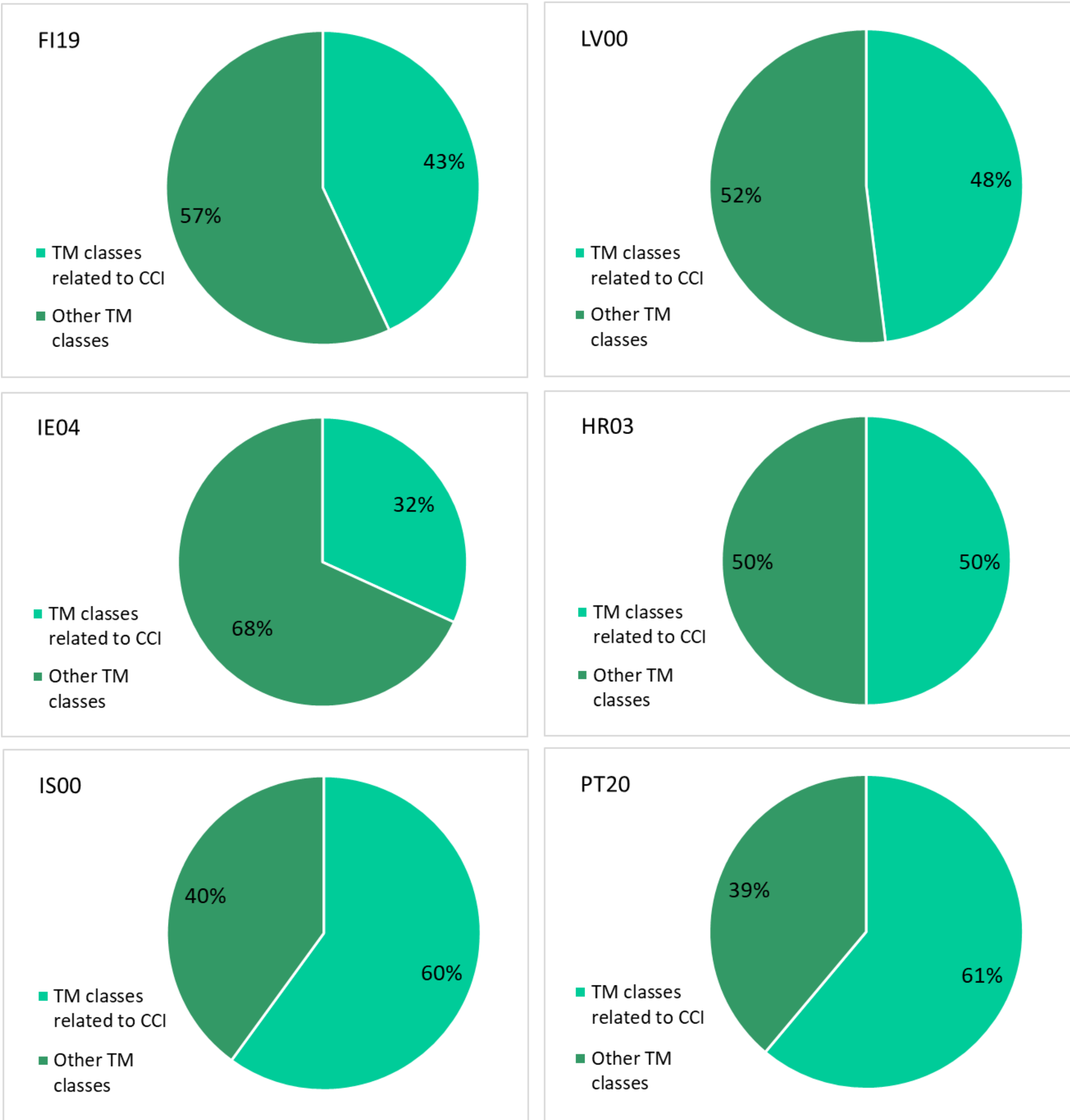


Source: Authors.

The proportion of CCI-related trademark classes varies between 32% (IE04) and 61% (PT20) of the total number of applications in the Lab regions (Figure 20). The Finnish and Latvian regions, which have the most applications compared to the other regions evaluated, have 43% and 48% in CCI-related trademark classes, respectively. A similar figure was found for Croatia (50%).

In general, in non-urban regions, the share of CCI-related trademark applications represents 59% of the total applications, while in urban regions this percentage drops to 49% (as can be seen in Appendix B, Figures B.1 and B.3).

Figure 20: Distribution of trademark applications by IN SITU Lab region and type (2019)



Source: Authors.

To find out in which classes of CCI-related trademarks the regions recorded the highest number of applications, we have drawn up Figure 21.

It is possible to identify a variety of the most frequent classes of trademarks in each of the regions. For example, classes 42, 9 and 35 (respectively, Scientific and technological services; Audio-visual apparatus and instruments; and Advertising and business management) are the most common in the Finnish region, and together account for around 70% of CCI-related trademark applications.

Although with proportionally lower values and different positions, these are also the most frequent classes in the Croatian region, accounting for 73.5% of all applications related to CCI in this region.

