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Socioeconomic contributions and spillovers of CCIs in non-urban regions

Work package WP1 – Mapping the socioeconomic contributions and resilience of CCIs

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[1] Deliverable 1.1 covers Task 1.1, which addresses trademarks in general, among other innovation indicators, and Task 1.2, which focuses only on collective trademarks. Therefore, collective trademarks are included in this Deliverable, D1.1, instead of D1.2.

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Executive summary

Innovation and regional development have received attention from extensive literature in regional studies and economic geography. However, the strong focus on innovation stemming from high-tech and science-based sectors tends to emphasise the role of urban contexts and agglomeration in spurring innovation. This urban bias is being challenged recently, with the acknowledgment that non-urban and peripheral regions contribute to innovation, albeit in different ways and industries.

To contribute to this topic and go beyond the high-tech sectors and urban context, we chose cultural and creative workers as key elements of our analysis. Cultural and creative workers are often at the forefront of generating new ideas. They can be found in almost all industries of the economy, supporting innovation at different stages of the process. In addition to contributing to innovation by building bridges and inspiring new ideas to do things, they are spread in practically all regions, being a better parameter for non-urban regions.

Aiming to assess the socio-economic contribution of creative and cultural workers to innovation in non-urban regions, we have divided this report into two parts.

In the first part (pp. 10–100), corresponding to **Task 1.1,** we focus on combining **patents and trademarks** as regional innovation metrics – to capture innovation more broadly and at different stages of technological development – and look at regions by separating them by urbanisation level (urban and non-urban, including intermediate and rural regions). We aim to understand whether a higher share of cultural and creative occupations is associated with an increase in innovation in the region. We explore the role of cultural and creative occupations on innovation (in terms of patents and trademarks) across urban, intermediate and rural regions. Additionally, we focus on the gender aspect and check whether a higher share of women in creative occupations is also associated with innovation in the region where they work.

In the second part (pp. 101–144), corresponding to **Task 1.2**, we investigate the extent to which **collective trademarks** could be used as original and complementary metrics to other available economic and innovation indicators. The collective nature of this type of intellectual property right makes them particularly interesting to use in initiatives where the key assets at play are collectively owned instead of privately controlled by one actor only. This task is highly **exploratory** since we only had hints from prior literature that collective trademarks might provide relevant information on creative and cultural activities in non-urban regions. We suggest that collective trademarks could be instrumental to creative and cultural activities in non-urban regions because they can help to build a brand and reputation for a local community or territory.

From the development of Task 1.1 and Task 1.2, we can summarise the results found in this report:

1. The **combination of patents and trademarks** as regional innovation metrics provides a different map of regional innovation and its distribution across urban and non-urban regions. In particular, we found patenting activities concentrated in urban and intermediate regions, while trademark filing was strong in both urban and rural regions.
2. Capturing innovation activities more broadly than those focused on technological invention reveals a more detailed picture of the role of creative activities, as different innovation metrics are characterised by different geographies and distributions across urban and non-urban regions. Results also showed a **stronger association of creative occupations to trademarks for rural regions**, suggesting that in those regions, the type of innovation activities leaves more space for the contribution of creativity.
3. Comparing two innovation metrics (patents and trademarks) reveals the **role of female creative occupations in a new way**. In non-urban regions, a high share of female creative occupations appears to be more strongly associated with trademarks, suggesting that using these innovation metrics might also help mitigate the gender bias of patents.
4. **Collective trademarks** appear related to activities that leverage territorial assets associated with heritage, culture and community. In this sense, we see a stronger link with the **cultural** element rather than the creative one.
5. **Collective trademarks** seem particularly interesting for **non-urban regions and suit rural contexts better**. This might be related to the type of goods and services they protect (particularly in the case of food and heritage promotion), but we see a range of different products related to other economic activities too.

Based on these insights, we advise policymakers to combine patents and trademarks as regional innovation indicators when monitoring the socio-economic contribution of creative occupations. While the two metrics are already part of the European regional innovation scoreboard and are also available from Eurostat, their combined application in research and monitoring is still limited. As for collective trademarks, there is a clear potential for further exploring this peculiar intellectual property right. Collective trademarks could reveal hidden elements of the economic and innovative contribution of creative and cultural activities in non-urban regions. Yet, further research is needed to provide more systematic empirical evidence on the actual use of collective trademarks in European regions.

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Part 1 – Task 1.1

1. Introduction

Regional development captures the way in which regions evolve over time and transform their socio-economic structures. Innovation plays a key role in this process and has received the needed attention from a large literature in regional studies and economic geography. In particular, the research strand of geography of innovation has focused on how innovative potential differs across regions and which activities support innovation (Feldman & Kogler, 2010). Traditionally, **this literature has had a strong focus on innovation stemming from high-tech and science-based sectors.** More recently, the contributions of other sectors have been acknowledged too. Such sectors also include creative and cultural sectors and those creative occupations employed across sectors (Boschma & Fritsch, 2009; Lee & Drever, 2013; Rodríguez-Pose & Lee, 2020) or an inventive class (Wojan, 2022).

The other strong focus in the geography of innovation literature has been on the role of urban contexts and agglomeration in spurring innovation, with **a clear 'urban bias' on innovation** (Florida, 2002; Panne, 2004; Carlino & Kerr, 2015). This urban bias is also being challenged recently, with the acknowledgement that non-urban and peripheral regions also contribute to innovation, albeit in different ways (Shearmur, 2017; Eder, 2019). Studies on the innovation performance of peripheral regions in Norway (Fitjar & Rodríguez-Pose, 2011), Italy (Pires et al., 2014), Sweden (Grillitsch & Nilsson, 2015), Austria (Eder & Trippl, 2019) and Canada (Petrov, 2012), just to name a few cases, report that remote areas are remarkably innovative, even in the absence of agglomeration benefits, critical mass and even with relatively low investmentt in R&D. In this sense, different forms of innovation exist and innovation performance can rely on a variegated set of organisational, social and economic factors relevant to the local context (Pires et al., 2014).

The efforts put towards acknowledging the contribution of creative and cultural activities and taking seriously innovation beyond urban regions have brought to the fore a number of **challenges related to measurement.** On one hand, many initiatives have focused on mapping the socio-economic contribution of creative and cultural activities (UNCTAD, 2010). On the other hand, innovation indicators have also broadened to account for innovation beyond high-tech innovation only (Castaldi & Mendonça, 2022) and beyond urban contexts (Wojan, 2019).

In Task 1.1 we take up the challenge of reassessing the evidence on the contribution of creative and cultural activities to non-urban regions, with a focus on innovation as our key regional performance of interest. To do so, we will integrate the traditional metrics based on patent data with new ones based on trademark data. Moreover, we will investigate specifically whether the contributions of creative and cultural activities are different between urban and rural contexts.

2. Literature review

2.1. Regional innovation: measures and mechanisms

The by now large literature on the geography of innovation has produced several stylised facts about the spatial concentration of innovation activities and the ways in which innovation matters for regional development (Feldman, 1994; Feldman & Kogler, 2010). The empirical evidence stemming from this strand of research has leveraged several metrics of innovation, with a strong reliance on patent data.

Patent data is a rich source of data on technological inventive activities (Carlino & Kerr, 2015). The main strength of patents for innovation measurement is that patent registrations requires demonstrating novelty. Hence there is a direct link between patent activities and novelty generation. Other attractive features of patent data are the possibility to locate patents, the availability of citations and the information on both inventors and owners of the technological inventions. At the same time the limitations of patents as innovation metrics are also known: they mostly capture innovation in high-tech sectors, they refer to invention rather than innovation and their complexity makes them mostly used by large firms in core regions (Wojan, 2019).

Trademarks are emerging as an alternative metric to capture regional innovation and entrepreneurship activities (Castaldi & Mendonça, 2022). Trademarks are signs used by economic actors to distinguish their goods and services in the marketplaces (Castaldi, 2020). Hence trademarks refer to commercialised products and trademark registrations requires proof of use in market. Trademarks are easier to file than patents. For this reason, they are used more broadly, by different firm types. They are relevant in all sectors. Research suggests that in technology-based sectors patents and trademarks are used in a complementary fashions, since they protect innovations at different stages of development (Seip et al., 2018). In other sectors trademarks may represent an alternative for protecting innovation, because patents are not an option of because the type of innovation is non-technological (Mendonça, Pereira & Godinho, 2004; Flikkema, De Man & Castaldi, 2014). There is evidence from the literature regarding the complementarity between patents and trademarks, with patents playing a role in protecting inventive R&D output, while trademarks are used at a later stage when actual innovations are being brought to market (Abbasiharofteh, Castaldi & Petralia, 2022).

Whether trademarks allow to capture innovation in creative and cultural industries is still an open question. Castaldi (2018) found that these industries make little use of intellectual property rights in general and also trademarks in particular. At the same time, in this report we focus on creative occupations. In this sense, the contribution of these occupations to innovation should be more prominent when using trademarks as innovation metrics. The reason is that trademarks relate to the downstream phases of the innovation process: in those activities symbolic knowledge and creative workers play a key role since the goal is to shape a new product that is attractive for potential users and customers (Stoneman, 2010a). New products often rely on creating new product categories, attach new meanings and come up with a persuasive value proposition (Mendonça, 2014).

Table 1: Key features of patents vs trademarks as innovation metric

	Patents	**Trademarks**
Subject matter	Novel technological inventions	Distinctive symbols
Phase of the innovation process	Research Development	Product Development Marketing
Main legal requirements for registration	Novelty Industrial applicability Nonobviousness	Distinctiveness (Intention to) Use in market
Knowledge/occupations involved	Technical/Engineers	Symbolic/Creative
Type of firms	Mostly large firms	All firm sizes
Sectoral context	Mostly high-tech sectors	All sectors, including service ones

Source: Authors.

Overall, the emerging evidence suggests that combining patent and trademark data allows to get a more complete picture of regional innovation activities (see key features in Table 1). In this report we will also combine the two metrics, for the sake of capturing more innovation activities than one would be able to capture using one type of data only.

2.2. Cultural and creative industries and occupations – concepts and definitions

A universally accepted definition of cultural and creative activities does not yet exist. According to the recent Eurostat Guide to Culture Statistics (Eurostat, 2018) and the OECD Cultural Report (OECD, 2022a), several classifications exist, employing different perspectives.

The main European statistical methodological framework in place in the European Union for culture is based on the UNESCO framework for cultural statistics (UNESCO, 2009). This framework included natural heritage, supporting materials, sports or tourism (Eurostat, 2018), while the Eurostat Office did not. In short, the European statistical framework covers ten domains, which are: heritage, archives, libraries, books and press, visual arts, performing arts, audio-visual and multimedia, architecture, advertising, art crafts and additionally six functions involving creation, production and publishing, dissemination and trade, preservation, management and regulation, and education. Over the years, the cultural scope of the terminology was extended to encompass creative activities as well: these go beyond traditionally accepted cultural roles (such as artists) and include activities which also strongly rely on creativity to perform tasks (for example, advertising, software developers and designers).

The UNESCO (2009) guide conceptualised cultural and creative industries with reference to stages of a production cycle, including the creation, production, dissemination, exhibition or consumption of cultural or creative products and services. UNCTAD (2010) similarly distinguished between upstream and downstream creative activities, the first related to production and the second with creative and cultural goods relating to the market. Another perspective was the concentric circle model of creative industries (Throsby, 2008), which described a core of artistic activity surrounded by concentric circles of broader cultural and creative activities, such as museums, galleries, libraries, architecture, design and computer games. This brief review demonstrates the many efforts towards mapping creative and cultural activities, but also underlines the lack on one standard definition.

Several studies within economic geography and geography of innovation have used industry-based definitions of creative and cultural activities to measure their role for regional development (Stam, De Jong & Marlet, 2008; Lee & Drever, 2013; Protogerou, Kontolaimou & Caloghirou, 2017; Innocenti & Lazzeretti, 2019; Lee, 2020). In a different way, Bakhshi & McVittie (2009) used input–output tables for the UK to evaluate creative industries. More recently, one sees 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 is able to map the contribution of these activities across the whole economy. Many creative workers are not employed in creative industries but rather in other industries, where they complement occupations based on other skills and talent (Cruz & Teixeira, 2012).

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

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

Nevertheless, we are aware that this approach also has limitations. A first one is that the surveys on the national labour force 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, 2022b). A second challenge is the availability of data at a useful level of granularity in the occupational classification (Higgs & Cunningham, 2008). The best scenario would be to achieve ISCO (International Standard Classification of Occupations) classification at four-digit disaggregation, but such information is rather rare to find and is not available in several countries (Stam, De Jong & Marlet, 2008; OECD, 2022a). A third issue relates to the selection of occupational categories that count as creative and cultural. There is no widely accepted list (Boschma & Fritsch, 2009). There are also some nuances to the ISCO code list that defines what creative occupations are, and these also vary slightly in some countries (Markusen et al., 2008). An 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, and 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 and luckily this group represents the largest share for measuring the CCO category. 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.

In addition, the Eurostat Guideline (Eurostat, 2018) argues that there are occupations 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, 2022b). However, this is not an easy task as this information is scarcely available in national statistics (Stam, De Jong & Marlet, 2008). That is why in most studies this cross-section of occupations-industry is not included in the exercise.

Yet, several examples in the literature have succeeded in adopting the occupation-based view. A seminal contribution of Florida (2002; 2004) uses data from the USA and the American classification of occupation (Standard Occupational Classification codes) to assess the creative class and its contribution to regional growth and innovation. Lee & Rodríguez-Pose (2014) were able to capture 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) have also evaluated the share of workers in creative occupations in US 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 also 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 measure by innovation. The authors found that although the presence of geek workers is a more relevant drive 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, as not all workers can necessarily contribute to patenting – in this case, the author proposes considering creative workers to weigh innovation results (instead of per capita values). Besides these studies, several other authors have sought to define and measure cultural and creative jobs in a specific region or to identify the geographical distribution within a country and their importance in the regional growth (for more details, see Cruz & Teixeira 2012).

In sum, recent research suggests that relying on CCOs provides a relevant measure of creative and cultural activities. Next, we discuss more in detail the actual mechanisms through which these occupations may contribute to regional innovation processes.

2.3. Cultural and creative occupations and regional innovation

Creative workers are often at the forefront of generating new ideas and concepts and can be found in almost all industries of the economy, supporting innovation at different stages of the process (Wojan, Lambert & Mcgranahan, 2007; Bakhshi, Freeman & Higgs, 2013; OECD, 2022b). For instance, creativity plays a key role in coming up with new ways of doing things, imagining and designing new products or services, but also finding creative solutions to trade-offs (Boschma, 2005; Grillitsch & Nilsson, 2015; Rodríguez-Pose & Lee, 2020).

The role of creative workers in economic and regional performance has inspired the curiosity of many researchers. Florida (2002) pointed out that different types of creativity, including technological, economic (in the sense of entrepreneurship) and artistic, shape a region's capacity to generate new knowledge and innovation and ultimately lead to regional growth. In another article, Florida (2004) also suggests that high concentrations of super-creative professionals like writers, editors, artists, cultural figures, and also scientists, engineers and designers, among others, make some cities more innovative than others.

Beyond that, cultural and creative professionals help drive innovation in the cultural and creative industry as well as across the broader economy (Boschma & Fritsch, 2009; Innocenti & Lazzeretti, 2019; Lee, 2020; Rodríguez-Pose & Lee, 2020). Cultural and creative workers encompass a wide range of professionals who are essential suppliers of ideas and new approaches for other activities (Boschma

& Fritsch, 2009; Lee & Rodríguez-Pose, 2014; Innocenti & Lazzeretti, 2019). As a result, different kinds of innovations can be achieved, not only technological ones but also what Stoneman (2010) has defined as 'soft innovation'.

While workers directly linked to science and technology (the so-called STEM categories – Science, Technology, Engineering and Mathematics) have traditionally been held mostly responsible for innovation, the current understanding is that workers with a creative profile are also critical. These workers have an essential role in the development and diffusion of innovation (Florida, 2002; Lee & Drever, 2013; Lee, 2020), particularly the more downstream phases of the innovation process. Rodríguez-Pose & Lee (2020) suggest that the combination of these two types of workers is what makes innovation thrive.

Creative workers are also an essential element that promotes organisational change and other non-technological innovations, particularly relevant in less technologically advanced regions (OECD, 2005; Galetti, Tessarin & Morceiro, 2021).

In general, cultural and creative workers tend to be highly educated and skilled compared to the overall workforce. OECD (2022a) reports that 62% of cultural and creative workers hold a tertiary degree, in contrast to 40% of workers in general in OECD countries. Cultural and creative workers possess skills closely related to innovative activities, non-repetitive technical skills and thinking and problem-solving ability (Markusen et al., 2008; OECD, 2022b). They also require a combination of original thought skills, problem-solving and collaborative relationships to deliver output (Bakhshi, Freeman & Higgs, 2013).

Even more broadly, creative workers can contribute to regional innovation by making bridges and inspiring, new ideas for doing things. Beyond economic types of innovation, cultural and creative workers can transform the region where they are located through social innovations producing positive social, environmental and cultural outcomes (Pires et al., 2014; Eder, 2019).

An alternative hypothesis to explain why the presence of creative workers enhances technological innovation is the empirical regularity that polymaths (e.g., engineers that are also amateur musicians or scientists that perform in community theatre) are much more innovative and inventive (Root-Bernstein & Root-Bernstein, 2021). These individuals are likely to be drawn to areas with richer cultural amenities.

2.4. Innovation in non-urban regions

The seminal work of Jane Jacobs (1969), *The Economy of Cities*, has had a significant impact on studies of innovation and economic geography. Jacobs viewed cities as the primary incubator of innovation, given their many opportunities for interactions between different people and organisations.

Later on, Florida (2002) revitalised the urban take on innovation posing that cities provided the ideal environment for creativity and innovation to flourish. Within his view, creative individuals and their occupations were at the heart of the urban innovation potential. He drew attention to the 'creative class' and noted how this specific group of individuals were highly concentrated in dynamic, diverse and tolerant places, mostly to be found in urban regions. According to Florida (2004), cities provide essential elements to the creative class: firstly, the infrastructure and networks necessary for technological development to take place (from infrastructure to research institutions and technology startups); secondly, talent, as a critical mass of highly skilled individuals who can potentially collaborate and interact with other professionals who support creative activities, such as business, law or physical and engineering science professionals; thirdly, the tolerance and open-minded spirit that attract people from different cultural and ethnic backgrounds. At the same time the creative class ideas have been criticised on both conceptual and empirical grounds. Asheim & Hansen (2009) proposed a focus on differentiated knowledge bases as a better to way to understand the distribution of different types of activities across regions. Boschma & Fritsch (2009) argued that the effect of tolerance and open-minded culture is more critical to innovation than an urban context per se.

Despite the critiques, a vast amount of literature explored the argument that creative and cultural people and innovation are concentrated in urban areas (for instance, see Shearmur, 2012). However, such a focus implied a disregard of non-urban and peripheral areas also host innovative activities. A few scholars recently started to reflects on the urban bias of geography of innovation studies (Shearmur, 2017).

The emerging innovation in the periphery literature suggests that innovation can take place beyond urban cores. In fact, peripheral regions lacking agglomeration might benefit from their very distance when it comes to creative potential. Eder & Trippl (2019) have proposed several properties that can constitute strengths of these regions. For instance, the institutional voids and distance to political centres might be a reason to deviate from usual patterns and develop radical alternatives. This might be particularly the case for creative and cultural activities where experimentation and opposition to dominant paradigms can be key (Grabher, 2018).

Empirical evidence also shows that innovation does not necessarily concentrate or drive economic development in cities more strongly than in other areas. For instance, Fitjar and Rodríguez-Pose (2011) found that Norwegian peripheral regions are remarkably innovative. The innovative capacity of these peripheral regions does not result from agglomeration, rather from other types of proximity, in particular cognitive and organisational proximity (Fitjar & Rodríguez-Pose, 2011).

When analysing peripheral regions in Northern Canada, Petrov (2012) also found accumulated creative capacities and innovative hotspots in the Canadian periphery. Creativity and innovation emerged as even more fundamental to creating new paths in peripheral regions than urban areas. In this case, social capital and community efforts favoured successful innovation.

To better understand innovation in non-urban environments, it is first necessary to note that they have specific characteristics. Many of them may not result in patents because patents appear concentrated in large cities, where the company's headquarters are located (Shearmur, 2017). Moreover, the type of innovation that prevails in peripheral regions tends to be more incremental and non-technological rather than technological innovation (Pires et al., 2014; Shearmur, 2017; Galetti, Tessarin & Morceiro, 2021). Peripheral regions may also offer a more attractive environment for small and medium-sized firms to innovate, while large firms prefer the diversity often found in cities (Eder, 2019; Galetti, Tessarin & Morceiro, 2022). At the same time, recent evidence using alternative measures of innovation also indicates that the urban bias of innovation might be exaggerated (Fritsch & Wyrwich, 2021). An alternative patent-derived measures elaborated by Dotzel & Wojan (2022) illustrated such bias. Patents per capita in urban areas has six times more productive than in rural areas, but decomposing patents per capita into composition and rate factors the authors found a productivity advantage of urban areas only twice that of rural areas.

Even though innovation in rural and peripheral areas may score lower in terms of technological impact and absolute numbers, innovation scores capturing relative innovation performance show less of an advantage of large cities. For instance, Ó hUallacháin & Douma (2021) notes how the contribution of smaller, secondary cities, can be better accounted for when taking patent numbers in relation to employment and population. On a more qualitative note, many found that innovation in rural and/or peripheral regions is also different in nature and often promotes the valorisation of local assets, social innovation and entrepreneurship (Pires et al., 2014).

2.5. Regional innovation and the gender perspective

The literature on regional innovation has given little consideration of issues of gender. Some insights are there, but scattered across different studies.

A group of studies have investigate the a gender gap in patenting activities, where the proportion of female inventors much lower than that of male inventors (Hunt et al., 2012). Women also appear less frequently as single inventors, are more present in larger inventor teams (Martinez, Raffo & Saito, 2016) and are less likely to choose STEM professions (Hunt et al., 2012). One of the primary reasons is that girls are less exposed to core hard science subjects at schools, which negatively impacts a woman's likelihood of becoming an inventor (Martinez, Raffo & Saito, 2016; Heikkilä, 2019). Looking at the technological areas of patents, it is evident that women cluster in particular fields, most prominent in biology and chemistry, and remain under-represented in engineering and mechanical (Cutura, 2019). The USPTO (2019) points to a potential underutilisation of highly skilled and innovative talents. Even when women work as scientific professionals and entrepreneurs, many factors limit their access to patenting more than men in the same position (Cutura, 2019; Menzel, 2021).

Overall, using patents as an innovation metrics has the additional limitation of a bias towards capturing activities of men.

Heikkilä (2019) brought evidence that there is a bias against of women across all intellectual property rights: patents, utility models, design rights or trademark filings made by Finnish inventors. The bias is less pronounced for trademarks than for patents, even though the evidence that Heikkilä (2019) presents is only based on the small share of trademarks filed by individuals and not by companies. At the same time, trademarks are used in more economic sectors than patents, including sectors with stronger female participation than high-tech sectors. Hence, one should expect a smaller gender gap using trademarks as innovation metrics other than patents.

Additionally, women face obstacles to advancing in their careers in cultural and creative occupations, similar to other economic activities (Tessarin & Morceiro, 2022). One key reason is that women still bear a more significant burden of unpaid work (such as domestic work and family care) and informal activities (Menzel, 2021; Tessarin & Morceiro, 2022). As for creative and cultural industries, the participation of women varies according to the country and activities; however, women are underrepresented in leadership positions. According to EIGE (2016), reasons include gender bias and stereotypes regarding the activities performed by each occupation and lack of access to resources and contact networks.

3. Data and methods

3.1. Data sources

In this report, we combined information on patents, trademarks and occupations from three different databases to study creative occupations across European regions and their contribution to innovation in urban and non-urban regions.

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 INSITU 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 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 and 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. **Patents**

We obtained patent data from the OECD REGPAT Database (August 2022 edition). This dataset provides utility patent applications filed from companies across EU 28 countries (plus OECD and BRICS countries – Brazil, Russia, India, China and South Africa) (OCDE, 2022).

We are counting applications, excluding only those originating outside the European Union. We use the addresses of inventors to link a patent to a region: the location of the inventor is the closest to the actual place where the invention was developed.

3.1.3. **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).[2] It provides detailed information on trademarks filed at the EUIPO and the USPTO (Neuhäusler, Frietsch & Rothengatter, 2021). We select the EUIPO trademark applications and focus on those filed by applicants with addresses in one of the European regions. We also excluded filings from Andorra, as there is no

[2] 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.

information for this region in the other databases. We also excluded incomplete occurrences, for instance, when there was no “applicant_ID”, because it is impossible to allocate a region in this case. After cleaning and processing the data, we dropped 5.5% of the dataset since there were applications with no NUTS code or other missing information.

Notice that the EUIPO filings different from trademarks filed at national trademark offices: these are not easily available for all countries. Flikkema et al. (2014) found that trademarks filed at the EUIPO had a higher probability to refer to innovation that 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.

3.1.4. **Data period**

For the purpose of this report, we consider a period of nine years – from 2011 to 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.

Secondly, the patent data is consolidated up to the year 2019. Due to a delay inherent in the patent application and registration process, the database is updated with a certain time lag. Thus, data from more recent applications is not yet fully computed, so we have chosen to drop the last years.

In addition, data for occupation in the latest classification starts in 2011 (ISCO-08, 2008 version), which allowed us to adopt a single occupational classification throughout the period.

3.1.5. **NUTS Regions**

As we are working with three 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 changed 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 NUTS level 2, several regions had names changed in Spain; Hungary had one region discontinued and three new ones created; Norway had seven regions rearranged into six, one had been through a large revamp, and a new one was created. In 2011, the NUTS1 code of Greece was changed from GR to EL, consequently changing the codes of all NUTS 2 and 3 level, 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 then 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 does not provide subnational information (only country-level information). The United Kingdom is included in the analysis, but it only provides regions at the 1-digit NUTS level, which means 12 NUTS regions.

As for patents and 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 at that level of analysis.

In total, our data covers 27 European countries (22 EU countries, 4 EFTA and the UK) accounting for 217 NUTS regions at 2-digits, plus 12 regions NUTS at 1-digit regarding the United Kingdom.

3.2. Typology to classify occupations and regions

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

A crucial step in this study is to identify a typology that defines which occupations are considered cultural and creative. Table 2 below 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, 2022b).

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, 2022b). 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, 431. 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 2: List of ISCO-08 codes (3 and 4-digit level) associated with cultural and creative occupation

ISCO-08 code	Cultural and creative occupations
216	Architects, planners, surveyors and designers
2161	Building architects

ISCO-08 code	Cultural and creative occupations
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
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

ISCO-08 code	Cultural and creative occupations
352	Telecommunications and broadcasting technicians
3521	Broadcasting and audio-visual 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. 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 also non-urban or intermediate and rural areas. For this, we again choose 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 the 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 centers 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 for 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[3], 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, intermediate or rural. In other words, a region is "**predominantly urban**" when the majority proportion of employed people work in an area classified as urban; "**predominantly intermediate**" when the majority portion of employed persons work in an area classified as intermediate; and finally, "**predominantly rural**" when the majority portion of employed people work in an area that is considered rural. Additionally, the "**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. In total, adding urban, intermediate and rural regions, we have 229 regions.

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

Country	Urban regions	Intermediate regions	Rural regions	Non-urban regions
AT	1	1	7	8
BE	1	8	2	10
CH	0	7	0	7
CY	1	0	0	0
CZ	1	2	5	7
DE	10	20	8	33
DK	1	0	4	4
EE	0	0	1	1

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

Country	Urban regions	Intermediate regions	Rural regions	Non-urban regions
EL	1	0	12	12
ES	15	1	3	11
FI	1	1	3	4
FR	6	0	20	23
HR	0	0	2	2
HU	1	1	6	7
IE	1	0	2	2
IS	1	0	0	0
IT	4	9	8	20
LI	0	1	0	1
LT	1	0	1	1
LU	0	0	1	1
LV	0	0	1	1
NO	1	1	5	7
PT	3	1	3	6
RO	1	0	7	7
SE	2	4	2	6
SK	1	0	3	3
UK	8	3	1	7
Total	**62**	**60**	**107**	**191**

Source: Authors, based on Eurostat and LFS.

In addition to the non-urban regions, we are also interested in investigating separately at the intermediate and rural regions. In this way, we can identify possible characteristics of relatively more remote regions (or less densely populated) regions from those closer to urban centres. Based on the theoretical review, we believe that the dynamics of these regions may differ and directly affect their potential to retain and/or attract creative workers and generate innovation.

3.3. Modelling framework

We applied a two-way fixed-effect model by time and region, yearly, for the time period from 2011 to 2019. The dependent variable represents the innovation measured either by patents per thousand employed persons or by trademarks per thousand employed persons – both in logarithmic scale since the distribution across regions is highly skewed. Our main independent variable of theoretical interest is the share of creative and cultural occupations (as a percentage of the total occupations). To account for the gender aspect, we also consider the share of women in creative and cultural occupations – or female creative occupations[4].

To control for the characteristics of the region, we selected the following control variables:

- the share of persons (from 25 to 64 years) with tertiary education (as a percentage of population) (tert_educ_sh), which represents human capital;
- the firm size given by the percentage of workers employed in firms with less than ten employees (smallsize_sh), which represent the business composition of the local economy or competition;
- the share of high and medium-high tech manufacturing (as a percentage of employment) (high_tech_manuf_sh);
- the share of knowledge-intensive high-tech services (as a percentage of employment) (high_tech_service_sh).

These last two variables account for the economic structure and are a common control in studies analysing regional innovation (e.g. Pinate et al., 2023).

Table 4 reports the descriptive statistics of the main variables.

Table 4: Descriptive statistics of variables

Variables	Definition	n	mean	sd	median	min	max	Source
patents_pc	Number of patents per 1,000 inhabitants	1966	0.16949	0.62791	0.05471	0.00008	10.77440	OECD REGPAT and Eurostat
ln_patents_employed	Ln of patents per 1,000 employed persons	1780	0.18032	0.19919	0.11012	0.00017	1.06651	
trademarks_pc	Number of trademarks per 1,000 inhabitants	2022	0.12213	0.17609	0.07812	0.00035	2.09023	EUIPO and Eurostat
ln_trademarks_ employed	Ln of trademarks per 1,000 employed persons	1838	0.19176	0.15068	0.16054	0.00093	1.20166	

[4] For the sake of simplicity, whenever we use the term *creative occupations* we refer to cultural and creative occupations.

Variables	Definition	n	mean	sd	median	min	max	Source
creative_sh	Share of creative occupations (%)	2038	5.06765	2.36884	4.52990	0.54604	14.44444	LFS
female_creative_sh	Share of creative female occupations (%)	2038	6.36306	3.41508	5.60445	0.00000	18.77859	LFS
tert_educ_sh	Share of population aged 25-64 with tertiary education (%)	2009	29.05540	9.65740	28.30000	9.90000	59.60000	Eurostat
smallsize_sh	Share of occupations in companies with less than 10 employees (%)	2038	35.95074	12.65161	33.20590	6.17796	83.60458	LFS
high_tech_service_sh	Knowledge-intensive high-technology services (% of employment)	1806	2.62957	1.57617	2.20000	0.50000	9.60000	Eurostat
high_tech_manuf_sh	High and medium-high tech manufacturing (% of employment)	1834	5.99411	3.88872	5.00000	0.20000	22.00000	Eurostat

Source: Authors.

We estimate a linear regression model focused on how CCOs contribute to innovation in regions with different degrees of urbanisation, as follows:

$$Innovation_{rt} = \beta_1 + \beta_2\ Creative\_sh_{rt} + \beta_3\ Tert\_educ\_sh_{rt} + \beta_4\ Smallsize\_sh_{rt} + \beta_5\ High\_tech\_service\_sh_{rt} + \beta_6\ High\_tech\_manuf\_sh_{rt} + \varphi_r + \sigma_t + \varepsilon_{rt}$$

where the dependent variable $Innovation_{rt}$ represents the two measures of innovation, which are patents and trademarks, in a region *r* at time *t*; $Creative\_sh_{rt}$ captures the share of CCOs and the other variables φ_r and σ_t represent the fixed effects, respectively, for region and time; and ε_{rt} is a regression residual.

Given the contemporaneous relationships, we are only assessing the association between cultural and creative occupations and regional innovation. Is a higher share of cultural and creative occupations associated with an increase of innovation in the region? We cannot make claims on causality and in fact we expect that there might be sources of endogeneity and effects going in both directions of the model.

After estimating the baseline models, we will explore if the role of cultural and creative occupations differs between urban, intermediate and rural regions.

Finally, we will focus on the gender aspect and check whether a higher share of women in creative occupations is also associated with innovation in the region where they work.

Appendix C shows the correlation tables between the variables for all econometrics models, by regions and by degree of urbanisation and female CCO.

4. Results

4.1. Descriptive analysis: The distribution of cultural and creative occupations across EU regions

We classify the NUTS 2 European regions by the degree of urbanisation, as explained in Section 3.2. Table 5 shows the CCO share of total occupations for the last year before the COVID-19 pandemic for all regions by type of urbanisation.

In 2019, 5.22% of total occupations were part of the CCO group, on average, for the 229 European regions in this study (Table 5). There is no substantial difference in such a percentage by the degree of urbanisation. Non-urban, urban and rural regions have, on average, 5.08%, 5.41% and 4.81% CCO out of total occupations.

Table 5: Share of CCO in Europe by degree of urbanisation of regions (2019)

Degree of urbanisation	CCO (% of the total employment)
Non-Urban	5.08
Urban	5.41
Intermediate	5.67
Rural	4.81
Total EU	**5.22**

Note: We use the average CCO share for each region and the whole EU.
Source: Authors, based on LFS.

However, there is substantial regional heterogeneity at the NUTS 2 level. To better illustrate this, we have made a ranking for the non-urban regions with the highest share of CCO in the workforce. Table 6 shows the first 20 positions.

Friuli-Venezia Giulia, a region in North-Eastern Italy (bordering Austria, Slovenia and the Adriatic Sea), leads the rankings, with 10.22% of jobs reported as CCO. Algarve, a region in the far south of Portugal, on the shores of the Mediterranean Sea, comes in second with 9.48% of occupations classified as CCO. In third place is another northern Italian region, Provincia Autonoma di Trento, an area that is part of the Italian Alps, with 8.54% of occupations classified as CCO.

In addition, another four non-urban regions from Italy, four from Denmark and four from Austria, and others from Greece, Belgium, Portugal and Cyprus appear in the Top 20, with a CCO share of total employment ranging from 7% to 8.5%.

Table 6: Top 20 non-urban regions in share of CCO (2019)

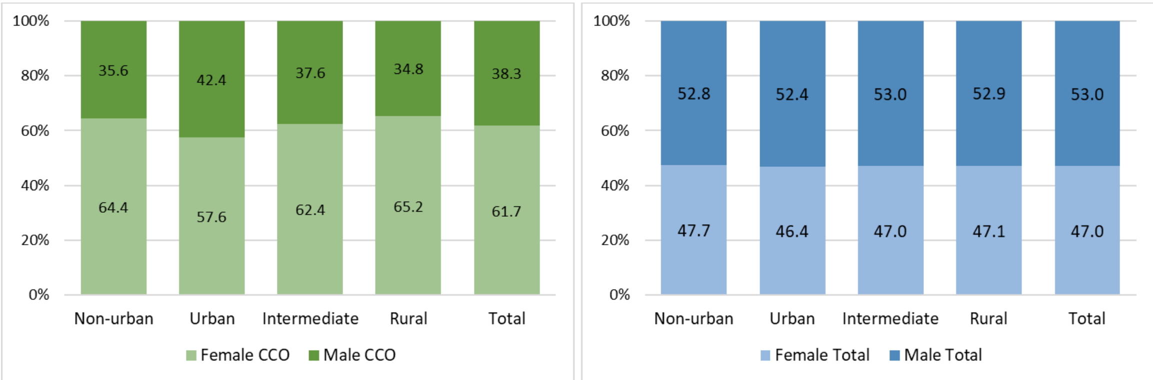
Rank	NUTS 2 code	Region name	CCO share (%)
1	ITH4	Friuli-Venezia Giulia	10.22
2	PT15	Algarve	9.48
3	ITH2	Provincia Autonoma di Trento	8.54
4	AT31	Oberösterreich	8.46
5	BE23	Oost-Vlaanderen	8.20
6	CY00	Kypros	8.13
7	ITH3	Veneto	8.12
8	ITI3	Marche	8.06
9	DK04	Midtjylland	7.88
10	AT32	Salzburg	7.87
11	DK02	Sjaelland	7.84
12	ITF6	Calabria	7.68
13	DK05	Nordjylland	7.66
14	EL54	Ipeiros	7.65
15	EL64	Sterea Ellada	7.43
16	AT33	Tirol	7.35
17	PT20	Região Autônoma dos Açores	7.26
18	BE25	West-Vlaanderen	7.18
19	ITH1	Provincia Autonoma di Bolzano	7.15
20	DK03	Syddanmark	7.13

Source: Authors, based on LFS.

Gender also matters when considering cultural and creative occupations, especially for non-urban regions. In Figure 1 (a), the last column of the panel shows that 61.7% of CCO are made up of women while 38.3% are men. Such a female percentage reaches 65.2% in rural regions and 64.4% in non-urban regions, lower in urban areas (57.6%).

As a comparison, Figure 1 (b), the last column the right, displays the distribution of total employment by gender and degree of urbanisation. Just over half of the total employment comprises men, regardless of the degree of urbanisation.