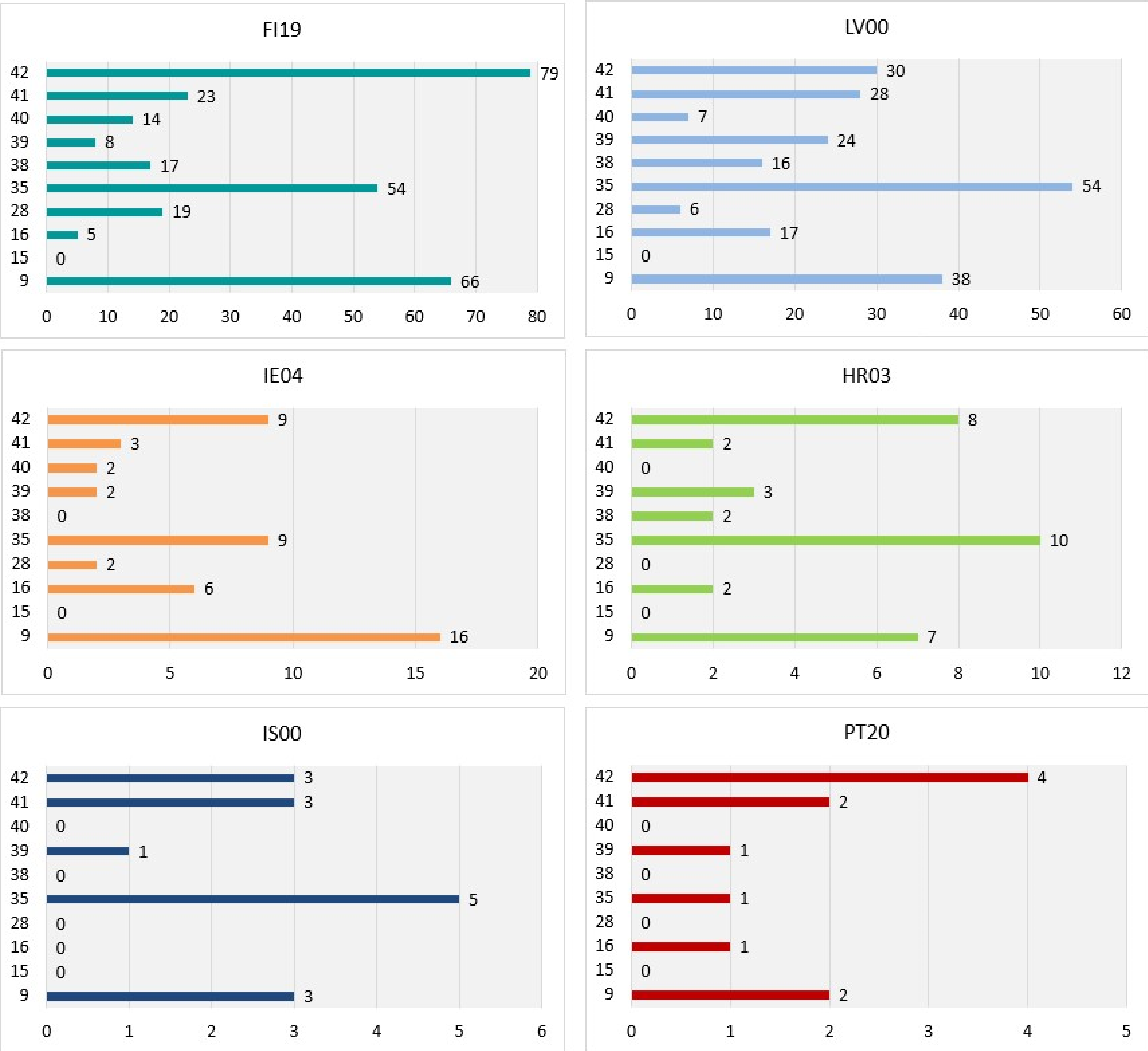
In the Latvia region, class 35 - Advertising and business management stands out. But then we notice a fine distribution in the participation of practically all the other classes, except for classes 28 and 40, which have less than ten applications in the year (in addition to class 15, which has no applications at all).

In the Irish region, class 9 - Audio-visual apparatus and instruments is the one with the largest share of CCI-related applications.

In the regions of Portugal and Iceland, there are few records of trademarks in general and related to CCIs, and they are not concentrated in just one class. In Iceland, registrations are spread over five classes and in Portugal, over six CCI-related classes.

It can be seen that there are no applications for trademarks in class 15 - Musical instruments in all regions. Some classes have no registrations in more than one region (such as classes 38, 28 and 40). Still, most classes generally have at least one application per year in the regions evaluated.

Figure 21: Distribution of trademark applications related to CCI by Nice class and IN SITU Lab region (2019)



Source: Authors.

This section was an initial effort to shed light on the regions of the IN SITU Labs about CCI-related trademarks. Subsequently, more research can be done to qualify better the profile of trademarks and the potential for new avenues for developing these market specialisations in non-urban regions.

This could also be an input for studies based on evolutionary framework of regional resilience (Crespo *et al.,* 2014) investigating how non-urban regions – or even the Lab regions – could promote growth using their local capabilities without getting lost in regional lock-out.

6. Final remarks

The main objective of this report was to identify opportunities for diversification for non-urban regions that stem from creative and cultural activities. To this end, we leveraged different contributions in the burgeoning literature on evolutionary economic geography and applied the relatedness approach to the context of creative and cultural occupations and trademarks in non-urban regions in Europe.

Three main findings emerge from our analysis.

Firstly, creative and cultural occupations play a fundamental role in non-urban regions. When considering the structure of the occupation space (Figures 2 and 3), the nodes representing CCOs appear to be much more central in the network for non-urban regions than for urban regions. This visual intuition is confirmed when studying the eigenvector centrality of each CCOs, which has systematically higher centrality scores in the case of non-urban regions (Figure 5). Importantly, this suggests that CCOs are positioned at or in close proximity to the core of the network of economic activities in CCOs and are, therefore, playing an essential role in the diversification dynamics of non-urban regions.

Secondly, the role of creative and cultural trademarks in non-urban regions appears to be much less marked than for occupations. Comparing networks of urban and non-urban regions, the nodes of creative trademarks are much more central in the former and more peripheral in the latter. The analysis of eigenvector centrality confirms this finding, highlighting a lower potential for market diversification opportunities in non-urban regions. When evaluating the six regions where the IN SITU Labs are located, we also identified a low number of trademark applications in some of them, indicating that trademarks are still being underused and the potential linked to this form of intellectual protection is not being tapped. This might be due to the smaller size of non-urban markets, but also to a potential lack of market and commercialisation capabilities.

Lastly, our analysis sheds important light on possible diversification dynamics for CCOs in IN SITU Labs regions. In this respect, creative and cultural workers across these six non-urban regions face somewhat different situations. While part of the higher density scores for the case of Iceland and Latvia may be affected by the data available from Eurostat, it is interesting to see how CCOs are very strongly connected to other occupations in regions like Šibenik-Knin (Croatia) and Länsi-Suomi (Finland).

We should also stress that our approach is not void of limitations, especially in terms of data. The main issues in this sense have to do with the granularity of the data both in terms of occupations as well as in terms of geography.