Figure 1: Distribution of CCO and total employment by gender and degree of urbanization (2019)



(a) CCO distribution; (b) Total employment distribution.

Source: Authors, based on LFS.

Table 7 shows that the share of CCO in relation to total employment is higher for women than for men in all regions by degree of urbanisation. The female CCO share is 65% higher for the whole EU region than the male portion. The percentual difference increases as the region becomes less urban, reaching 87.7% in rural regions while 35.6% in urban regions.

Besides that, the share of CCO in non-urban regions is slightly higher than in urban regions.

Table 7: Share of CCO by gender and degree of urbanisation (2019)

Degree of urbanisation	CCO (% of the total employment)		
	Female	Male	Percentage difference (Female-Male)/Male
Non-urban	6.53	3.80	71.8%
Urban	6.29	4.64	35.6%
Intermediate	7.17	4.32	66.0%
Rural	6.40	3.41	87.7%
Total EU	**6.60**	**4.01**	**64.6%**

Note: We use the average CCO share for each region and the whole EU.
Source: Authors, based on LFS.

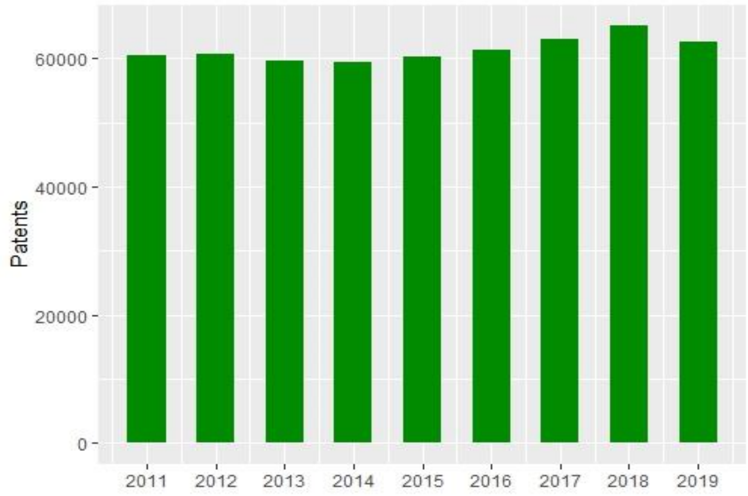
Additionally, we calculate an index for the share of female CCO akin to regional specialisation measures commonly used in the economic literature. This index, based on the Balassa Index (REF), allows us to identify if a NUTS 2 regions has higher than average female CCO. Our measure is calculated as the share of two shares: the share of female CCO over total CCO in the region divided by the share of female CCO over the total CCO for the European Union. When our index takes a value greater than 1, it means the share of female CCOs in the region is higher than the share of female CCOs in the EU as a whole. This index showed that 86% of the regions are specialised in female CCO. Only in 14% of the regions the intensity of male CCO exceeds the intensity of total creative occupations.

In summary, cultural and creative occupations have a stronger female participation, especially for non-urban and rural regions. Therefore, gender is a relevant issue to address in studies on cultural and creative activities, especially in non-urban regions.

4.2. The distribution of innovation across EU regions: Comparing patents and trademarks

In this section, we present the innovation landscape in the European Union and its regions, including the distribution by the degree of urbanisation. Starting with patents, we note from Figure 2 that the absolute number of applications has been relatively stable over the last decade, showing a growth of 3.5% between 2011 and 2019. In 2019, there were 62,630 patent applications for the 27 EU countries comprised in this report.

Figure 2: Total patents application per year



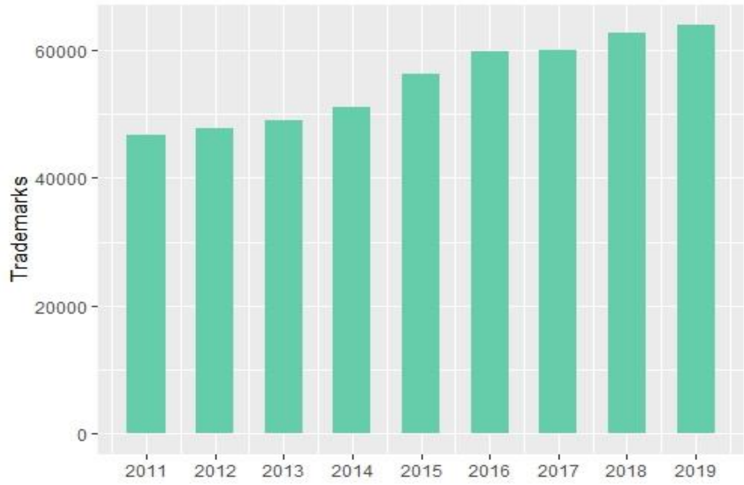
Source: Authors, based on REGPAT.

Among the countries with the highest number of patents are Germany, France and Switzerland, respectively, with 33.21%, 13.18% and 9.03% of the total 2019 applications – the top patenting regions in these countries are: Oberbayern, Stuttgart and Düsseldorf in Germany; Île de France, Rhône-Alpes and Midi-Pyrénées in France; Nordwestschweiz, Région lémanique and Espace Mittelland in Switzerland.

Regarding trademarks, we identified an impressive growth in the absolute number of applications (Figure 3). Between 2011 and 2019, there was a 37% growth in the total number of applications, reaching almost 63,900 applications in 2019 for the 27 EU countries analysed in this report. This in line with other evidence reporting the increasing importance of intangible assets (Castaldi, 2020).

Among the countries that made the most applications in 2019 Germany, Italy and Spain are in the lead, accounting for 20.31%, 12.20% and 10.76% of total applications that year. As for trademarks, the top regions in these countries are: Oberbayern, Berlin and Düsseldorf in Germany; Piemonte, Valle d'Aosta and Liguria in Italy; and Comunidad de Madrid, Cataluña and Comunitat Valenciana.

Figure 3: Total trademarks application per year



Source: Authors, based on EUIPO.

Table 8 shows the top-10 non-urban regions with the most patents and trademarks per employee. The Province Brabant Wallon in Belgium stands out in both ranks, ranking first for patents and second for trademarks. Luxemburg, which ranks first for trademarks, ranks fifth for patents. In addition, the Swedish region of Sydsverige appears in fourth position in both rankings.

Other NUTS 2 regions appear in the top-10 but only in one of the ranks, showing diversity in the composition of regions regarding innovation when considering either patent or trademark data. This is an important point to stress as the limited overlap between the two top-10 distributions signals the value added of combining the two metrics.

Table 8: Top 10 non-urban regions in patents and trademark application per employed (2019)

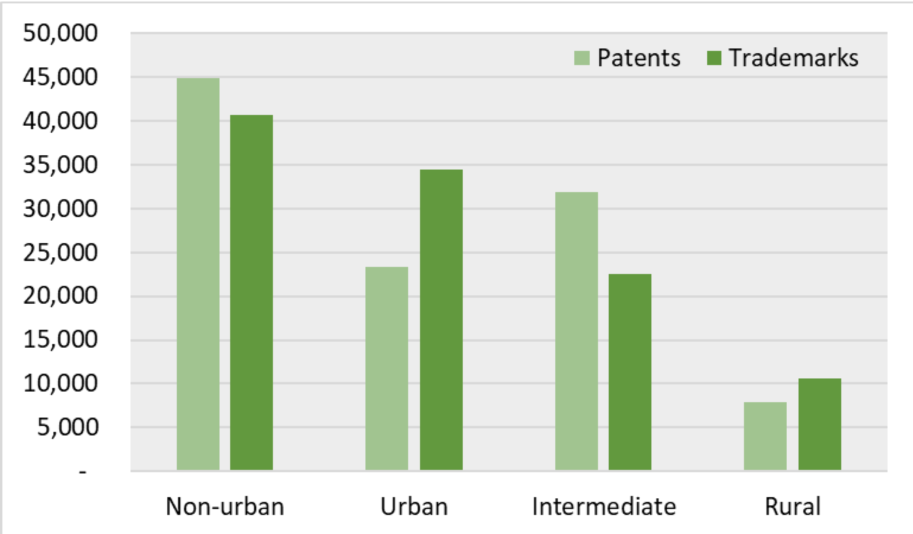
Rank	NUTS 2 code	TOP 10 in patents per employed	Rank	NUTS 2 code	TOP 10 in trademarks per employed
1	BE31	Province Brabant Wallon	1	LU00	Luxembourg
2	DK04	Midtjylland	2	BE31	Province Brabant Wallon
3	DE91	Braunschweig	3	ITH1	Provincia Autonoma di Bolzano
4	SE22	Sydsverige	4	SE22	Sydsverige
5	LU00	Luxembourg	5	AT32	Salzburg
6	DE14	Tübingen	6	AT31	Burgenland
7	DE13	Freiburg	7	DK03	Syddanmark
8	DE23	Oberpfalz	8	DK04	Midtjylland
9	AT31	Burgenland	9	ITH5	Emilia-Romagna
10	FRK1	Auvergne	10	PT18	Alentejo

Source: Authors, based on REGPAT and EUIPO.

The distribution of patents and trademarks among regions by the degree of urbanisation appears in Figure 4. The number of trademarks is lower for lower degrees of urbanisation, but this is not true for patents. Notably, intermediate regions have more patents than urban regions. This confirms that the European innovation landscape might not align with the urban bias found for the United States (Fritsch & Wyrwich, 2021).

Patents are filed more than trademarks in intermediate regions, while trademarks appear in greater volume than patents in rural and urban regions (Figure 4).

Figure 4: Patents and trademarks applications by degree of urbanisation (2019)

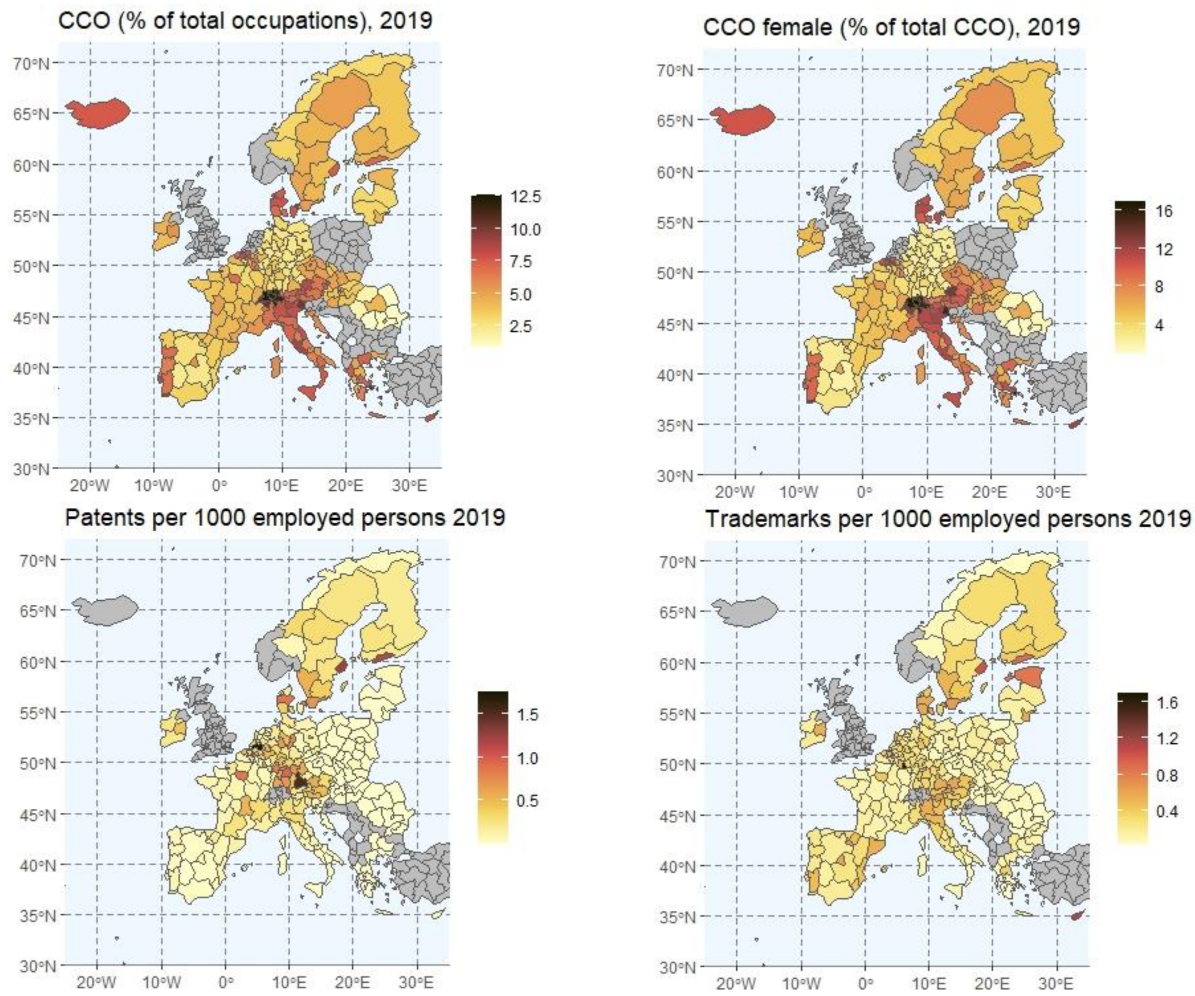


Source: Authors, based on REGPAT and EUIPO.

4.3. The geography of CCOs and its relationship with innovation

Figure 5 shows maps for the distribution of our key variables of theoretical interest for all 229 NUTS 2 regions. Map 1 (top left) illustrates the distribution of CCOs relative to total employment; Map 2 (top right) shows the distribution of female CCO relative to total CCO; Map 3 (bottom left) shows the distribution of patents weighted per thousand employed; and Map 4 (bottom right) shows the distribution of trademarks weighted per thousand employed.

Figure 5: Share of CCO, patents and trademarks across de EU regions



Source: Authors, based on LFS, REGPAT and EUIPO.

The maps at the top of the Figure 5 (CCO share and female CCO share) are similar since 62% of creative occupations are made up of women. In both, we notice that practically all regions of Switzerland, Italy and Portugal stand out among those with the highest CCO share. On the other hand, the regions of Romania and Germany show a slightly lower intensity compared to the others NUTS 2 regions.

As for the innovation indicators (maps at the bottom), it can be seen that patents are more concentrated in some NUTS 2 regions than trademarks regionally.

As a complementary task, Appendix D further elaborates on the profiles of the NUTS level 2 regions corresponding to the location of the IN SITU Labs, which represent creative collaborative incubators designed within the scope of the IN SITU Project.

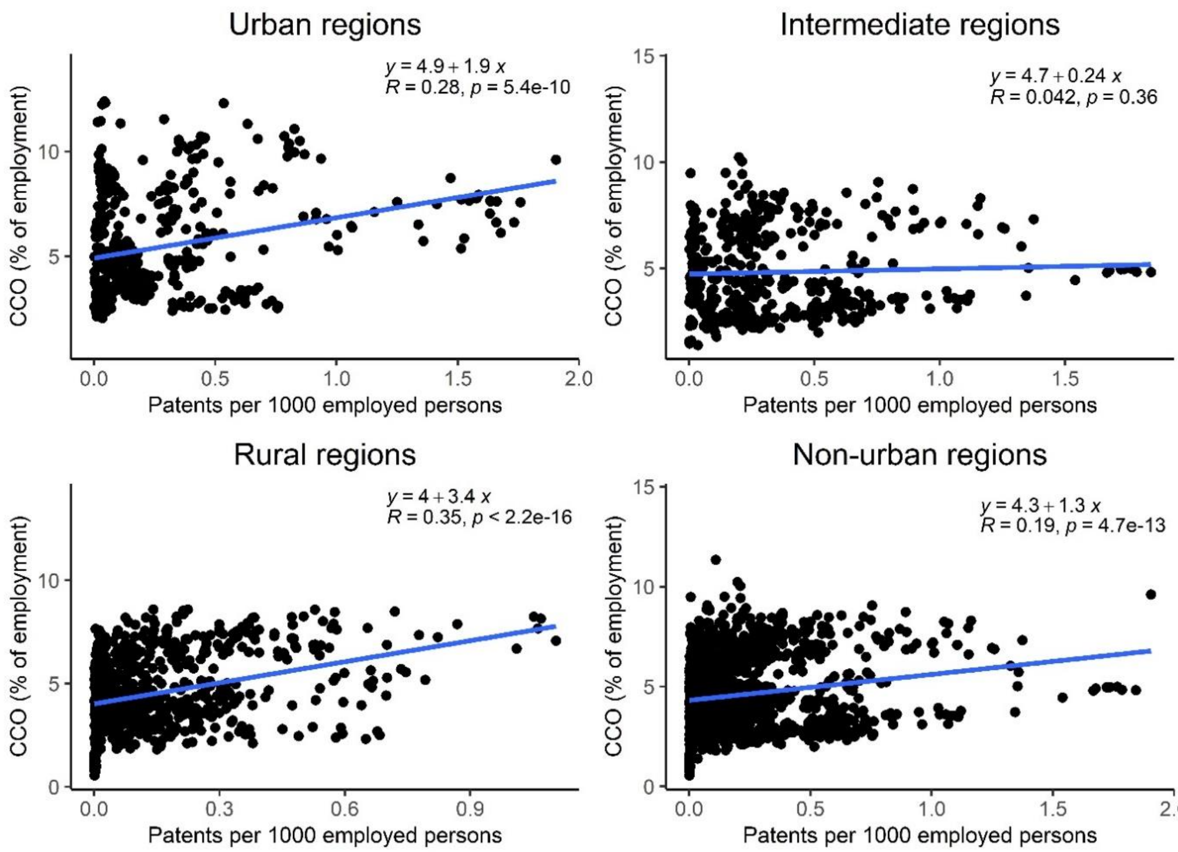
The previous maps show that regions with a higher share of CCO also seem to have higher intensity in the two innovation indicators. To investigate this relationship further, Figures 6 and 7 display the correlation between CCO and the two innovation indicators for all regions and by the degree of urbanisation.

We see a positive correlation between the share of CCO and the two innovation indicators (Figures 6 and 7). The correlation between the share of CCO and trademarks is higher for non-urban than urban regions (Figure 7). Thus, we can expect that cultural and creative occupation will play a significant role in fostering innovation in non-urban regions. The opposite occurs in the case of patents, with the positive correlation being higher in urban than non-urban regions (Figure 6).

It is also interesting to note that the dispersion of patents per thousand persons employed (x-axis of Figure 7) is larger than for trademarks per thousand persons employed (x-axis of Figure 6).