First, as for the geographical level, the limitation of the data to define urban and non-urban regions requires more validity checks with different classifications. For instance, some non-urban regions may have the characteristics of urban regions due to a consistent urban or populational agglomeration in the surrounding area. This could be circumvented by making official statistics available at more granular regional breakdown levels (i.e., NUTS 3 regions) enabling public policies to be proposed and evaluated more effectively.

Second, as for occupational data, this work went beyond the industry perspective to discuss the contribution of workers to regional cultural and creative activity. The focus on CCO highlighted a complement to the understanding regional performance. However, the level of occupational classification available currently (i.e., ISCO 3-digit) did not allow us to carry out a more specific analysis of occupations exclusively associated with culture and creativity. In this sense, making access to cultural and creative occupation data at ISCO 4-digit public could improve the results of this and future research. Besides, researchers can also go further and investigate occupations focus on the skills demanded by CCOs and possible ramifications for other occupations.

A third issue relates to the definition of creative and cultural occupations and trademarks. Our attempt to define trademarks related to the CCOs was experimental and is open for further methodological work. We provided a first qualitative overview of how regions protect cultural and creative activities developed locally. In this sense, the selection can be refined to include other activities, for example chefs and culinary arts, which may be considered important for the cultural and creative activity of regions. Another specific group of trademarks and intellectual protection – that can be even more important in non-urban contexts – is the geographical indication of origin, most used for food, drink and agricultural products, could also be included in the future analysis.

Moreover, if creative and cultural goods are mostly provided locally, they might not be captured well with international trademark filings. Further research could rely on national filings. However, issues related to differences in procedures adopted in granting trademarks and language differences make it difficult to jointly analyse across countries without using international trademark filings.

In this sense, exploring further and understanding the differences between the analysis using different regional level, CCOs and trademarks will be necessary.

While we rely on methodologies frequently used in the relevant literature and, therefore, our approach is in line with the state of the art, the approaches are still exploratory and need further validation for different regional levels.

Despite these limitations, this deliverable has offered an original take on how non-urban regions can spur development paths stemming from their creative and cultural activities.

Leveraging established theories and frameworks on novel datasets has provided a fresh perspective that can inform research and policy alike. While many publications concluded that non-urban regions may not have many diversification opportunities (e.g., Pinheiro *et al.,* 2022a), our analyses show that this deserves closer attention. Non-urban regions may be able to develop and take advantage of diversification opportunities, especially if occupations and trademarks with greater potential are identified and supported by local policy interventions.

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Appendices

Appendix A – List of Nice classes and full description

Nice Class	Trademark type	Nice description
1	Others TM	Chemicals for use in industry, science and photography, as well as in agriculture, horticulture and forestry; unprocessed artificial resins, unprocessed plastics; fire extinguishing and fire prevention compositions; tempering and soldering preparations; substances for tanning animal skins and hides; adhesives for use in industry; putties and other paste fillers; compost, manures, fertilizers; biological preparations for use in industry and science.
2	Others TM	Paints, varnishes, lacquers; preservatives against rust and against deterioration of wood; colorants, dyes; inks for printing, marking and engraving; raw natural resins; metals in foil and powder form for use in painting, decorating, printing and art.
3	Others TM	Non-medicated cosmetics and toiletry preparations; non-medicated dentifrices; perfumery, essential oils; bleaching preparations and other substances for laundry use; cleaning, polishing, scouring and abrasive preparations.
4	Others TM	Industrial oils and greases, wax; lubricants; dust absorbing, wetting and binding compositions; fuels and illuminants; candles and wicks for lighting.
5	Others TM	Pharmaceuticals, medical and veterinary preparations; sanitary preparations for medical purposes; dietetic food and substances adapted for medical or veterinary use, food for babies; dietary supplements for human beings and animals; plasters, materials for dressings; material for stopping teeth, dental wax; disinfectants; preparations for destroying vermin; fungicides, herbicides.
6	Others TM	Common metals and their alloys, ores; metal materials for building and construction; transportable buildings of metal; non-electric cables and wires of common metal; small items of metal hardware; metal containers for storage or transport; safes.
7	Others TM	Machines, machine tools, power-operated tools; motors and engines, except for land vehicles; machine coupling and transmission components, except for land vehicles; agricultural implements, other than hand-operated hand tools; incubators for eggs; automatic vending machines.
8	Others TM	Hand tools and implements, hand-operated; cutlery; side arms, except firearms; razors.
9	TM related to CCI	Scientific, research, navigation, surveying, photographic, cinematographic, audiovisual, optical, weighing, measuring, signaling, detecting, testing, inspecting, life-saving and teaching apparatus and instruments; apparatus and instruments for conducting, switching, transforming, accumulating, regulating or controlling the distribution or use of electricity; apparatus and instruments for recording, transmitting, reproducing or processing sound, images or data; recorded and downloadable media, computer software, blank digital or analogue recording and storage media; mechanisms for coin-operated apparatus; cash registers, calculating devices; computers and computer peripheral devices; diving suits, divers' masks, ear plugs for divers, nose clips for divers and swimmers, gloves for divers, breathing apparatus for underwater swimming; fire-extinguishing apparatus.