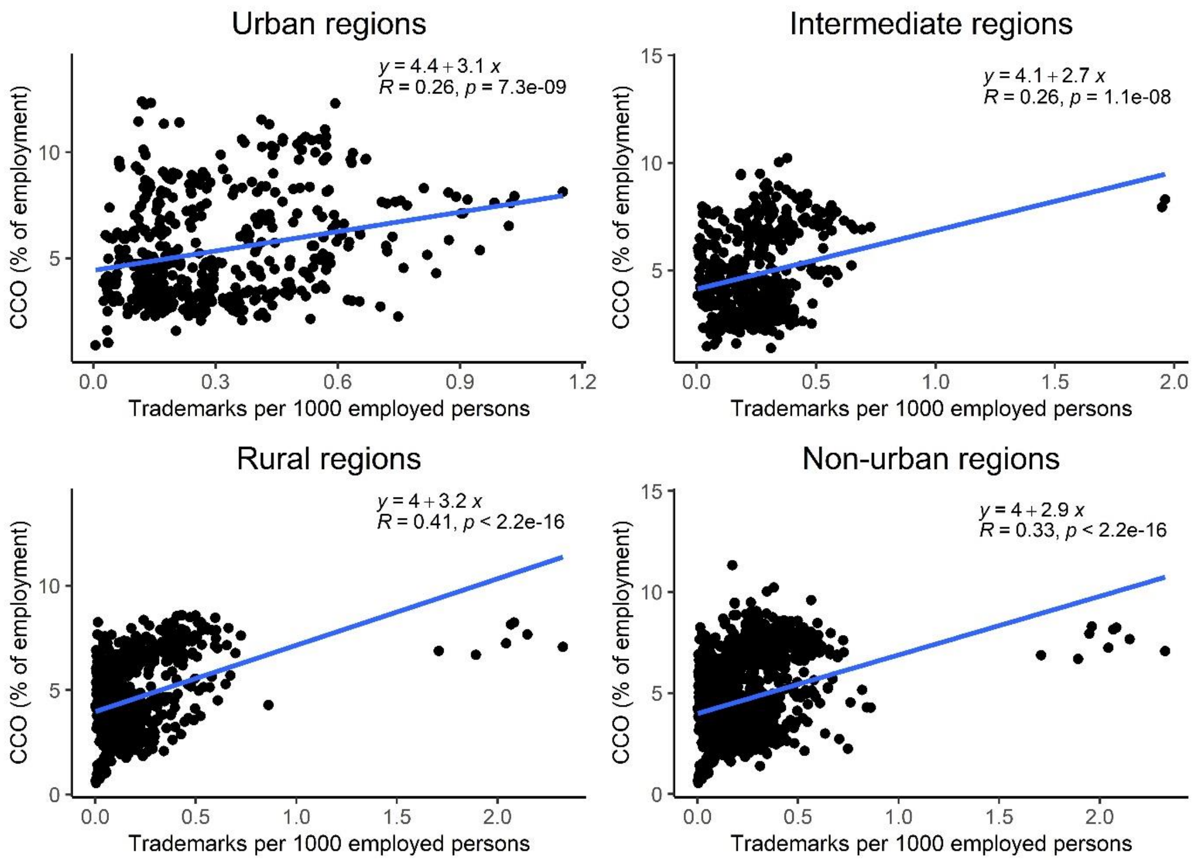
In the case of the intermediate regions, the correlation between CCO share and patents is the lowest compared to the other regions.

Figure 6: Correlation between CCO share and patents by degree of urbanisation (2011-2019)



Source: Authors, based on LFS and EUIPO.

Figure 7: Correlation between CCO share and trademarks by degree of urbanisation (2011-2019)



Source: Authors, based on LFS and EUIPO.

In the next section, we will address statistical results to investigate how CCOs can be associated with innovation in regions with different levels of urbanisation.

4.4. Regression analysis: Creative occupations and regional innovation

In this section, we present the results of the econometric analysis that investigates whether creative workers[5] contribute to innovation, inclusive in non-urban regions. First, we will present the baseline models, where all regions are considered in the regressions, and then the regressions for regions by the degree of urbanisation. The following models were run considering only the main variable of

[5] For the sake of simplicity, here we use the term *creative occupations* or *creative share* to refer to the share of CCO in relation to total employment.

interest (columns 1 and 2 of the tables) and a version with the complete model, including the control variables (columns 3 and 4).

The econometric results show that creative occupations in a region are positively associated with regional innovation (Table 9). The estimated coefficients for the creative share and the number of patents and trademarks per thousand employed persons are positive and statistically significant at 1%.

Such an association is stronger for trademarks than for patents. This means that a greater share of creative occupations in a region tends to increase trademark applications more strongly than the increase in patents in the same region.

The control variables have the expected sign and are statistically different from 0 in most estimations using trademarks. Only the share of the economically active population with tertiary education (tert_educ_sh), which is a measure of skilled human capital, contributes positively to both models - that is, both to promoting patents and trademarks. This aligns with the already established idea that skilled human capital is relevant in promoting regions' development. As the results in Table 9 may be driven by urban regions, we further explore if and how our findings change when splitting the sample of analysis between predominantly urban and non-urban areas.

Table 9: Baseline results – Association between CCO and innovation

FE (year and region), PT and TM per thousand employed - baseline				
	Dependent variable:			
	patents_employ(ln)		trademarks_employ(ln)	
	(1)	(2)	(3)	(4)
creative_sh	0.34114***	0.38162***	0.60073***	0.51258***
	(0.08391)	(0.09568)	(0.09661)	(0.10372)
tert_educ_sh		0.12633**		0.22693***
		(0.05222)		(0.05675)
smallsize_sh		-0.03630		0.09571***
		(0.02979)		(0.03221)
high_tech_service_sh		0.10383		0.28971
		(0.24705)		(0.26843)
high_tech_manuf_sh		-0.12913		-0.36409**
		(0.13587)		(0.14589)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	1,763	1,569	1,818	1,577
R^2	0.98049	0.98081	0.95258	0.96039
Adjusted R^2	0.97778	0.97802	0.94618	0.95467
Residual Std. Error	0.02975	0.02968	0.03497	0.03224

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses. Patents and trademarks are divided by thousand employed persons and are in Ln, and all control variables are stated as share in all regressions.

The positive association between creative occupations and innovation holds also in the case of non-urban regions (Table 10)[6]. However, the coefficients in the patent models are smaller than in the baseline model and statistically significant only at 10% in the full model. The coefficients of creative occupations in the trademark models for non-urban regions are three times higher than in the patent models and significant at 1%. Comparing these results to the baseline suggests that an increase in CCO

[6] Regressions to urban regions have also been performed and can be seen in Appendix A – Tables A.1 and A.2.

in non-urban areas is associated with a stronger increase in trademarks and a less marked increase in patents.

In non-urban regions, a higher share of skilled human capital is similarly associated with the two measures of innovation. Thus, human capital acts in a complementary way to creative occupations on the potential to generate innovations in the regions (Table 10).

On the one hand, small companies (smallsize_sh) in non-urban regions have a positive association with a higher volume of trademarks in that region. On the other hand, small companies have a negative coefficient associated with patents in non-urban regions, but this coefficient is not statistically significant (as in the baseline model, Table 9). As we know from the literature, patents increase with the size of companies, but we cannot confirm this from our results.

Table 10: Association between CCO and innovation in Non-urban regions

FE (year and region), PT and TM per thousand employed - Non-Urban				
	Dependent variable:			
	patents_employ(ln)		trademarks_employ(ln)	
	(1)	(2)	(3)	(4)
creative_sh	0.19143**	0.20685*	0.65770***	0.59208***
	(0.09700)	(0.11215)	(0.10989)	(0.12203)
tert_educ_sh		0.16076***		0.17434***
		(0.05624)		(0.06139)
smallsize_sh		-0.02669		0.06773*
		(0.03209)		(0.03479)
high_tech_service_sh		0.33762		0.26380
		(0.29295)		(0.31977)
high_tech_manuf_sh		-0.12808		-0.39314***
		(0.14018)		(0.15104)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	1,475	1,291	1,522	1,299
R^2	0.97784	0.97822	0.94918	0.95677
Adjusted R^2	0.97457	0.97480	0.94192	0.95004
Residual Std. Error	0.02936	0.02905	0.03394	0.03168

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses.

Finally, we further split the group of predominantly non-urban regions between "intermediate" and "rural" areas. In intermediate regions (Table 11), creative occupations are only positively and statistically associated with innovation in trademark models. The greater presence of skilled human capital and small size of companies reinforces this effect. We found no statistically significant association between CCO share and innovation in patent models. This suggest that, even when increasing the share of creative occupations in intermediate regions, the number of patents tends not to increase, unlike the number of trademarks.

Table 11: Association between CCO and innovation in Intermediate regions

FE (year and region), PT and TM per thousand employed - Intermediate				
	Dependent variable:			
	patents_employ(ln)		trademarks_employ(ln)	
	(1)	(2)	(3)	(4)
creative_sh	0.13764	0.02381	0.88140***	0.50988***
	(0.20070)	(0.22265)	(0.17262)	(0.19656)
tert_educ_sh		0.21070		0.53138***
		(0.14677)		(0.12957)
smallsize_sh		0.07338		0.10678**
		(0.06016)		(0.05311)
high_tech_service_sh		1.22278*		-0.52898
		(0.65029)		(0.57407)
high_tech_manuf_sh		0.24552		-0.67278**
		(0.34866)		(0.30780)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	478	444	488	444
R^2	0.98252	0.98261	0.95971	0.95693
Adjusted R^2	0.97735	0.97747	0.94782	0.94422
Residual Std. Error	0.03320	0.03174	0.02872	0.02802

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses.

The same finding holds in rural regions (Table 12), where creative occupations also present a positive and statistically significant association at 1% value with innovation only in trademark models. This result is in line with idea that trademarks might better capture actual innovation, developed with the help of symbolic workers, and also more soft innovation, where creative occupation play a more prominent role. This result applies to all types of regions.

Note that a higher share of skilled human capital (working population with tertiary education) is not statistically significant for stimulating innovation in rural regions. Thus, rural regions rely primarily on creative occupations to innovate.

Table 12: Association between CCO and innovation in Rural regions

FE (year and region), PT and TM per thousand employed - Rural				
	Dependent variable:			
	patents_employ(ln)		trademarks_employ(ln)	
	(1)	(2)	(3)	(4)
creative_sh	0.19973	0.21341	0.70666^{***}	0.68528^{***}
	(0.15113)	(0.18098)	(0.19954)	(0.22659)
tert_educ_sh		0.18584^{***}		0.11796
		(0.06257)		(0.07858)
smallsize_sh		-0.05359		0.08670
		(0.04584)		(0.05695)
high_tech_service_sh		-0.05963		0.82767^{*}
		(0.36477)		(0.45850)
high_tech_manuf_sh		-0.26676		-0.42578^{**}
		(0.16390)		(0.20418)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	815	682	849	689
R^2	0.96889	0.97220	0.94835	0.96097
Adjusted R^2	0.96309	0.96637	0.93900	0.95288
Residual Std. Error	0.02656	0.02651	0.03597	0.03328

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses.

On the other hand, patents require conditions often found in urban environments to flourish, such as technological diversity, specific funding, high population density and a large pool of diversified workers, among other factors.

The high and medium-high tech manufacturing share (high_tech_manuf_sh) is negatively associated and statistically significant with innovation across all trademark models. This result again can be seen in line with the idea that trademarks capture non-technological innovation.

Creative occupations are more strongly associated with trademarks than patents in the baseline and non-urban regions estimations. Creative occupations are even more relevant for rural regions, where the skilled human capital variable was not statistically significant.

To test robustness, we run the same regressions using GDP to classify regions by degree of urbanisation. We also did a robustness check dividing the two innovation measures by a set of occupations named 'inventive class' proposed by Dotzel & Wojan (2022) to see how the regression models perform using an unbiased patent productivity measure (Dotzel & Wojan, 2022; Wojan, 2022). According to the authors, there is a bias when considering patents per capita as a measure of productivity or only STEM as workers responsible for patenting. Assuming that only STEM workers patent is empirically incorrect, as many other creative workers can also contribute to generating new ideas and patents (Wojan, 2022). To avoid such bias, we use the 'inventive class' suggested by Dotzel & Wojan (2022) to weigh the innovation measures in our robustness test. Inventive class encompasses the Science, Engineering, and Technical workforce category and other 11 occupations that demonstrated a consistent association with patenting in randomised tests (Dotzel & Wojan, 2022; Wojan, 2022). Such alternative measures provide a more interesting robustness check, especially for rural areas, which may suffer more with the employment composition bias.

All tables with the robustness tests can be seen in Appendix B. Tables B.1 to B.8 present the results regarding the classification of regions by level of urbanisation using GDP; Tables B.10 to B.19 shows the results for the innovation measures divided by inventive class' employment; and from B.20 to B.29 we employed a limited group of occupations named restricted inventive class. Besides that, Table B.9 indicates the ISCO-08 codes at 3 and 4-digit for inventive class. We also tested our dependent variable by dividing them by other variables, such as patents and trademarks per capita and by employed persons – however, for space reasons, they were not included in this report. Our results are robust, following the trend presented in this section.

4.5. Female creative occupations and regional innovation

In this section, we discuss the results of the econometric tests using the female creative share instead of the overall creative share. As the descriptive statistics section showed, gender is expected to play a key role in creative occupations. We want to understand whether, at the regional level, female creative occupations are associated to regional innovation, especially in non-urban regions.

In the baseline model for all regions (Table 13), the results show that an increase in the share of female creative workers tends to promote gains in innovation, both in patents and trademarks. However, the difference in female creative workers' potential contribution to innovation is less evident than in the Table 9 model, which has the same observations. Thus, women in creative occupations tend to contribute to patents and innovation to a similar extent.

In addition, the skilled human capital variable has a positive association with innovation in the estimations for two measures.

Table 13: Baseline results – Association between women in CCO and innovation

FE (year and region), PT and TM per thousand employed, female baseline				
	Dependent variable:			
	patents_employ(ln)		trademarks_employ(ln)	
	(1)	(2)	(3)	(4)
female_creative_sh	0.22025***	0.26196***	0.34492***	0.29787***
	(0.05089)	(0.05718)	(0.05847)	(0.06211)
tert_educ_sh		0.12258**		0.23235***
		(0.05197)		(0.05662)
smallsize_sh		-0.03921		0.09541***
		(0.02976)		(0.03225)
high_tech_service_sh		0.10928		0.31523
		(0.24623)		(0.26818)
high_tech_manuf_sh		-0.13854		-0.36512**
		(0.13567)		(0.14602)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	1,763	1,569	1,818	1,577
R^2	0.98052	0.98088	0.95246	0.96035
Adjusted R^2	0.97781	0.97810	0.94605	0.95462
Residual Std. Error	0.02973	0.02963	0.03501	0.03226

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses.

When considering only non-urban regions (Table 14), we can also state that female creative occupations positively correlate with regional innovation. However, this relationship is stronger in trademark estimates than for patents. The results for female creative occupations in urban regions are shown in Appendix A: Table A.2.

As for the control variables, the share of the economically active population with higher education (tert_educ_sh) is positive and statistically significant in all models, the small size of companies is positive and significant only in the estimation for trademarks, and the high and medium-high tech manufacturing share is negatively associated with trademarks. All these coefficients are similar in size and direction to those in Table 10, which considers the total creative occupations.

Table 14: Association between women in CCO and innovation in Non-urban region

FE (year and region), PT and TM per thousand employed – Female, Non-Urban				
	Dependent variable:			
	patents_employ(ln)		trademarks_employ(ln)	
	(1)	(2)	(3)	(4)
female_creative_sh	0.15055**	0.18490***	0.36185***	0.30921***
	(0.05884)	(0.06612)	(0.06645)	(0.07222)
tert_educ_sh		0.15161***		0.18476***
		(0.05598)		(0.06138)
smallsize_sh		-0.03098		0.07141**
		(0.03200)		(0.03484)
high_tech_service_sh		0.32494		0.29257
		(0.29214)		(0.32025)
high_tech_manuf_sh		-0.13754		-0.38397**
		(0.13987)		(0.15134)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	1,475	1,291	1,522	1,299
R^2	0.97789	0.97830	0.94895	0.95657
Adjusted R^2	0.97462	0.97490	0.94166	0.94981
Residual Std. Error	0.02933	0.02899	0.03402	0.03176

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses.

Next, we present the estimates for the intermediate non-urban and rural regions.

As for female creative occupations in intermediate regions, we also find a positive and significant association only for trademarks, while it is not significant for patents (Table 15). The control variables have similar direction and statistical significance to the previous case (non-urban regions).

Table 15: Association between women in CCO and innovation in Intermediate region

FE (year and region), PT and TM per thousand employed – Female, Intermediate				
	Dependent variable:			
	patents_employ(ln)		trademarks_employ(ln)	
	(1)	(2)	(3)	(4)
female_creative_sh	0.14608	0.09552	0.50319^{***}	0.29382^{**}
	(0.12006)	(0.13176)	(0.10368)	(0.11647)
tert_educ_sh		0.19203		0.53119^{***}
		(0.14684)		(0.12979)
smallsize_sh		0.06487		0.10746^{**}
		(0.06013)		(0.05315)
high_tech_service_sh		1.20414^{*}		-0.50884
		(0.64936)		(0.57399)
high_tech_manuf_sh		0.25656		-0.69666^{**}
		(0.34770)		(0.30734)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	478	444	488	444
R^2	0.98257	0.98264	0.95946	0.95689
Adjusted R^2	0.97741	0.97751	0.94749	0.94416
Residual Std. Error	0.03315	0.03171	0.02881	0.02803

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses.

We also find a positive association for rural regions (Table 16) for the primary variable of interest, meaning that women in creative occupations working in such a region contribute to innovation, but only with significant results for trademark estimations.

The rural region is the only case in which the existence of skilled human capital is not reinforcing the region's ability to innovate via trademarks. Here the main element is the female creative share. For patents, the opposite occurs. Female creative occupations do not present a statistically significant coefficient associated with patent generation; however, skilled human capital, on the other hand, has a positive association (Table 16).

Moreover, a higher share of high-tech services appears positively associated with trademarks only in rural regions. In all other regions, the high-tech services industries did not show a significant coefficient associated with innovation (except in intermediate regions in the patent models).

Table 16: Association between women in CCO and innovation in Rural region

FE (year and region), PT and TM per thousand employed – Female, Rural				
	Dependent variable:			
	patents_employ(ln)		trademarks_employ(ln)	
	(1)	(2)	(3)	(4)
female_creative_sh	0.08000	0.11974	0.35731***	0.31267**
	(0.09412)	(0.10691)	(0.12132)	(0.13405)
tert_educ_sh		0.18708***		0.12631
		(0.06250)		(0.07873)
smallsize_sh		-0.05197		0.09353
		(0.04576)		(0.05702)
high_tech_service_sh		-0.05016		0.87906*
		(0.36417)		(0.45921)
high_tech_manuf_sh		-0.26081		-0.39386*
		(0.16340)		(0.20416)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	815	682	849	689
R^2	0.96884	0.97219	0.94808	0.96071
Adjusted R^2	0.96303	0.96636	0.93868	0.95258
Residual Std. Error	0.02658	0.02651	0.03606	0.03338

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses.

The robustness tests for the models considering women in creative occupations are shown in Appendix B (Tables B5 to B8). In general, they confirm the trend presented in this section, providing robustness to the results.

Our results show that women in creative occupations play a more critical role in regional innovation when this is measured with trademarks rather than patents, especially in non-urban and rural regions.

5. Conclusion

Our aim in this part of the report was to assess the socio-economic contribution of creative and cultural activities in non-urban regions. We approached this aim with **a focus on the role played by creative activities in regional innovation processes**. We built on insights from recent research across economic geography, innovation studies, urban and rural studies and designed an original empirical study focused on the experience of European regions in the period 2011-2019.

Our analysis revealed three sets of novel and relevant empirical findings.

First, we showed how the **combination of patents and trademarks** as regional innovation metrics allows to provide a different map of regional innovation and its distribution across urban and non-urban regions. In particular, we found patenting activities concentrated in urban and intermediate regions, while trademark filing was strong in both urban and rural regions.

Second, and related to the previous remark, the ability to capture innovation activities more broadly than those focused on technological invention only, resulted in revealing a more detailed picture of the role of creative activities. Importantly, creative occupations appear to be positively and strongly associated with both forms of innovation. Yet, results also showed a **stronger association of creative occupations to trademarks for rural regions**, suggesting that in those regions the type of innovation activities leaves more space for the contribution of creativity.

Third, conducting the analysis with the two innovation metrics also allowed us to reveal the role of **female creative occupations** in a new way. In non-urban regions, a high share of female creative occupations appears to be more strongly associated with trademarks, suggesting that using this innovation metrics might also help mitigate the gender bias of patents.

All three findings have key implications for policy. Based on the insights, we would advise policymakers to combine patents and trademarks as regional innovation indicators when monitoring the socio-economic contribution of creative occupations. While the two metrics are already part of the European regional innovation scoreboard and by now also available from Eurostat, their combined application in research and monitoring is still limited.

We should also note a number of limitations of this study, which prompt potential areas for further research.

A first remark concerns our innovation metrics. The combination of patent and trademarks proved already very useful, but this set could be further expanded with a third IPR, namely design rights. This extension could be particularly relevant given that designers are part of creative workers and given the role that design might play in innovation processes of rural regions. On the other hand, design rights also have weaknesses as innovation indicators (Filitz, Henkel & Tether, 2015). These relate for instance to the very low tendency of designers to formally protect their creations (Vankan, Frenken & Castaldi, 2014). Still, one could follow recent studies (Wojan & Nichols, 2018; Pinate et al., 2023) and include design rights in the innovation measurement toolbox. Of course, the well-known overall limitation of using IPRs remains: much innovation happens without being formally protected. Innovation that happens more informally or is developed by actors that are not only driven by economic motivations or even innovation in public organisations and households remains under the radar of IPR metrics. Hence, it remains important to complement these metrics with complementary data on for instance, entrepreneurship, innovation surveys, innovation events and many others.

A second remark is that our quantitative analysis offered insights that remain complementary to more detailed or process-like explorations of the actual mechanisms behind the significant correlations found in our regressions. One already has several hints on how creative workers contribute to innovation, yet the specific ways in which these workers play a role in rural regions can be further unpacked. In particular, studies on the role of female creators have the potential to offer evidence with both scientific and policy relevance.

A final remark concerns the definition of creative and cultural activities, which remains highly debated, with some convergence to commonly used classifications. In this study we have leveraged the most recent insights and worked with occupational data instead of industry ones. One could try to better combine the two levels or even go beyond them in original new ways.

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Appendices (Task 1.1)

Appendix A: Results for urban regions

Additionally, we performed the same regression for the urban regions. Since this report focuses on non-urban regions, we chose not to include this table with the main results.

The result shows that a more significant share of creative occupations in urban regions contributes similarly to the increase in patents and trademarks, while in the other regions previously presented, the largest association occurs with trademarks than patents.

*Table A.1: Association between creative occupations and innovation in **Urban regions***

FE (year and region), PT and TM per thousand employed – Urban region				
	Dependent variable:			
	patents_employ(ln)		trademarks_employ(ln)	
	(1)	(2)	(3)	(4)
creative_sh	0.33255**	0.42209**	0.38441*	0.45602**
	(0.15685)	(0.17416)	(0.20235)	(0.19596)
tert_educ_sh		0.07059		0.43371***
		(0.11536)		(0.12981)
smallsize_sh		-0.14999**		0.22541***
		(0.06206)		(0.06983)
high_tech_service_sh		-0.10521		-0.41165
		(0.38628)		(0.43464)
high_tech_manuf_sh		-0.16294		0.20323
		(0.38219)		(0.43005)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	470	443	481	444
R^2	0.98737	0.98759	0.94894	0.96276
Adjusted R^2	0.98454	0.98468	0.93748	0.95392
Residual Std. Error	0.02874	0.02874	0.03791	0.03234

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses.

The following table shows the regression results using female creative share in urban regions.

An increase in female creative share is also associated with increased innovation in urban regions. However, the effect is more significant for trademarks than for patents.

*Table A2: Association between women in creative occupations and innovation in **Urban regions***

FE (year and region), PT and TM per thousand employed - Female Urban				
	Dependent variable:			
	patents_employ(ln)		trademarks_employ(ln)	
	(1)	(2)	(3)	(4)
female_creative_sh	0.15359	0.21827**	0.27190**	0.33342***
	(0.09567)	(0.10891)	(0.12336)	(0.12189)
tert_educ_sh		0.08323		0.41606***
		(0.11588)		(0.12969)
smallsize_sh		-0.15120**		0.22036***
		(0.06229)		(0.06971)
high_tech_service_sh		-0.07513		-0.39872
		(0.38668)		(0.43275)
high_tech_manuf_sh		-0.16304		0.14370
		(0.38497)		(0.43084)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	470	443	481	444
R^2	0.98731	0.98752	0.94910	0.96298
Adjusted R^2	0.98446	0.98460	0.93767	0.95418
Residual Std. Error	0.02882	0.02881	0.03785	0.03225

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses.

Appendix B: Robustness check

As a robustness test, we classify the regions by degree of urbanisation considering the GDP. Thus, most GDP defines whether a region is non-urban, urban, intermediate or rural. With this new classification, we again ran the regressions presented in Section 4.4 and 4.5. Below, we show the tables in the same sequence as in Section 4.4. The tests confirm the trend presented and the robustness of the results.

Table B.1: Association between CCO and innovation in ***Non-Urban regions, by GDP***

FE (year and region), PT and TM per thousand employed – Non-Urban				
	Dependent variable:			
	patents_employ(ln)		trademarks_employ(ln)	
	(1)	(2)	(3)	(4)
creative_sh	0.20265**	0.19354	0.67829***	0.60563***
	(0.10274)	(0.12424)	(0.12090)	(0.13751)
tert_educ_sh		0.11172*		0.23346***
		(0.06062)		(0.06736)
smallsize_sh		-0.02895		0.03292
		(0.03692)		(0.04070)
high_tech_service_sh		0.11494		-0.62347
		(0.34487)		(0.38326)
high_tech_manuf_sh		-0.17473		-0.28922*
		(0.15137)		(0.16597)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	1,141	977	1,189	985
R^2	0.96922	0.96998	0.95407	0.96229
Adjusted R^2	0.96473	0.96533	0.94768	0.95650
Residual Std. Error	0.02843	0.02903	0.03418	0.03223

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses.

Table B.2: Association between CCO and innovation in ***Intermediate region, by GDP***

FE (year and region), PT and TM per thousand employed – Intermediate				
	Dependent variable:			
	patents_employ(ln)		trademarks_employ(ln)	
	(1)	(2)	(3)	(4)
creative_sh	0.18782	0.19739	0.67757***	0.52768***
	(0.13315)	(0.15270)	(0.13878)	(0.15418)
tert_educ_sh		0.17458**		0.30226***
		(0.08007)		(0.08110)
smallsize_sh		-0.05626		0.02640
		(0.04514)		(0.04545)
high_tech_service_sh		0.24282		-0.48428
		(0.41910)		(0.42406)
high_tech_manuf_sh		-0.32280		-0.30387
		(0.19749)		(0.19657)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	801	723	824	728
R^2	0.96881	0.96920	0.96275	0.96729
Adjusted R^2	0.96404	0.96424	0.95724	0.96207
Residual Std. Error	0.03100	0.03145	0.03309	0.03187

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses.

Table B.3: Association between CCO and innovation in ***Rural region, by GDP***

FE (year and region), PT and TM per thousand employed - Rural				
	Dependent variable:			
	patents_employ(ln)		trademarks_employ(ln)	
	(1)	(2)	(3)	(4)
creative_sh	0.28176*	0.08425	0.62588**	0.75163**
	(0.14999)	(0.21178)	(0.25353)	(0.34965)
tert_educ_sh		-0.06838		0.17912
		(0.08520)		(0.14128)
smallsize_sh		0.04384		0.03326
		(0.05777)		(0.09461)
high_tech_service_sh		-0.56457		-1.27813
		(0.54966)		(0.91761)
high_tech_manuf_sh		0.08376		-0.32974
		(0.20161)		(0.33173)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	340	254	365	257
R^2	0.96640	0.97373	0.91329	0.93609
Adjusted R^2	0.96017	0.96758	0.89852	0.92134
Residual Std. Error	0.02109	0.02022	0.03653	0.03338

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses.

*Table B.4: Association between CCO and innovation in **Urban region, by GDP***

FE (year and region), PT and TM per thousand employed – Urban				
	Dependent variable:			
	patents_employ(ln)		trademarks_employ(ln)	
	(1)	(2)	(3)	(4)
creative_sh	0.51615***	0.56534***	0.49522***	0.37454**
	(0.14588)	(0.15462)	(0.16202)	(0.15967)
tert_educ_sh		0.17059*		0.27084**
		(0.10187)		(0.10519)
smallsize_sh		-0.02682		0.22183***
		(0.05018)		(0.05182)
high_tech_service_sh		0.08683		1.03315***
		(0.35897)		(0.37069)
high_tech_manuf_sh		-0.15007		-0.25682
		(0.32097)		(0.33145)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	610	580	617	580
R^2	0.98679	0.98755	0.94152	0.95502
Adjusted R^2	0.98482	0.98553	0.93279	0.94771
Residual Std. Error	0.03153	0.03019	0.03577	0.03118

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses.

Table B.5: Association between women in CCO and innovation in ***Non-Urban region, by GDP***

FE (year and region), PT and TM per thousand employed - Female Non-Urban				
	Dependent variable:			
	patents_employ(ln)		trademarks_employ(ln)	
	(1)	(2)	(3)	(4)
female_creative_sh	0.12040**	0.14102**	0.37683***	0.33249***
	(0.06103)	(0.07171)	(0.07140)	(0.07950)
tert_educ_sh		0.10890*		0.24063***
		(0.06039)		(0.06724)
smallsize_sh		-0.03055		0.03628
		(0.03682)		(0.04067)
high_tech_service_sh		0.11871		-0.58612
		(0.34416)		(0.38326)
high_tech_manuf_sh		-0.17699		-0.28059*
		(0.15115)		(0.16605)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	1,141	977	1,189	985
R^2	0.96922	0.97003	0.95391	0.96221
Adjusted R^2	0.96473	0.96539	0.94750	0.95640
Residual Std. Error	0.02843	0.02901	0.03424	0.03226

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses.

Table B.6: Association between women in CCO and innovation in ***Intermediate region, by GDP***

FE (year and region), PT and TM per thousand employed - Female Intermediate				
	Dependent variable:			
	patents_employ(ln)		trademarks_employ(ln)	
	(1)	(2)	(3)	(4)
female_creative_sh	0.11797	0.13896	0.36155***	0.27344***
	(0.07703)	(0.08610)	(0.08048)	(0.08713)
tert_educ_sh		0.17269**		0.31450***
		(0.07954)		(0.08074)
smallsize_sh		-0.05796		0.02958
		(0.04503)		(0.04546)
high_tech_service_sh		0.24820		-0.45586
		(0.41854)		(0.42443)
high_tech_manuf_sh		-0.32851*		-0.31050
		(0.19742)		(0.19695)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	801	723	824	728
R^2	0.96882	0.96924	0.96256	0.96719
Adjusted R^2	0.96406	0.96430	0.95703	0.96196
Residual Std. Error	0.03099	0.03142	0.03317	0.03191

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses.

Table B.7: Association between women in CCO and innovation in ***Rural region, by GDP***

FE (year and region), PT and TM per thousand employed - Female Rural				
	Dependent variable:			
	patents_employ(ln)		trademarks_employ(ln)	
	(1)	(2)	(3)	(4)
female_creative_sh	0.15977*	0.13055	0.39528**	0.49917**
	(0.09502)	(0.12975)	(0.15516)	(0.21404)
tert_educ_sh		-0.07330		0.16503
		(0.08519)		(0.14132)
smallsize_sh		0.04110		0.03550
		(0.05756)		(0.09427)
high_tech_service_sh		-0.59211		-1.25829
		(0.54749)		(0.91433)
high_tech_manuf_sh		0.07169		-0.29570
		(0.19932)		(0.32790)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	340	254	365	257
R^2	0.96632	0.97384	0.91340	0.93633
Adjusted R^2	0.96007	0.96771	0.89864	0.92164
Residual Std. Error	0.02112	0.02018	0.03650	0.03332

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses.

*Table B.8: Association between women in CCO and innovation in **Urban region, by GDP***

FE (year and region), PT and TM per thousand employed - Female Urban				
	Dependent variable:			
	patents_employ(ln)		trademarks_employ(ln)	
	(1)	(2)	(3)	(4)
female_creative_sh	0.22988*	0.19704	0.14595	0.30259*
	(0.13738)	(0.15166)	(0.17759)	(0.17277)
tert_educ_sh		0.27297*		0.25087
		(0.14058)		(0.16014)
smallsize_sh		-0.07991		0.34515***
		(0.08533)		(0.09720)
high_tech_service_sh		-0.02779		0.07190
		(0.48219)		(0.54930)
high_tech_manuf_sh		-0.65109		0.29471
		(0.53209)		(0.60615)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	288	278	296	278
R^2	0.98974	0.98992	0.95619	0.96706
Adjusted R^2	0.98703	0.98701	0.94477	0.95755
Residual Std. Error	0.02966	0.02986	0.03968	0.03402

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses.

As a second robustness check, we choose a different variable to weigh the innovation measures (patents and trademarks). In the following regressions, we use the inventive class employment developed for the United States by Dotzel & Wojan (2022) and Wojan (2022) to replace the previous indicator (patents and trademarks per employed person) with patents and trademarks per employed people within the inventive class.

The inventive class developed by Dotzel & Wojan (2022) adopts the American occupational classification (Standard Occupational Classification System – SOC) and has an ISCO-08 crosswalk. However, we made some adjustments. First, since the crosswalk indicates ISCO-08 at the 4-digit level, we have to regroup them into ISCO-08 3-digit, the same level we are working on in this report. In total, we have 21 codes for the inventive class at the ISCO-08 3-digit level.

Second, after regrouping them, we identified some codes not completely covered. Of the 21 codes, nine were fully covered and five were almost complete – except for one or two occupations. Seven others codes mixed many non-inventive class occupations at ISCO-08 3-dig. To avoid including too many codes not classified as an inventive class, we excluded those seven codes (which are: 264, 313, 315, 331, 343, 818, 821 ISCO-08 codes) to obtain a 'restricted inventive class' (or inventive2) and then we perform the regressions again.

Table B.9 below presents the classification for inventive class at ISCO-08 3 and 4-digit levels and indicates with (**) the excluded codes to obtain the restricted inventive class.

Table B.9: Classification for inventive class occupations by ISCO-08 3 and 4-digit

ISCO 3D	ISCO 4D	Description	Inventive class
122	1221	Sales and Marketing Managers	Yes
	1222	Advertising and Public Relations Managers	No
	1223	Research and Development Managers	Yes
211	2111	Physicists and Astronomers	Yes
	2112	Meteorologists	Yes
	2113	Chemists	Yes
	2114	Geologists and Geophysicists	Yes
212	2120	Mathematicians, Actuaries and Statisticians	Yes
213	2131	Biologists, Botanists, Zoologists and Related Professionals	Yes
	2132	Farming, Forestry and Fisheries Advisers	Yes
	2133	Environmental Protection Professionals	Yes
214	2141	Industrial and Production Engineers	Yes
	2142	Civil Engineers	Yes
	2143	Environmental Engineers	Yes
	2144	Mechanical Engineers	Yes
	2145	Chemical Engineers	Yes
	2146	Mining Engineers, Metallurgists and Related Professionals	Yes
	2149	Engineering Professionals n.e.c.	Yes

ISCO 3D	ISCO 4D	Description	Inventive class
215	2151	Electrical Engineers	Yes
	2152	Electronics Engineers	Yes
	2153	Telecommunications Engineers	Yes
216	2161	Building Architects	Yes
	2162	Landscape Architects	Yes
	2163	Product and Garment Designers	Yes
	2164	Town and Traffic Planners	No
	2165	Cartographers and Surveyors	Yes
	2166	Graphic and Multimedia Designers	Yes
251	2511	Systems Analysts	Yes
	2512	Software Developers	Yes
	2513	Web and Multimedia Developers	Yes
	2514	Applications Programmers	Yes
	2519	Software and Applications Developers and Analysts n.e.c.	Yes
252	2521	Database Designers and Administrators	Yes
	2522	Systems Administrators	Yes
	2523	Computer Network Professionals	Yes
	2529	Database and Network Professionals n.e.c.	Yes
264 (**)	2641	Authors and Related Writers	Yes
	2642	Journalists	No
	2643	Translators, Interpreters and Other Linguists	No
311	3111	Chemical and Physical Science Technicians	Yes
	3112	Civil Engineering Technicians	Yes
	3113	Electrical Engineering Technicians	Yes
	3114	Electronics Engineering Technicians	Yes
	3115	Mechanical Engineering Technicians	Yes
	3116	Chemical Engineering Technicians	Yes
	3117	Mining and Metallurgical Technicians	Yes
	3118	Draughtspersons	Yes
	3119	Physical and Engineering Science Technicians n.e.c.	Yes
313 (**)	3131	Power Production Plant Operators	No
	3132	Incinerator and Water Treatment Plant Operators	No
	3133	Chemical Processing Plant Controllers	No
	3134	Petroleum and Natural Gas Refining Plant Operators	No
	3135	Metal Production Process Controllers	No
	3139	Process Control Technicians Not Elsewhere Classified	Yes
314	3141	Life Science Technicians (excluding Medical)	Yes
	3142	Agricultural Technicians	Yes
	3143	Forestry Technicians	Yes
315 (**)	3151	Ships' Engineers	No
	3152	Ships' Deck Officers and Pilots	No
	3153	Aircraft Pilots and Related Associate Professionals	No
	3154	Air Traffic Controllers	No
	3155	Air Traffic Safety Electronics Technicians	Yes
331 (**)	3311	Securities and Finance Dealers and Brokers	No
	3312	Credit and Loans Officers	No
	3313	Accounting Associate Professionals	No
	3314	Statistical, Mathematical and Related Associate Professionals	Yes

ISCO 3D	ISCO 4D	Description	Inventive class
	3315	Valuers and Loss Assessors	No
343 (**)	3431	Photographers	No
	3432	Interior Designers and Decorators	Yes
	3433	Gallery, Museum and Library Technicians	No
	3434	Chefs	No
	3435	Other Artistic and Cultural Associate Professionals	No
351	3511	Information and Communications Technology Operations Technicians	No
	3512	Information and Communications Technology User Support Technicians	Yes
	3513	Computer Network and Systems Technicians	Yes
	3514	Web Technicians	Yes
352	3521	Broadcasting and Audiovisual Technicians	No
	3522	Telecommunications Engineering Technicians	Yes
722	7221	Blacksmiths, Hammersmiths and Forging Press Workers	No
	7222	Toolmakers and Related Workers	Yes
	7223	Metal Working Machine Tool Setters and Operators	Yes
	7224	Metal Polishers, Wheel Grinders and Tool Sharpeners	No
818 (**)	8181	Glass and Ceramics Plant Operators	No
	8182	Steam Engine and Boiler Operators	No
	8183	Packing, Bottling and Labelling Machine Operators	No
	8189	Stationary Plant and Machine Operators n.e.c.	Yes
821 (**)	8211	Mechanical Machinery Assemblers	No
	8212	Electrical and Electronic Equipment Assemblers	Yes
	8219	Assemblers Not Elsewhere Classified	No

Source: Author's elaboration based on Dotzel & Wojan (2022).