Nice Class	Trademark type	Nice description
10	Others TM	Surgical, medical, dental and veterinary apparatus and instruments; artificial limbs, eyes and teeth; orthopedic articles; suture materials; therapeutic and assistive devices adapted for the disabled; massage apparatus; apparatus, devices and articles for nursing infants; sexual activity apparatus, devices and articles.
11	Others TM	Apparatus and installations for lighting, heating, cooling, steam generating, cooking, drying, ventilating, water supply and sanitary purposes.
12	Others TM	Vehicles; apparatus for locomotion by land, air or water.
13	Others TM	Firearms; ammunition and projectiles; explosives; fireworks.
14	Others TM	Precious metals and their alloys; jewellery, precious and semi-precious stones; horological and chronometric instruments.
15	TM related to CCI	Musical instruments; music stands and stands for musical instruments; conductors' batons.
16	TM related to CCI	Paper and cardboard; printed matter; bookbinding material; photographs; stationery and office requisites, except furniture; adhesives for stationery or household purposes; drawing materials and materials for artists; paintbrushes; instructional and teaching materials; plastic sheets, films and bags for wrapping and packaging; printers' type, printing blocks.
17	Others TM	Unprocessed and semi-processed rubber, gutta-percha, gum, asbestos, mica and substitutes for all these materials; plastics and resins in extruded form for use in manufacture; packing, stopping and insulating materials; flexible pipes, tubes and hoses, not of metal.
18	Others TM	Leather and imitations of leather; animal skins and hides; luggage and carrying bags; umbrellas and parasols; walking sticks; whips, harness and saddlery; collars, leashes and clothing for animals.
19	Others TM	Leather and imitations of leather; animal skins and hides; luggage and carrying bags; umbrellas and parasols; walking sticks; whips, harness and saddlery; collars, leashes and clothing for animals.
20	Others TM	Furniture, mirrors, picture frames; containers, not of metal, for storage or transport; unworked or semi-worked bone, horn, whalebone or mother-of-pearl; shells; meerschaum; yellow amber.
21	Others TM	Household or kitchen utensils and containers; cookware and tableware, except forks, knives and spoons; combs and sponges; brushes, except paintbrushes; brush-making materials; articles for cleaning purposes; unworked or semi-worked glass, except building glass; glassware, porcelain and earthenware.
22	Others TM	Ropes and string; nets; tents and tarpaulins; awnings of textile or synthetic materials; sails; sacks for the transport and storage of materials in bulk; padding, cushioning and stuffing materials, except of paper, cardboard, rubber or plastics; raw fibrous textile materials and substitutes therefor.
23	Others TM	Yarns and threads for textile use.
24	Others TM	Textiles and substitutes for textiles; household linen; curtains of textile or plastic.
25	Others TM	Clothing, footwear, headwear.
26	Others TM	Lace, braid and embroidery, and haberdashery ribbons and bows; buttons, hooks and eyes, pins and needles; artificial flowers; hair decorations; false hair.
27	Others TM	Carpets, rugs, mats and matting, linoleum and other materials for covering existing floors; wall hangings, not of textile.

Nice Class	Trademark type	Nice description
28	TM related to CCI	Games, toys and playthings; video game apparatus; gymnastic and sporting articles; decorations for Christmas trees.
29	Others TM	Meat, fish, poultry and game; meat extracts; preserved, frozen, dried and cooked fruits and vegetables; jellies, jams, compotes; eggs; milk, cheese, butter, yoghurt and other milk products; oils and fats for food.
30	Others TM	Coffee, tea, cocoa and artificial coffee; rice, pasta and noodles; tapioca and sago; flour and preparations made from cereals; bread, pastries and confectionery; chocolate; ice cream, sorbets and other edible ices; sugar, honey, treacle; yeast, baking-powder; salt, seasonings, spices, preserved herbs; vinegar, sauces and other condiments; ice (frozen water).
31	Others TM	Raw and unprocessed agricultural, aquacultural, horticultural and forestry products; raw and unprocessed grains and seeds; fresh fruits and vegetables, fresh herbs; natural plants and flowers; bulbs, seedlings and seeds for planting; live animals; foodstuffs and beverages for animals; malt.
32	Others TM	Beers; non-alcoholic beverages; mineral and aerated waters; fruit beverages and fruit juices; syrups and other non-alcoholic preparations for making beverages.
33	Others TM	Alcoholic beverages, except beers; alcoholic preparations for making beverages.
34	Others TM	Tobacco and tobacco substitutes; cigarettes and cigars; electronic cigarettes and oral vaporizers for smokers; smokers' articles; matches.
35	TM related to CCI	Advertising; business management; business administration; office functions.
36	Others TM	Insurance; financial affairs; monetary affairs; real estate affairs.
37	Others TM	Building construction; repair; installation services.
38	TM related to CCI	Telecommunications.
39	TM related to CCI	Transport; packaging and storage of goods; travel arrangement.
40	TM related to CCI	Treatment of materials.
41	TM related to CCI	Education; providing of training; entertainment; sporting and cultural activities.
42	TM related to CCI	Scientific and technological services and research and design relating thereto; industrial analysis and industrial research services; design and development of computer hardware and software.
43	Others TM	Services for providing food and drink; temporary accommodation.
44	Others TM	Medical services; veterinary services; hygienic and beauty care for human beings or animals; agriculture, horticulture and forestry services.
45	Others TM	Legal services; security services for the physical protection of tangible property and individuals; personal and social services rendered by others to meet the needs of individuals.

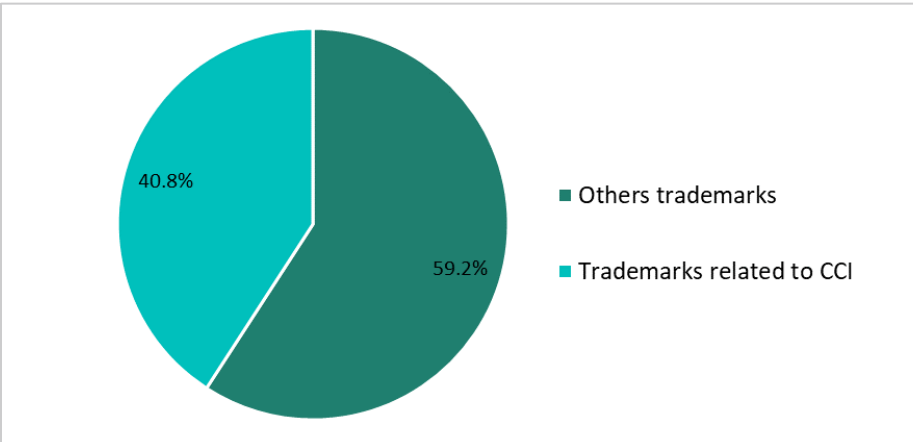
Source: Authors based on EUIPO.

Appendix B – Descriptive analysis of trademarks related to CCI

According to the methodology described in Section 3.2.2, we based ourselves on Zolas, Lybbert & Bhattacharyya (2017) to connect trademark classes to industrial classifications to later identify trademark classes related to cultural and creative activities. As this is the first effort to measure this specific type of trademark, we will present below a characterisation of the results found using the EUIPO dataset.