Below we present the results using all the creative class at ISCO-08 3-digit codes. The urbanisation degree was calculated using the number of employed persons in a region (same as in the Section 4.4 and 4.5).

Table B.10: Baseline results – Association between CCO and innovation (all regions)

FE (year and region), baseline – PT and TM per inventive employment – Baseline				
	Dependent variable:			
	patents_inventive(ln)		trademarks_inventive(ln)	
	(1)	(2)	(3)	(4)
creative_sh	1.22906***	1.34368***	1.54175***	1.89246***
	(0.28764)	(0.30108)	(0.40805)	(0.36258)
tert_educ_sh		-0.09446		-0.06315
		(0.16334)		(0.19699)
smalllsize_sh		0.07147		0.48062***
		(0.09373)		(0.11247)
high_tech_service_sh		-0.59093		-0.47762
		(0.77270)		(0.93195)
high_tech_manuf_sh		-0.67169		-1.33810***
		(0.42373)		(0.50491)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	1,686	1,542	1,707	1,547
R^2	0.97278	0.97675	0.92482	0.95275
Adjusted R^2	0.96907	0.97341	0.91467	0.94597
Residual Std. Error	0.09986	0.09243	0.14313	0.11140

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses. Patents and trademarks are divided by persons employed in inventive class and are in Ln, and all control variables are stated as share in all regressions.

Table B.11: Association between CCO and innovation in ***Non-Urban regions***

FE (year and region), PT and TM per inventive employment – Non-Urban				
	Dependent variable:			
	patents_inventive(ln)		trademarks_inventive(ln)	
	(1)	(2)	(3)	(4)
creative_sh	0.83494**	0.91008**	2.32908***	2.02992***
	(0.33958)	(0.35706)	(0.42965)	(0.43886)
tert_educ_sh		0.02231		-0.06607
		(0.17938)		(0.22090)
smallsize_sh		0.08849		0.36716***
		(0.10236)		(0.12523)
high_tech_service_sh		-0.93261		-1.23345
		(0.93301)		(1.14917)
high_tech_manuf_sh		-0.52148		-1.35105**
		(0.44557)		(0.54152)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	1,407	1,273	1,420	1,278
R^2	0.97121	0.97598	0.93648	0.94890
Adjusted R^2	0.96703	0.97225	0.92737	0.94100
Residual Std. Error	0.10087	0.09223	0.12830	0.11347

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses. Patents and trademarks are divided by persons employed in inventive class and are in Ln, and all control variables are stated as share in all regressions.

*Table B.12: Association between CCO and innovation in **Urban regions***

FE (year and region), PT and TM per inventive employment – Urban				
	Dependent variable:			
	patents_inventive(ln)		trademarks_inventive(ln)	
	(1)	(2)	(3)	(4)
creative_sh	1.82555***	1.22401*	-2.96187**	1.03838
	(0.68244)	(0.70243)	(1.50268)	(0.83172)
tert_educ_sh		0.20703		-0.03661
		(0.39711)		(0.47020)
smallsize_sh		-0.04842		1.03460***
		(0.25096)		(0.29716)
high_tech_service_sh		0.71650		1.34483
		(1.36593)		(1.61735)
high_tech_manuf_sh		-2.21339		0.76717
		(1.49214)		(1.76679)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	279	269	287	269
R^2	0.98452	0.98598	0.86495	0.96405
Adjusted R^2	0.98036	0.98185	0.82910	0.95346
Residual Std. Error	0.08741	0.08391	0.20079	0.09936

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses. Patents and trademarks are divided by persons employed in inventive class and are in Ln, and all control variables are stated as share in all regressions.

Table B.13: Association between CCO and innovation in **Intermediate region**

FE (year and region), PT and TM per inventive employment – Intermediate				
	Dependent variable:			
	ln_patents_inventive		ln_tm_ inventive	
	(1)	(2)	(3)	(4)
creative_sh	0.19203	0.28060	3.55193***	2.03519***
	(0.59031)	(0.67261)	(0.65134)	(0.71668)
tert_educ_sh		0.06385		0.89217*
		(0.44246)		(0.47145)
smallsize_sh		0.28437		0.56667***
		(0.18166)		(0.19356)
high_tech_service_sh		0.75686		-3.38902
		(1.96141)		(2.08992)
high_tech_manuf_sh		-1.07610		-3.31003***
		(1.05111)		(1.11998)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	471	441	471	441
R^2	0.97790	0.97714	0.93386	0.93608
Adjusted R^2	0.97162	0.97042	0.91507	0.91728
Residual Std. Error	0.09753	0.09567	0.10771	0.10194

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses. Patents and trademarks are divided by persons employed in inventive class and are in Ln, and all control variables are stated as share in all regressions.

*Table B.14: Association between CCO and innovation in **Rural region***

FE (year and region), PT and TM per inventive employment – Rural				
	Dependent variable:			
	patents_inventive(ln)		trademarks_inventive(ln)	
	(1)	(2)	(3)	(4)
creative_sh	1.02238*	1.00765*	1.79438**	1.92235**
	(0.60368)	(0.60086)	(0.80959)	(0.80229)
tert_educ_sh		0.09366		-0.35414
		(0.20837)		(0.27860)
smallsize_sh		0.08163		0.43387**
		(0.15285)		(0.20234)
high_tech_service_sh		-2.00926*		0.82811
		(1.21156)		(1.62308)
high_tech_manuf_sh		-0.51884		-1.27752*
		(0.54346)		(0.72078)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	756	668	767	673
R^2	0.96514	0.97567	0.93504	0.95229
Adjusted R^2	0.95875	0.97065	0.92322	0.94255
Residual Std. Error	0.10137	0.08771	0.13600	0.11721

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses. Patents and trademarks are divided by persons employed in inventive class and are in Ln, and all control variables are stated as share in all regressions.

Table B.15: Baseline results – Association between women in CCO and innovation (all regions)

FE (year and region), PT and TM per inventive employment - Female Baseline				
	Dependent variable:			
	ln_patents_inventive		ln_tm_inventive	
	(1)	(2)	(3)	(4)
female_creative_sh	0.76299***	0.92470***	1.04719***	1.23121***
	(0.17359)	(0.17960)	(0.24542)	(0.21644)
tert_educ_sh		-0.10972		-0.07101
		(0.16255)		(0.19615)
smallsize_sh		0.06091		0.47057***
		(0.09356)		(0.11234)
high_tech_service_sh		-0.56571		-0.41997
		(0.76979)		(0.92899)
high_tech_manuf_sh		-0.70522*		-1.36957***
		(0.42285)		(0.50414)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	1,686	1,542	1,707	1,547
R^2	0.97280	0.97686	0.92501	0.95292
Adjusted R^2	0.96909	0.97353	0.91489	0.94617
Residual Std. Error	0.09982	0.09221	0.14295	0.11120

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses. Patents and trademarks are divided by persons employed in inventive class and are in Ln, and all control variables are stated as share in all regressions.

*Table B.16: Baseline results – Association between women in CCO and innovation, **Non-Urban region***

FE (year and region), PT and TM per inventive class employed, Female Non-Urban				
	Dependent variable:			
	patents_inventive(ln)		trademarks_inventive(ln)	
	(1)	(2)	(3)	(4)
female_creative_sh	0.53880***	0.69705***	1.36336***	1.20975***
	(0.20505)	(0.21062)	(0.25847)	(0.25940)
tert_educ_sh		0.00010		-0.05727
		(0.17864)		(0.22041)
smallsize_sh		0.07772		0.36820***
		(0.10209)		(0.12515)
high_tech_service_sh		-0.95046		-1.17673
		(0.93042)		(1.14814)
high_tech_manuf_sh		-0.54403		-1.34379**
		(0.44456)		(0.54128)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	1,407	1,273	1,420	1,278
R^2	0.97123	0.97607	0.93640	0.94892
Adjusted R^2	0.96706	0.97236	0.92728	0.94102
Residual Std. Error	0.10083	0.09205	0.12838	0.11345

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses. Patents and trademarks are divided by persons employed in inventive class and are in Ln, and all control variables are stated as share in all regressions.

Table B.17: Baseline results – Association between women in CCO and innovation, ***Urban region***

FE (year and region), PT and TM per inventive class employed – Female Urban				
	Dependent variable:			
	patents_inventive(ln)		trademarks_inventive(ln)	
	(1)	(2)	(3)	(4)
female_creative_sh	0.93029**	0.65114	-1.12465	1.14228**
	(0.42187)	(0.44636)	(0.93255)	(0.52336)
tert_educ_sh		0.23555		-0.11343
		(0.39716)		(0.46568)
smallsize_sh		-0.04394		0.99887***
		(0.25176)		(0.29520)
high_tech_service_sh		0.84256		1.39634
		(1.36530)		(1.60085)
high_tech_manuf_sh		-2.26630		0.38131
		(1.50602)		(1.76586)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	279	269	287	269
R^2	0.98437	0.98592	0.86351	0.96459
Adjusted R^2	0.98015	0.98177	0.82727	0.95416
Residual Std. Error	0.08786	0.08409	0.20186	0.09860

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses. Patents and trademarks are divided by persons employed in inventive class and are in Ln, and all control variables are stated as share in all regressions.

Table B.18: Baseline results – Association between women in CCO and innovation, ***Intermediate region***

FE (year and region), PT and TM per inventive class employed – Female Intermediate				
	Dependent variable:			
	patents_inventive(ln)		trademarks_inventive(ln)	
	(1)	(2)	(3)	(4)
female_creative_sh	0.31630	0.43478	2.11915***	1.29973***
	(0.35316)	(0.39757)	(0.39019)	(0.42343)
tert_educ_sh		0.00185		0.86227*
		(0.44235)		(0.47113)
smallsize_sh		0.25591		0.55600***
		(0.18144)		(0.19324)
high_tech_service_sh		0.70035		-3.33896
		(1.95710)		(2.08439)
high_tech_manuf_sh		-1.04835		-3.38619***
		(1.04742)		(1.11554)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	471	441	471	441
R^2	0.97794	0.97721	0.93382	0.93632
Adjusted R^2	0.97167	0.97051	0.91501	0.91760
Residual Std. Error	0.09743	0.09553	0.10775	0.10174

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses. Patents and trademarks are divided by persons employed in inventive class and are in Ln, and all control variables are stated as share in all regressions.

Table B.19: Baseline results – Association between women in CCO and innovation, ***Rural region***

FE (year and region), PT and TM per inventive employed – Female Rural				
	Dependent variable:			
	patents_inventive(ln)		trademarks_inventive(ln)	
	(1)	(2)	(3)	(4)
female_creative_sh	0.31744	0.53841	0.85876*	1.02206**
	(0.37249)	(0.35557)	(0.49012)	(0.47519)
Tert_educ_sh		0.10023		-0.34144
		(0.20827)		(0.27863)
smallsize_sh		0.08945		0.44799**
		(0.15265)		(0.20220)
high_tech_service_sh		-1.95518		0.92922
		(1.21000)		(1.62207)
high_tech_manuf_sh		-0.48577		-1.21325*
		(0.54196)		(0.71911)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	756	668	767	673
R^2	0.96502	0.97565	0.93486	0.95220
Adjusted R^2	0.95861	0.97063	0.92300	0.94243
Residual Std. Error	0.10154	0.08775	0.13619	0.11732

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses. Patents and trademarks are divided by persons employed in inventive class and are in Ln, and all control variables are stated as share in all regressions.

From this point on, we present the results using the **restricted creative class** at ISCO 3-digit codes. As in the previous tables, the degree of urbanisation was calculated using the number of employed persons in a region (same as in the Section 4.4 and 4.5).

Table B.20: Baseline results – Association between CCO and innovation (all regions)

FE (year and region), PT and TM per restricted inventive class - Baseline				
	Dependent variable:			
	patents_inventive2(ln)		trademarks_inventive2(ln)	
	(1)	(2)	(3)	(4)
creative_sh	1.12706***	1.26657***	1.63113***	1.93884***
	(0.33577)	(0.34631)	(0.48484)	(0.41105)
tert_educ_sh		-0.24684		-0.29099
		(0.18788)		(0.22333)
smallsize_sh		0.13770		0.61170***
		(0.10781)		(0.12751)
high_tech_service_sh		-1.15578		-1.23219
		(0.88878)		(1.05655)
high_tech_manuf_sh		-0.56674		-1.28412**
		(0.48738)		(0.57241)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	1,686	1,542	1,707	1,547
R^2	0.96957	0.97490	0.91635	0.95178
Adjusted R^2	0.96542	0.97128	0.90505	0.94486
Residual Std. Error	0.11657	0.10632	0.17007	0.12630

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses. Patents and trademarks are divided by persons employed in inventive class and are in Ln, and all control variables are stated as share in all regressions.

*Table B.21: Association between CCO and innovation in **Non-Urban regions***

FE (year and region), PT and TM per restricted inventive class - Non-Urban				
	Dependent variable:			
	patents_inventive2(ln)		trademarks_inventive2(ln)	
	(1)	(2)	(3)	(4)
creative_sh	0.70117*	0.78107*	2.16155***	2.03772***
	(0.39634)	(0.40969)	(0.49132)	(0.49769)
tert_educ_sh		-0.08944		-0.24984
		(0.20582)		(0.25052)
smallsize_sh		0.14085		0.46100***
		(0.11744)		(0.14202)
high_tech_service_sh		-1.72646		-2.08641
		(1.07052)		(1.30323)
high_tech_manuf_sh		-0.40771		-1.34028**
		(0.51124)		(0.61412)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	1,407	1,273	1,420	1,278
R^2	0.96783	0.97421	0.93421	0.94782
Adjusted R^2	0.96317	0.97021	0.92478	0.93975
Residual Std. Error	0.11773	0.10583	0.14671	0.12868

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses. Patents and trademarks are divided by persons employed in inventive class and are in Ln, and all control variables are stated as share in all regressions.

*Table B.22: Association between CCO and innovation in **Urban regions***

FE (year and region), PT and TM per restricted inventive class - Urban				
	Dependent variable:			
	patents_inventive2(ln)		trademarks_inventive2(ln)	
	(1)	(2)	(3)	(4)
creative_sh	1.90576**	1.22589	-1.37045	1.22932
	(0.79591)	(0.81672)	(1.93859)	(0.94295)
tert_educ_sh		0.11018		-0.19737
		(0.46172)		(0.53308)
smallsize_sh		0.05748		1.25818***
		(0.29180)		(0.33690)
high_tech_service_sh		0.87319		1.13484
		(1.58818)		(1.83365)
high_tech_manuf_sh		-2.54361		0.85065
		(1.73492)		(2.00307)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	279	269	287	269
R^2	0.98272	0.98449	0.83130	0.96384
Adjusted R^2	0.97806	0.97991	0.78651	0.95318
Residual Std. Error	0.10195	0.09757	0.25904	0.11265

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses. Patents and trademarks are divided by persons employed in inventive class and are in Ln, and all control variables are stated as share in all regressions.

*Table B.23: Association between CCO and innovation in **Intermediate region***

FE (year and region), PT and TM per restricted inventive class - Intermediate				
	Dependent variable:			
	patents_inventive2(ln)		trademarks_inventive2(ln)	
	(1)	(2)	(3)	(4)
creative_sh	-0.65786	-0.41438	3.04970***	1.59167*
	(0.65610)	(0.74112)	(0.74562)	(0.82532)
tert_educ_sh		-0.01999		0.73879
		(0.48753)		(0.54292)
smallsize_sh		0.32545		0.71262***
		(0.20017)		(0.22291)
high_tech_service_sh		-0.10079		-4.73825**
		(2.16120)		(2.40673)
high_tech_manuf_sh		-0.78919		-3.18118**
		(1.15817)		(1.28975)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	471	441	471	441
R^2	0.97608	0.97576	0.93090	0.93359
Adjusted R^2	0.96929	0.96864	0.91126	0.91405
Residual Std. Error	0.10839	0.10542	0.12331	0.11739

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses. Patents and trademarks are divided by persons employed in inventive class and are in Ln, and all control variables are stated as share in all regressions.

Table B.24: Association between CCO and innovation in ***Rural region***

FE (year and region), PT and TM per restricted inventive class - Rural				
	Dependent variable:			
	patents_inventive2(ln)		trademarks_inventive2(ln)	
	(1)	(2)	(3)	(4)
creative_sh	1.32989*	0.91890	1.63244*	1.81172**
	(0.72551)	(0.70695)	(0.93662)	(0.91483)
tert_educ_sh		-0.02733		-0.55849*
		(0.24515)		(0.31768)
smallsize_sh		0.16301		0.53708**
		(0.17984)		(0.23072)
high_tech_service_sh		-3.17277**		-0.11345
		(1.42546)		(1.85076)
high_tech_manuf_sh		-0.46379		-1.34457
		(0.63941)		(0.82189)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	756	668	767	673
R^2	0.96079	0.97379	0.93223	0.95100
Adjusted R^2	0.95360	0.96839	0.91989	0.94099
Residual Std. Error	0.12182	0.10319	0.15734	0.13365

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses. Patents and trademarks are divided by persons employed in inventive class and are in Ln, and all control variables are stated as share in all regressions.