Figures B.1 and B.2 show information about CCI-related and non-CIC-related trademark classes for non-urban regions. Of the total of approximately 119,6 thousand trademark applications in 2019, 40.8% referred to Nice classes classified as CCI-related (Figure B.1).

Figure B.1: Total trademark applications in non-urban regions – by type (2019)



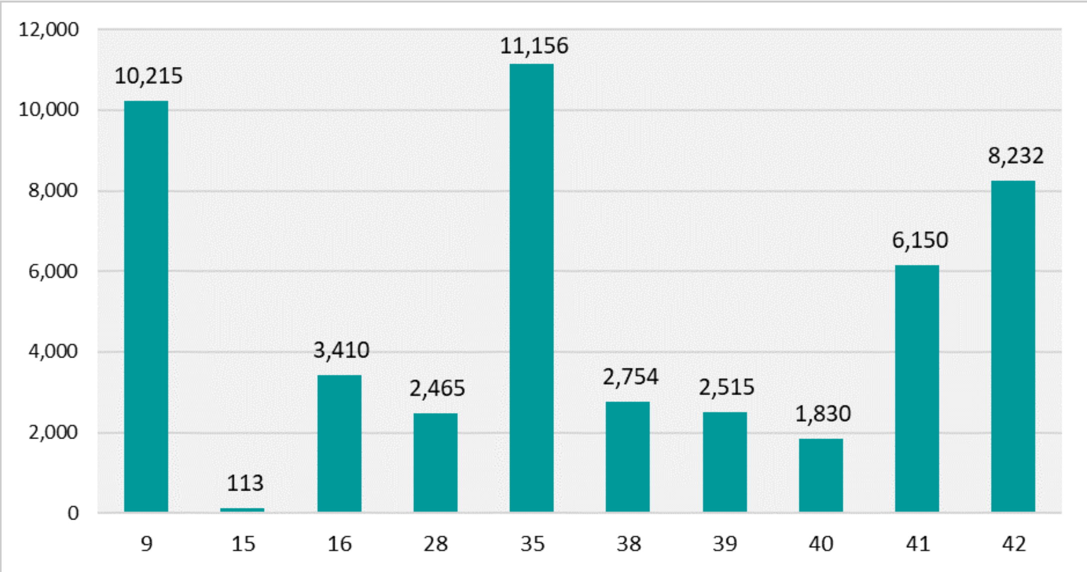
Source: Authors.

Our methodology for identifying trademark classes related to CCI resulted in a group of 10 classes. Figure B.2 shows trademark applications that mention one of these 10 classes for non-urban regions. With the exception of class 15 (Musical instruments), all classes had at least 1,000 applications, and four classes accounted for 73% of all CCI-related applications.

Of these four classes, two are related to goods and two to services. The two goods classes were the most cited in the year evaluated: 9 - Scientific, research, navigation, photographic, cinematographic, audiovisual, optical, and measuring apparatus and instruments, instruments for recording sound, images or data; and 35 – Advertising and business management (respectively, 10,215 and 11,156).

Next, two classes of services appear at the top of the rank of CCI-related applications (Figure B.2): 41 – Education, training, entertainment, sporting and cultural activities; and 42 - Scientific and technological services and research and design, industrial research services, design and development of computer hardware and software (totalling respectively 6,150 and 8,232 applications in the period).

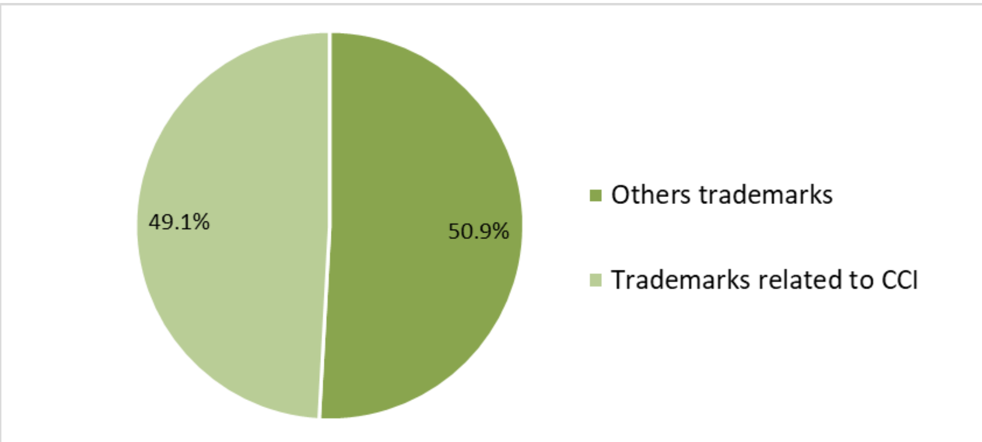
Figure B.2: Total trademark applications in non-urban regions by Nice class related to CCI (2019)



Source: Authors.

We also identified the distribution of trademark classes related to CCI in urban contexts in 2019 (Figure B.3). In this case, the share of trademark classes related to CCI (49.1%) is very similar to the other trademarks (50.9% of the total).

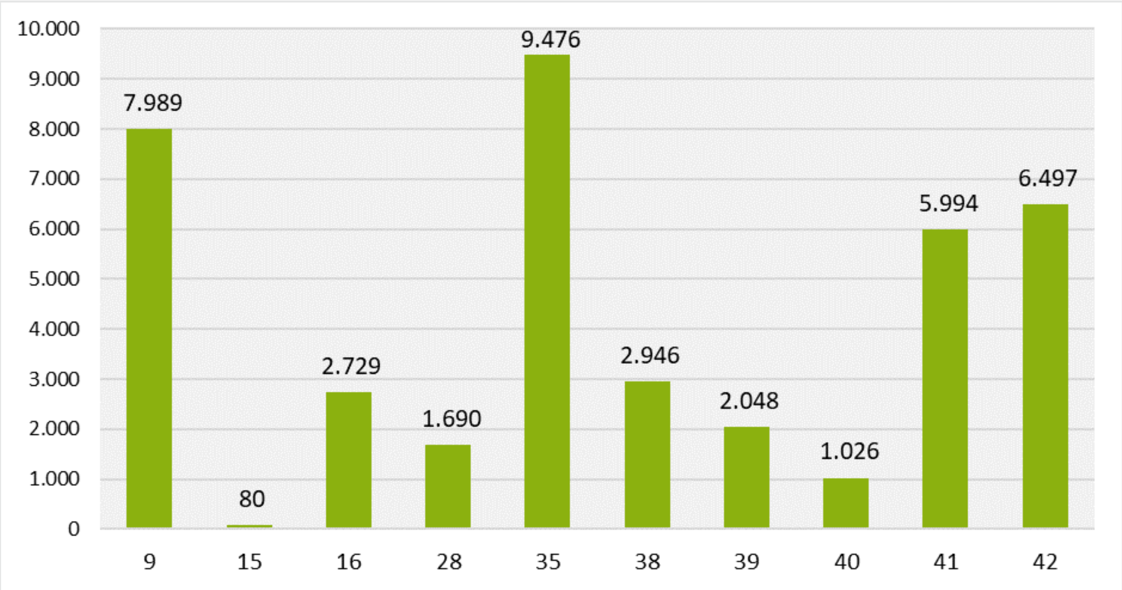
Figure B.3: Total trademark applications in urban regions – by type (2019)