Table B.25: Baseline results – Association between women in CCO and innovation (all regions)

FE (year and region), PT and TM per restricted inventive class - Female Baseline				
	Dependent variable:			
	patents_inventive2(ln)		trademarks_inventive2(ln)	
	(1)	(2)	(3)	(4)
female_creative_sh	0.65733***	0.84918***	1.17026***	1.23377***
	(0.20275)	(0.20681)	(0.29152)	(0.24556)
tert_educ_sh		-0.25688		-0.29368
		(0.18717)		(0.22254)
smallsize_sh		0.12938		0.60341***
		(0.10773)		(0.12745)
high_tech_service_sh		-1.12539		-1.16529
		(0.88643)		(1.05400)
high_tech_manuf_sh		-0.59347		-1.31039**
		(0.48692)		(0.57198)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	1,686	1,542	1,707	1,547
R^2	0.96955	0.97496	0.91661	0.95188
Adjusted R^2	0.96540	0.97135	0.90535	0.94498
Residual Std. Error	0.11660	0.10618	0.16980	0.12616

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses. Patents and trademarks are divided by persons employed in inventive class and are in Ln, and all control variables are stated as share in all regressions.

*Table B.26: Baseline results – Association between women in CCO and innovation, **Non-Urban region***

FE (year and region), PT and TM per restricted inventive class - Female Non-Urban				
	Dependent variable:			
	patents_inventive2(ln)		trademarks_inventive2(ln)	
	(1)	(2)	(3)	(4)
female_creative_sh	0.38784	0.57818**	1.22938***	1.16277***
	(0.23946)	(0.24192)	(0.29564)	(0.29438)
tert_educ_sh		-0.10511		-0.23223
		(0.20519)		(0.25012)
smallsize_sh		0.13309		0.46584***
		(0.11726)		(0.14202)
high_tech_service_sh		-1.73617		-2.01571
		(1.06869)		(1.30294)
high_tech_manuf_sh		-0.42374		-1.32445**
		(0.51062)		(0.61426)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	1,407	1,273	1,420	1,278
R^2	0.96782	0.97426	0.93411	0.94777
Adjusted R^2	0.96316	0.97026	0.92465	0.93969
Residual Std. Error	0.11775	0.10573	0.14683	0.12875

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses. Patents and trademarks are divided by persons employed in inventive class and are in Ln, and all control variables are stated as share in all regressions.

*Table B.27: Baseline results – Association between women in CCO and innovation, **Urban region***

FE (year and region), PT and TM per restricted inventive class - Female Urban				
	Dependent variable:			
	patents_inventive2(ln)		trademarks_inventive2(ln)	
	(1)	(2)	(3)	(4)
female_creative_sh	0.98929**	0.61639	0.52337	1.28686**
	(0.49136)	(0.51890)	(1.19751)	(0.59365)
tert_educ_sh		0.14486		-0.27711
		(0.46171)		(0.52822)
smallsize_sh		0.06436		1.22026***
		(0.29268)		(0.33484)
high_tech_service_sh		1.00280		1.20197
		(1.58720)		(1.81583)
high_tech_manuf_sh		-2.57594		0.43168
		(1.75080)		(2.00300)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	279	269	287	269
R^2	0.98259	0.98442	0.83107	0.96435
Adjusted R^2	0.97789	0.97983	0.78622	0.95385
Residual Std. Error	0.10233	0.09776	0.25922	0.11184

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses. Patents and trademarks are divided by persons employed in inventive class and are in Ln, and all control variables are stated as share in all regressions.

*Table B.28: Baseline results – Association between women in CCO and innovation, **Intermediate region***

FE (year and region), PT and TM per restricted inventive class - Female Intermediate				
	Dependent variable:			
	patents_inventive2(ln)		trademarks_inventive2(ln)	
	(1)	(2)	(3)	(4)
female_creative_sh	-0.21462	-0.01006	1.79857***	1.00171**
	(0.39327)	(0.43892)	(0.44684)	(0.48821)
tert_educ_sh		-0.07156		0.71875
		(0.48837)		(0.54321)
smallsize_sh		0.30074		0.70584***
		(0.20031)		(0.22281)
high_tech_service_sh		-0.17415		-4.69544*
		(2.16067)		(2.40332)
high_tech_manuf_sh		-0.73558		-3.24296**
		(1.15637)		(1.28623)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	471	441	471	441
R^2	0.97604	0.97574	0.93080	0.93368
Adjusted R^2	0.96923	0.96861	0.91114	0.91418
Residual Std. Error	0.10850	0.10547	0.12339	0.11731

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses. Patents and trademarks are divided by persons employed in inventive class and are in Ln, and all control variables are stated as share in all regressions.

*Table B.29: Baseline results – Association between women in CCO and innovation, **Rural region***

FE (year and region), PT and TM per restricted inventive class - Female Rural				
	Dependent variable:			
	patents_inventive2(ln)		trademarks_inventive2(ln)	
	(1)	(2)	(3)	(4)
female_creative_sh	0.25540	0.31547	0.65579	0.82138
	(0.44797)	(0.41857)	(0.56697)	(0.54210)
tert_educ_sh		-0.00998		-0.53726*
		(0.24517)		(0.31786)
smallsize_sh		0.17463		0.55422**
		(0.17970)		(0.23067)
high_tech_service_sh		-3.07123**		0.02194
		(1.42440)		(1.85046)
high_tech_manuf_sh		-0.40252		-1.25868
		(0.63799)		(0.82037)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	756	668	767	673
R^2	0.96060	0.97374	0.93205	0.95086
Adjusted R^2	0.95338	0.96832	0.91968	0.94082
Residual Std. Error	0.12211	0.10330	0.15754	0.13384

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses. Patents and trademarks are divided by persons employed in inventive class and are in Ln, and all control variables are stated as share in all regressions.

Appendix C: Correlation tables for all regressions – by degree of urbanisation and female CCO

Table C.1: Correlation table (pearson-method): baseline model

	ln_patents_employed	*trademarks_employ(ln)*	*creative_sh*	*tert_educ_sh*	*smallsize_sh*	*high_tech_service_sh*
trademarks_employ(ln)	0.626***					
creative_sh	0.255***	0.389***				
tert_educ_sh	0.415***	0.484***	0.260***			
smallsize_sh	-0.425***	-0.155***	0.026	-0.277***		
high_tech_service_sh	0.387***	0.424***	0.491***	0.677***	-0.269***	
high_tech_manuf_sh	0.226***	-0.097***	-0.252***	-0.258***	-0.408***	-0.201***

Table C.2: Correlation table (pearson-method): non-urban regions

	patents_employ(ln)	*trademarks_employ(ln)*	*creative_sh*	*tert_educ_sh*	*smallsize_sh*	*high_tech_service_sh*
trademarks_employ(ln)	0.630***					
creative_sh	0.215***	0.386***				
tert_educ_sh	0.429***	0.398***	0.141***			
smallsize_sh	-0.444***	-0.153***	0.139***	-0.261***		
high_tech_service_sh	0.403***	0.373***	0.383***	0.606***	-0.171***	
high_tech_manuf_sh	0.291***	-0.037	-0.217***	-0.194***	-0.482***	-0.090**

Table C.3: Correlation table (pearson-method): intermediate regions

	patents_employ(ln)	*trademarks_employ(ln)*	*creative_sh*	*tert_educ_sh*	*smallsize_sh*	*high_tech_service_sh*
trademarks_employ(ln)	0.654***					
creative_sh	0.023	0.271***				
tert_educ_sh	0.530***	0.425***	0.092			
smallsize_sh	-0.483***	-0.201***	0.386***	-0.386***		
high_tech_service_sh	0.501***	0.436***	0.299***	0.705***	-0.210***	
high_tech_manuf_sh	0.480***	0.127**	-0.308***	-0.05	-0.493***	-0.007

Table C.4: Correlation table (pearson-method): rural regions

	patents_employ(ln)	*trademarks_employ(ln)*	*creative_sh*	*tert_educ_sh*	*smallsize_sh*	*high_tech_service_sh*
trademarks_employ(ln)	0.724***					
creative_sh	0.417***	0.522***				
tert_educ_sh	0.480***	0.418***	0.223***			
smallsize_sh	-0.293***	-0.155***	0.02	-0.219***		
high_tech_service_sh	0.412***	0.438***	0.359***	0.640***	-0.125**	
high_tech_manuf_sh	-0.054	-0.178***	-0.201***	-0.311***	-0.403***	-0.200***

Table C.5: Correlation table (pearson-method): urban regions

	patents_employ(ln)	*trademarks_employ(ln)*	*creative_sh*	*tert_educ_sh*	*smallsize_sh*	*high_tech_service_sh*
trademarks_employ(ln)	0.538***					
creative_sh	0.285***	0.237***				
tert_educ_sh	0.328***	0.482***	0.275***			
smallsize_sh	-0.463***	-0.062	-0.204***	-0.296***		
high_tech_service_sh	0.390***	0.322***	0.595***	0.638***	-0.461***	
high_tech_manuf_sh	0.274***	-0.071	-0.213***	-0.193***	-0.348***	-0.174***

Table C.6: Correlation table (pearson-method): baseline model for female creative occupations

	patents_employ(ln)	*trademarks_employ(ln)*	*female_creative_sh*	*tert_educ_sh*	*smallsize_sh*	*high_tech_service_sh*
trademarks_employ(ln)	0.626***					
female_creative_sh	0.165***	0.290***				
tert_educ_sh	0.415***	0.484***	0.131***			
smallsize_sh	-0.425***	-0.155***	0.050*	-0.277***		
high_tech_service_sh	0.387***	0.424***	0.363***	0.677***	-0.269***	
high_tech_manuf_sh	0.226***	-0.097***	-0.176***	-0.258***	-0.408***	-0.201***

Table C.7: Correlation table (pearson-method): non-urban regions and female creative occupations

	patents_employ(ln)	*trademarks_employ(ln)*	*female_creative_sh*	*tert_educ_sh*	*smallsize_sh*	*high_tech_service_sh*
trademarks_employ(ln)	0.630***					
female_creative_sh	0.132***	0.297***				
tert_educ_sh	0.429***	0.398***	0.035			
smallsize_sh	-0.444***	-0.153***	0.130***	-0.261***		
high_tech_service_sh	0.403***	0.373***	0.291***	0.606***	-0.171***	
high_tech_manuf_sh	0.291***	-0.037	-0.150***	-0.194***	-0.482***	-0.090**

Table C.8: Correlation table (pearson-method): intermediate regions and female creative occupations

	patents_employ(ln)	trademarks_employ(ln)	female_creative_sh	tert_educ_sh	smallsize_sh	high_tech_service_sh
trademarks_employ(ln)	0.654***					
female_creative_sh	-0.054	0.202***				
tert_educ_sh	0.530***	0.425***	0.03			
smallsize_sh	-0.483***	-0.201***	0.379***	-0.386***		
high_tech_service_sh	0.501***	0.436***	0.234***	0.705***	-0.210***	
high_tech_manuf_sh	0.480***	0.127**	-0.276***	-0.05	-0.493***	-0.007

Table C.9: Correlation table (pearson-method): rural regions and female creative occupations

	patents_employ(ln)	trademarks_employ(ln)	female_creative_sh	tert_educ_sh	smallsize_sh	high_tech_service_sh
trademarks_employ(ln)	0.724***					
female_creative_sh	0.333***	0.433***				
tert_educ_sh	0.480***	0.418***	0.086*			
smallsize_sh	-0.293***	-0.155***	-0.011	-0.219***		
high_tech_service_sh	0.412***	0.438***	0.273***	0.640***	-0.125**	
high_tech_manuf_sh	-0.054	-0.178***	-0.094*	-0.311***	-0.403***	-0.200***

Table C.10: Correlation table (pearson-method): urban regions and female creative occupations

	patents_employ(ln)	trademarks_employ(ln)	female_creative_sh	tert_educ_sh	smallsize_sh	high_tech_service_sh
trademarks_employ(ln)	0.538***					
female_creative_sh	0.223***	0.175***				
tert_educ_sh	0.328***	0.482***	0.210***			
smallsize_sh	-0.463***	-0.062	-0.154**	-0.296***		
high_tech_service_sh	0.390***	0.322***	0.519***	0.638***	-0.461***	
high_tech_manuf_sh	0.274***	-0.071	-0.163***	-0.193***	-0.348***	-0.174***

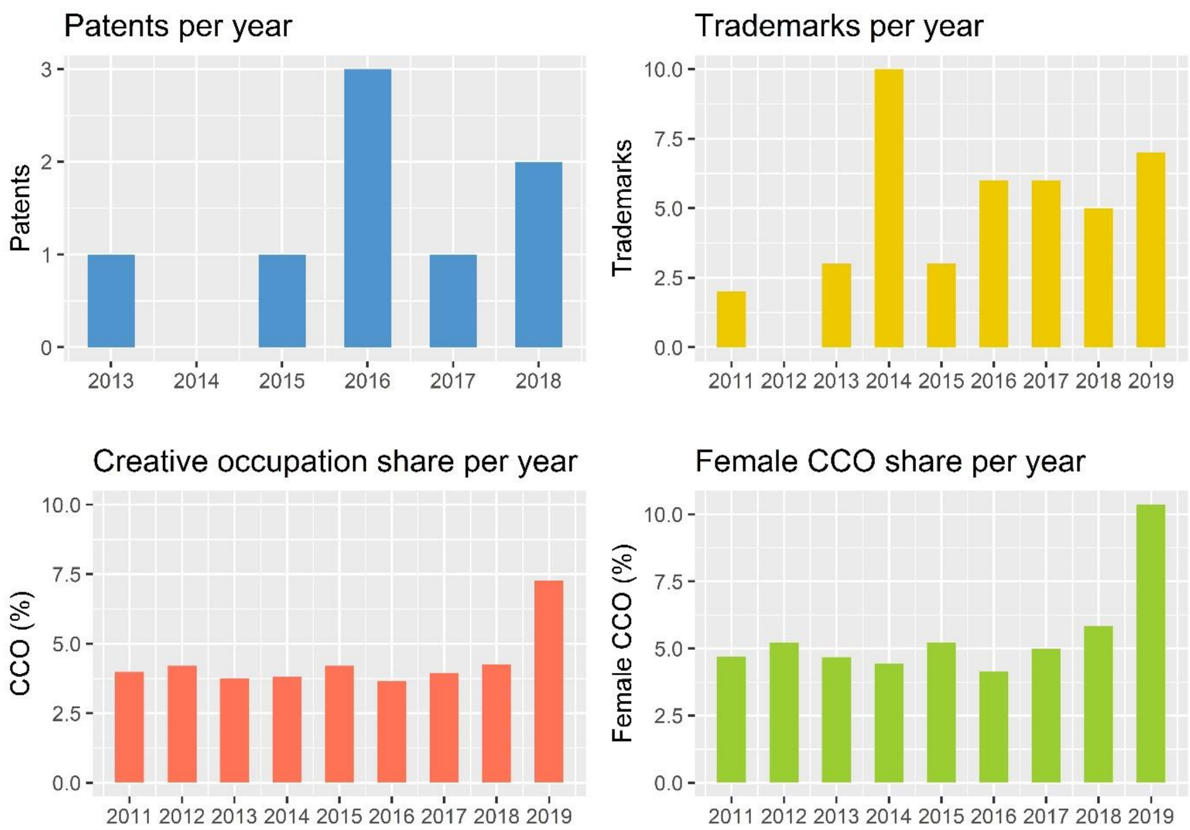
Appendix D: Geography of innovation in the regions of the IN SITU Labs

One of the central aspects of the IN SITU project is to build creative collaborative incubators, called "IN SITU Labs". The idea is to link research and practice through place-based hubs. The aim is to design a capacity-building programme to promote new entrepreneurial social and business models and, ultimately, innovation. To this end, 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, we sought to link this report with the other IN SITU Project tasks. To do so, we selected the NUTS 2 regions where each of the IN SITU Labs belongs and calculated some indicators, the same ones prepared for this report. We expect to contribute with an illustrative scenario of the geography of innovation in the IN SITU Labs' regions.

IN SITU Lab 1: Azores, Portugal

Figure D.1: Innovation indicators for the Azores region – PT



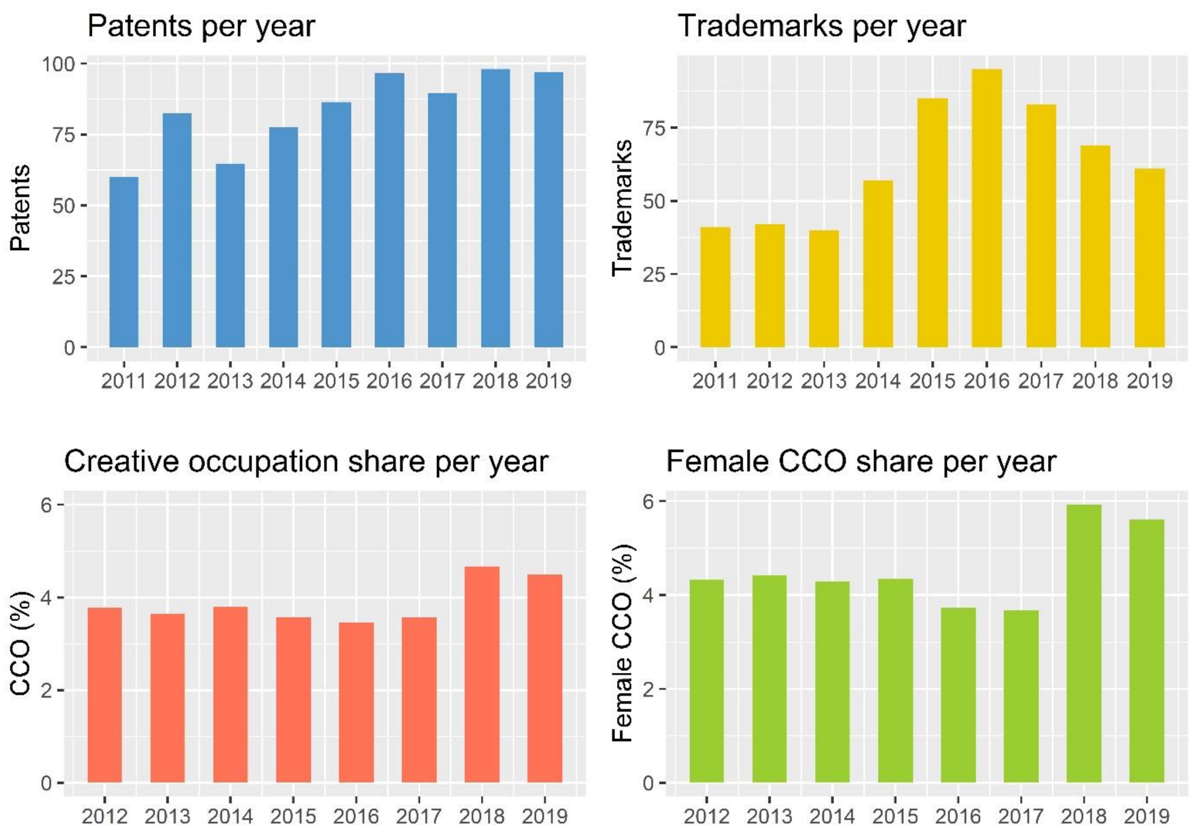
Note: corresponds to the Região Autónoma dos Açores (PT20) at NUTS level 2.
Source: Authors, based on LFS, REGPAT and EUIPO.