Source: Authors.

As in the non-urban regions, there is also a high concentration in the same four Nice classes related to CCI in the urban regions (Figure B.4). In fact, Figure B.4 is very similar to Figure B.2. Thus, whether the region is urban or non-urban matters little to the relative distribution between the 10 Nice classes related to CCI.

Figure B.4: Total trademark applications in urban regions by Nice class related to CCI (2019)



Source: Authors.

Appendix C – Treemap by occupation of the IN SITU Lab regions

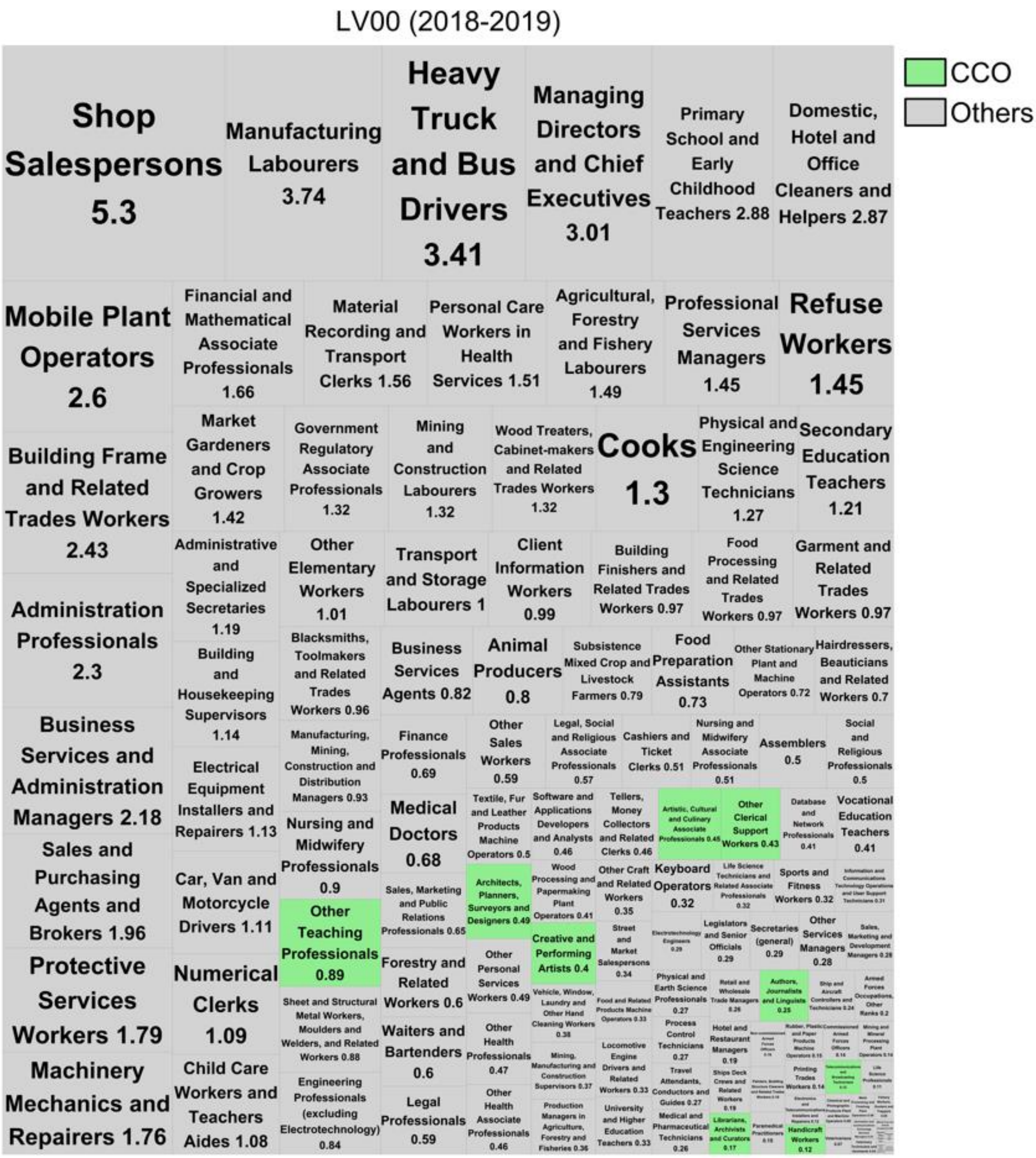
We have drawn up the treemaps using the package elaborated by Tennekes (2023) on R software. We calculated the average number of occupations for 2018 and 2019 to avoid sporadic shocks from a specific year. Figure C.1 shows the participation of all occupations in the occupational structure of the Autonomous Region of the Azores (PT20).

Figure C.1 - Percentage distribution of occupations in the region PT20

Source: Authors based on LFS.

Figure C.2 shows the participation of all occupations in the occupational structure of the Latvia region (LV00), which includes the Valmiera County region.

Figure C.2 - Percentage distribution of occupations in the region LV00



Source: Authors based on LFS.

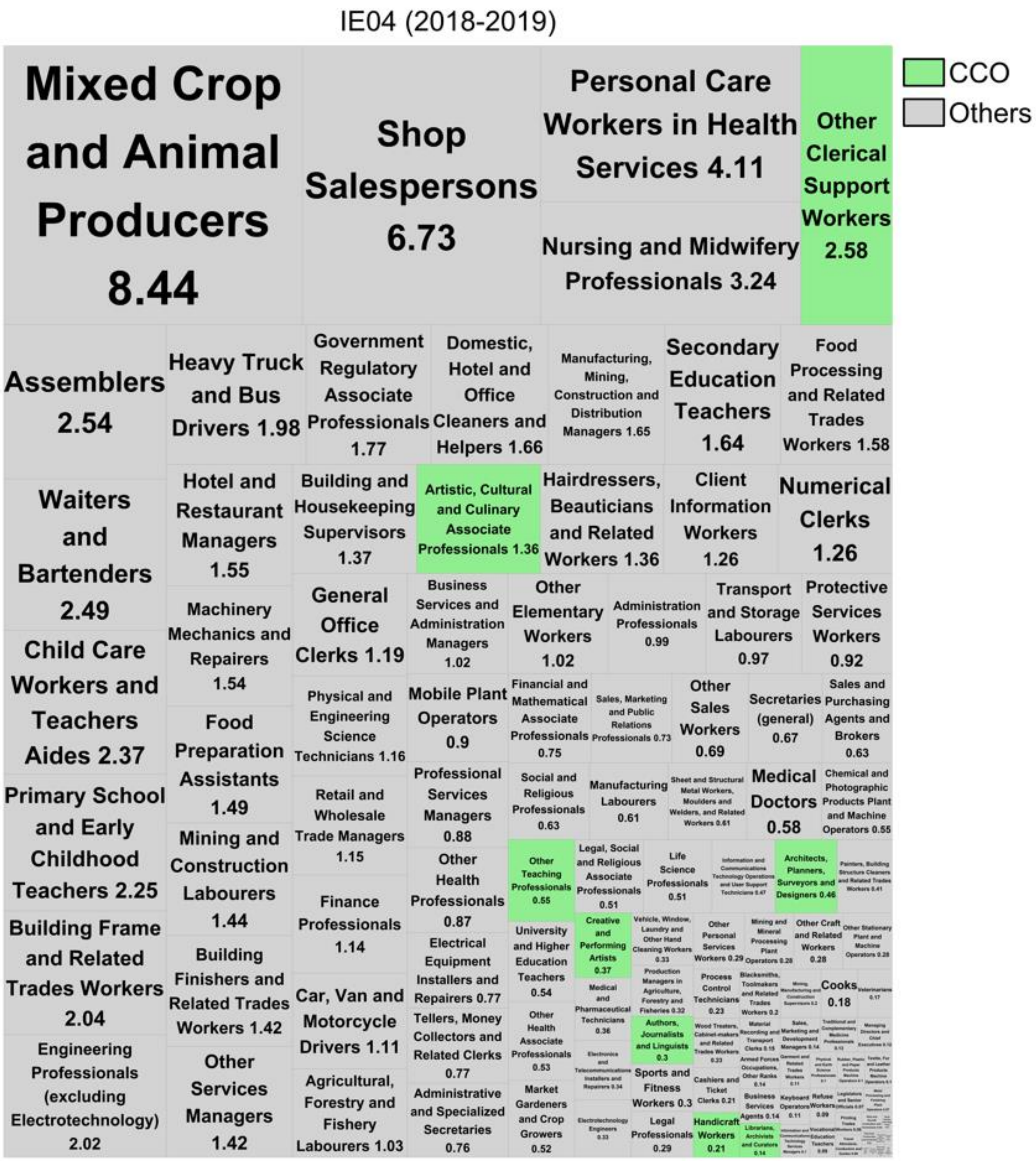
Figure C.3 shows the participation of all occupations in the occupational structure of Iceland (IS00), which includes the West Region.

Figure C.3 - Percentage distribution of occupations in the region IS00

Source: Authors based on LFS.

Figure C.4 shows the participation of all occupations in the occupational structure of the Western Coastal Periphery (IE04), in Ireland.

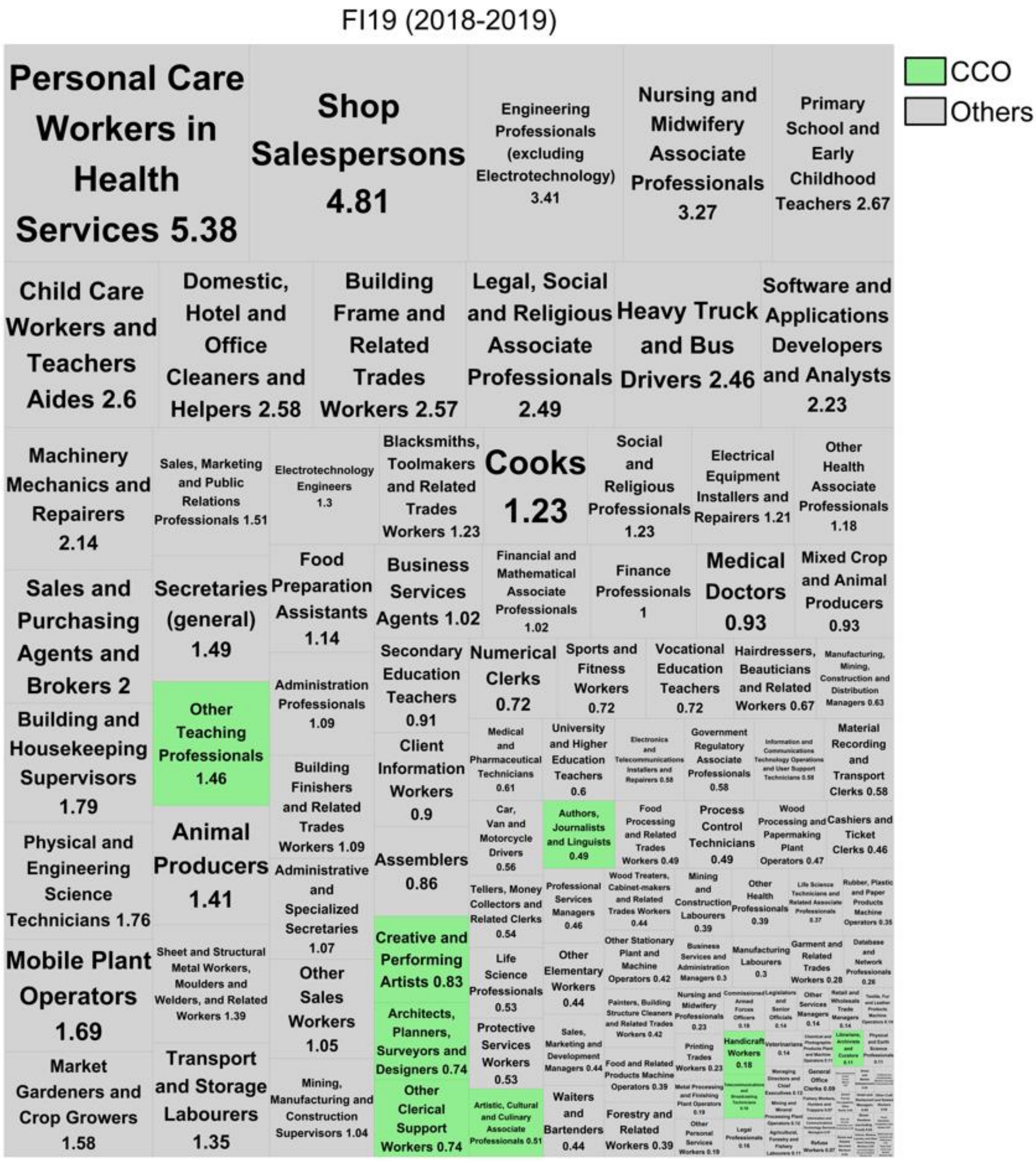
Figure C.4 - Percentage distribution of occupations in the region IE04



Source: Authors based on LFS.

Figure C.5 shows the participation of all occupations in the occupational structure of the region Länsi-Suomi (FI19), in Finland.

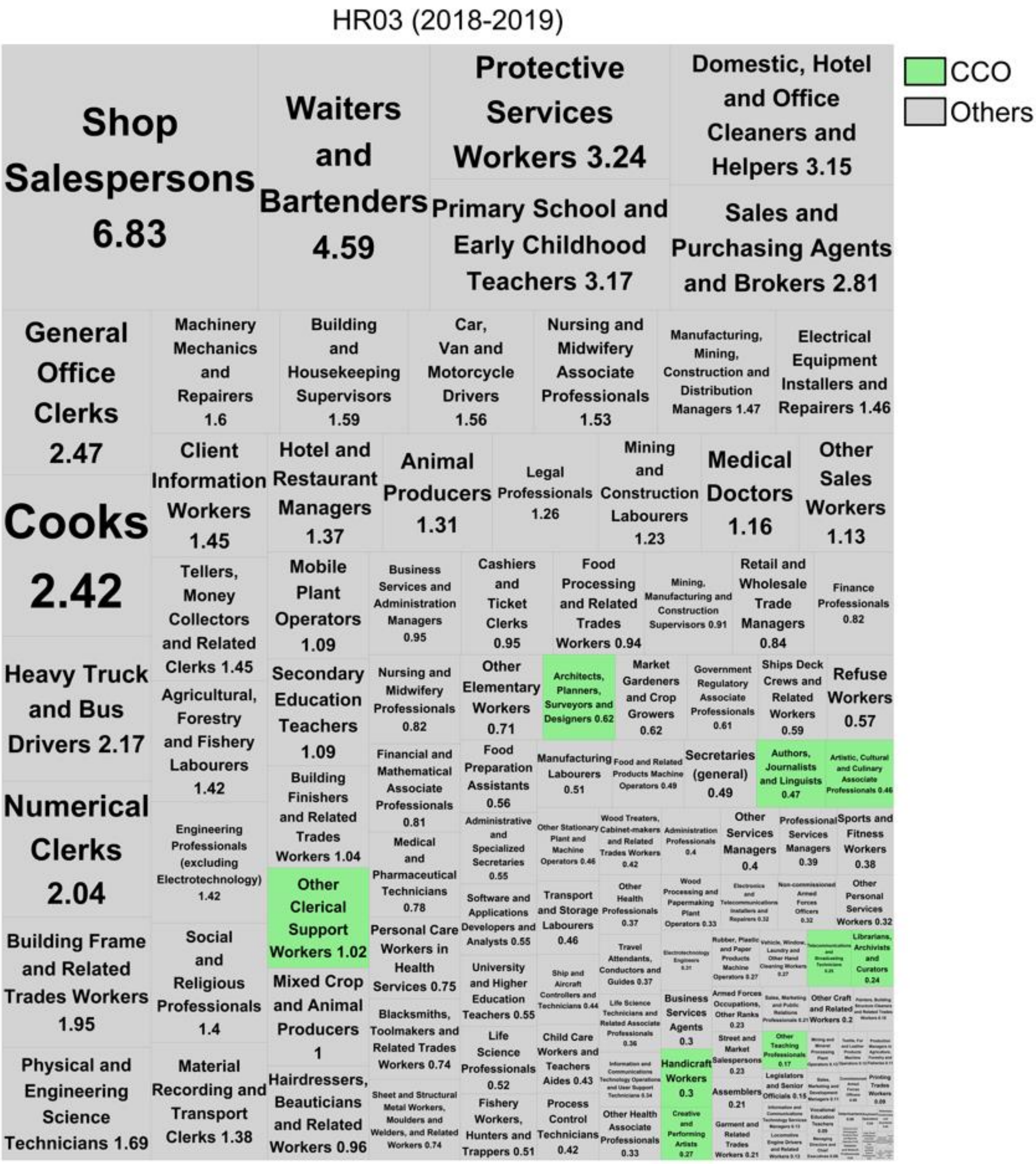
Figure C.5 - Percentage distribution of occupations in the region FI19



Source: Authors based on LFS.

Figure C.6 shows the participation of all occupations in the occupational structure of the HR03 region in Croatia, which includes Šibenik-Knin County.

Figure C.6 - Percentage distribution of occupations in the region HR03



Source: Authors based on LFS.