Among all the regions that host an IN SITU Lab, the Azores region is the one that registered the lowest number of patent applications (in 2022, 2012, 2014 and 2019 there is no record). Trademark applications are still low compared to other regions but have grown in the period 2011-2019.

The CCO share accounted for about 4% of the total workforce in the region, a constant percentage over the past eight years. In 2019, there was a significant increase, reaching about 7.5%. The female CCO share represents a slightly higher share in relation to the CCO share (around 5% over the years, exceeding 10% in 2019).

IN SITU Lab 2: Western coastal periphery, Ireland

Figure D.2: Innovation indicators for the Northern and Western region – IE



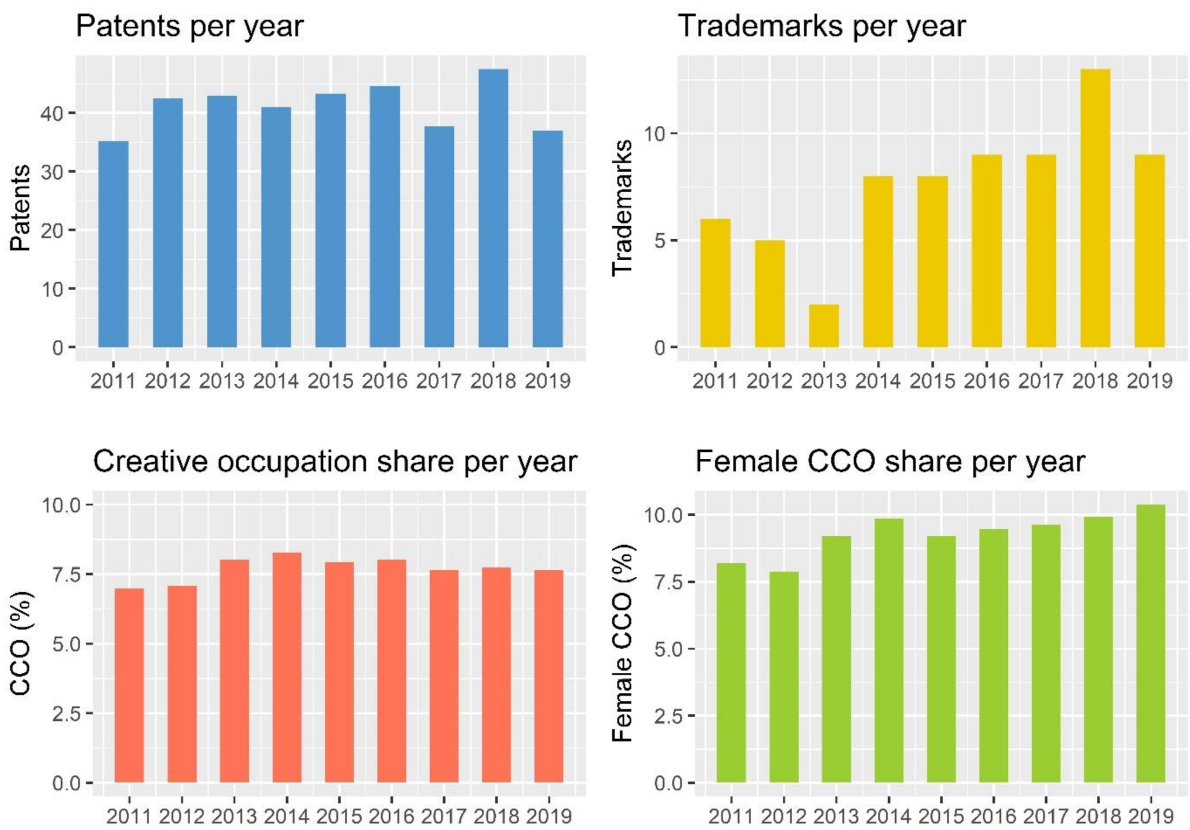
Note: corresponds to the Northern and Western (IE04) region at NUTS level 2.
Source: Authors, based on LFS, REGPAT and EUIPO.

The Western coastal periphery of Ireland, which is part of the Northern and Western region, has been showing significant growth in patent volume. In 2018 and 2019 it registered about 100 patents per year. Trademarks, after a growth between 2011-2016, has been showing a decline in total annual volume (reaching about 60 trademarks in 2019).

The CCO share relative to total employment in the region is similar to that of the Azores. Both CCOs and female CCOs were around 4% of the workforce. In 2018 and 2019, this percentage started to rise more strongly for the female CCO share.

IN SITU Lab 3: West region, Iceland

Figure D.3: Innovation indicators - Island region – IS



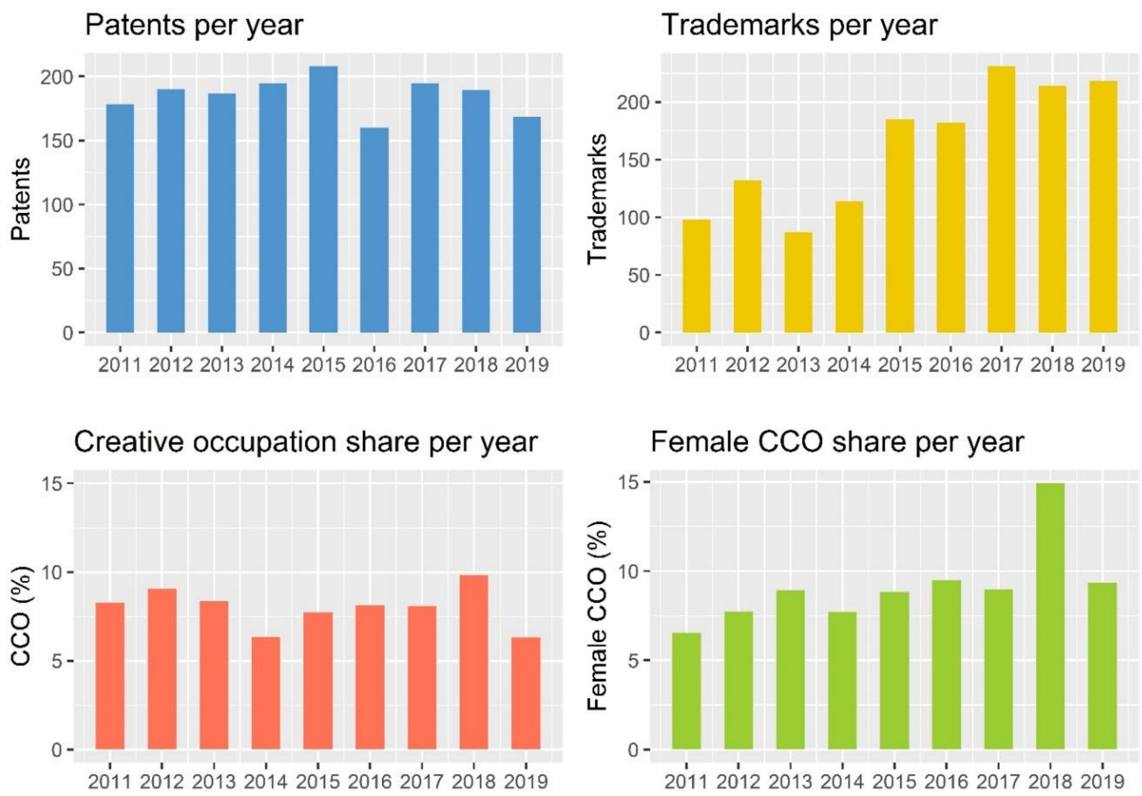
Note: corresponds to Ísland (IS00) at NUTS level 2.
Source: Authors, based on LFS, REGPAT and EUIPO.

The Icelandic region – which comprises only one region at NUTS 2 level for the whole country – shows a notable difference between the number of patents and trademarks. During the period 2011-2019, about 40 patents were applied annually. Trademarks have a smaller number, slightly under 10 per year on average.

The CCO share has a stable percentage over the period (approximately 7.5%), while the female CCO share has grown slightly more over the last four years evaluated and has surpassed 10% in 2019. This is one of the highest CCO and female CCO percentages among the other IN SITU Labs regions.

IN SITU Lab 4: Rauma and Eurajoki, West Coast and Baltic Sea archipelago, Finland

Figure D.4: Innovation indicators Länsi-Suomi and Åland (Finland)



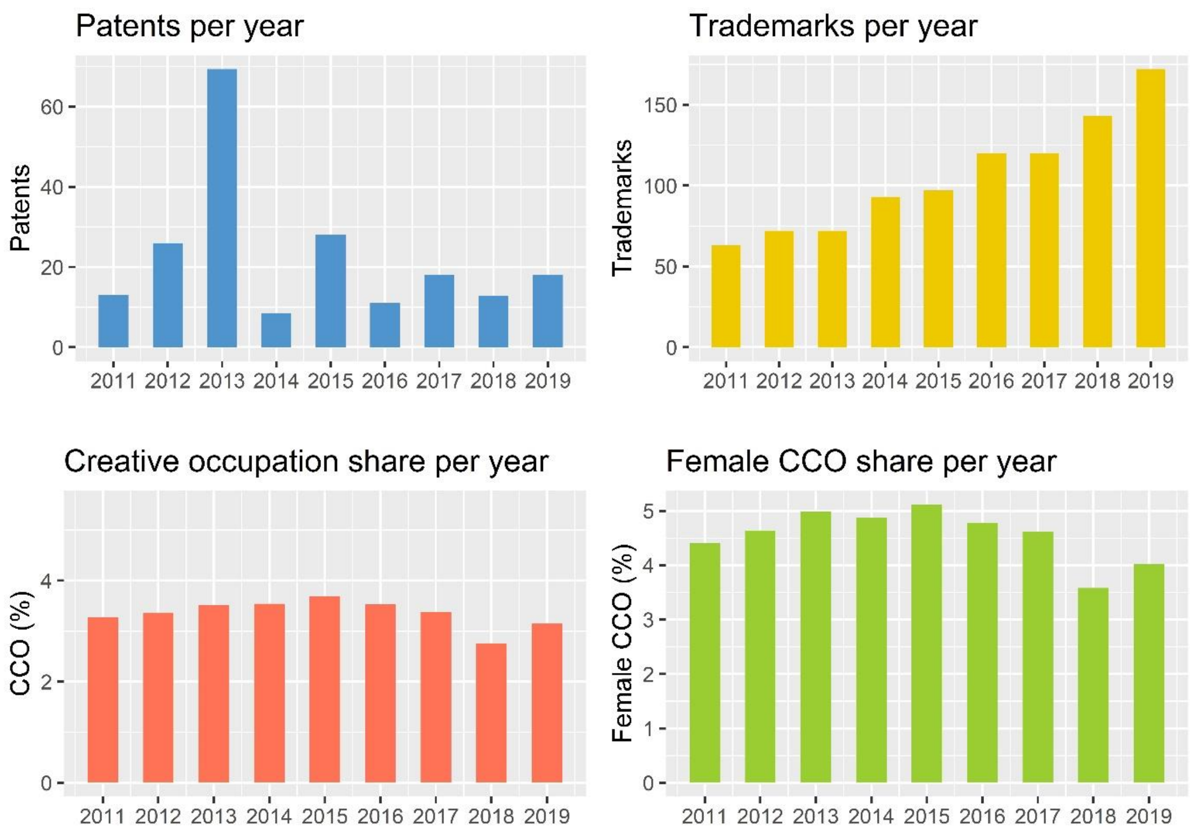
Note: corresponds to the Länsi-Suomi (FI19) and Åland (FI20) at NUTS level 2.
Source: Authors, based on LFS, REGPAT and EUIPO.

In Finland, the IN SITU Lab regions comprise two regions at the NUTS 2 level – covering the West Coast and the archipelago. This region is the most representative in terms of patents and trademarks compared to the other regions. About 180 patents were registered per year, while trademarks more than doubled in value after 2014, exceeding 200 patents per year from 2017 to 2019.

CCO share is also among the highest of the six regions evaluated. The CCO varied a little over the period, remaining around 7% of total employment in the region. Female CCO share fluctuated less than the CCO share, accounting for about 10% of female occupations (despite a drop in 2019, unlike in the other Labs regions).

IN SITU Lab 5: Valmiera county, Latvia

Figure D.5: Innovation indicators Latvija (Latvia)



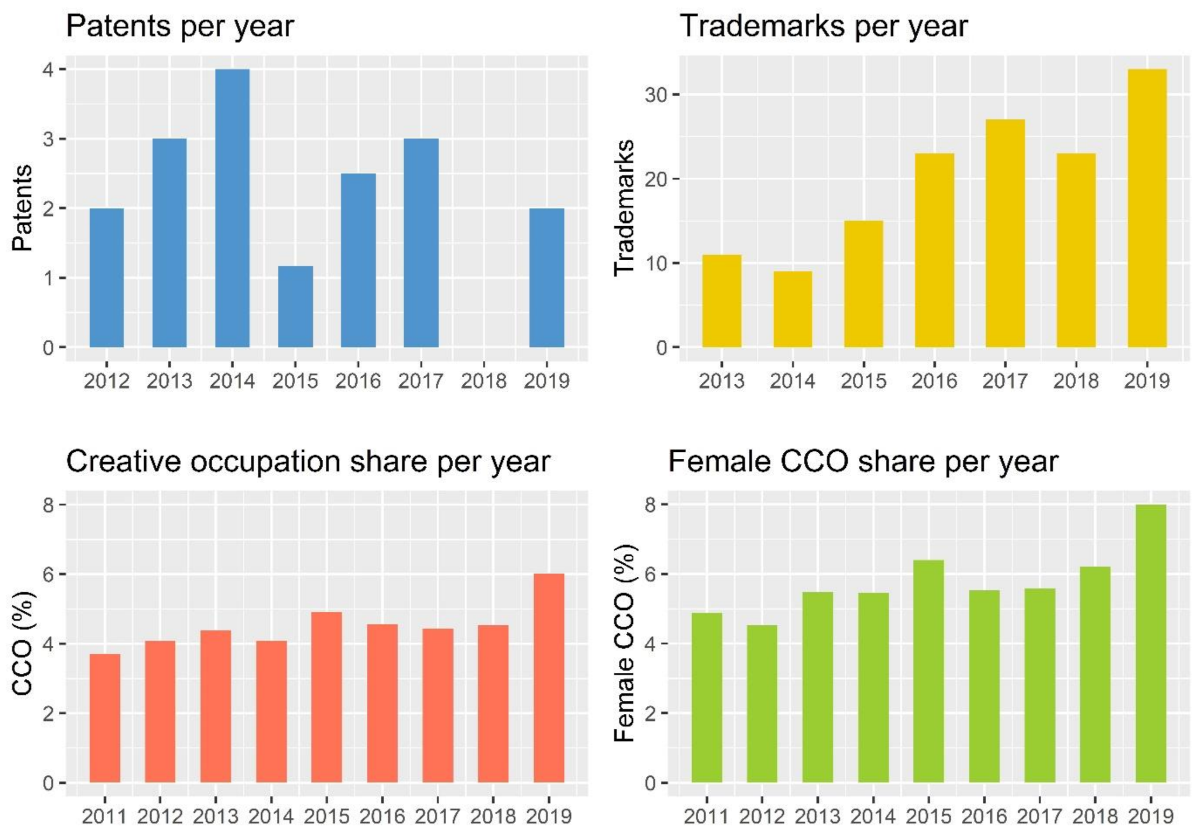
Note: corresponds to the Latvija (LV00) at NUTS level 2.
Source: Authors, based on LFS, REGPAT and EUIPO.

Latvia has only one region at the NUTS 2 level, so these data are for the whole country. Here too we note an opposite situation between patents and trademarks, but unlike Iceland, trademarks far exceed patents. While patents fluctuate considerably, trademarks have shown vigorous growth, rising from about 60 applications in 2011 to almost 175 in 2019.

CCO share and female CCO share represent just over 3% and 4%, respectively, in this region.

IN SITU Lab 6: Šibenik-Knin County, Croatia

Figure D.6: Innovation indicators Jadranska Hrvatska (Croatia)



Note: corresponds to the Jadranska Hrvatska (HR03) at NUTS level 2.
Source: Authors, based on LFS, REGPAT and EUIPO.

The region of Croatia where IN SITU Lab is located is the region with the second lowest number of patents per year (after Portugal region). In comparison, trademarks are far more widely used than in the region of Portugal (and also Iceland), showing a growth from 10 to over 30 applications per year between 2013 and 2019.

As for CCO share and female CCO share, in the whole period it was around 4.5% to 5.5%, respectively. And just like in the regions of Portugal and Ireland, in the last year evaluated there was a stronger growth reaching 6% CCO share and 8% female in CCO.

Socioeconomic contributions and spillovers of CCIs in non-urban regions

Work package WP1 – Mapping the socioeconomic contributions and resilience of CCIs

Version 1.0

Part 2 – Task 1.2

1. Introduction

1.1. Collective trademarks as original metrics for creative and cultural activities in non-urban regions?

Assessing the socio-economic and innovative contribution of creative and cultural activities in non-urban regions using standard indicators has important limitations, many of which we already highlighted in the discussion of Task 1.1. Within Task 1.2, we investigate the extent to which **collective trademarks** could be used as an original and complementary metrics to other available economic and innovation indicators.

To start with a brief definition: collective trademarks are a type of trademark owned by a group of individuals or businesses, rather than by a single entity. These trademarks are used to indicate that the products or services offered by the members of the group meet certain quality standards or possess specific characteristics.

The collective nature of this type of intellectual property right (IPR) makes them particularly interesting to use in initiatives where the key assets at play are collectively owned instead of privately controlled by one actor only. This was the key intuition that prompted us to propose Task 1.2. We should note that this task is **highly exploratory** since we only had a few hints from prior literature that collective trademarks might provide relevant information on creative and cultural activities in non-urban regions.

Our **initial hints** were basically of two kinds. First, there is an understanding that profit-motivated strategies of idea appropriation through private rights, like patents and trademarks, might clash with economic activities that are about leveraging collective cultural assets, heritage and community resources (Castaldi & Mendonça, 2022; Jimenez et al., 2022). Instead, collective ownership solutions, like those offered by collective trademarks, geographical indications and certification marks could reveal activities that remain under the radar when considering privately owned rights. Second, another intuition was that in non-urban regions one would be more likely to observe creative and cultural activities related to heritage, territory and communities, than in urban regions (Gülümser, Baycan-Levent & Nijkamp, 2010). In this sense, collective trademarks could be instrumental to creative and cultural activities in non-urban regions because they can help to build a brand and reputation for a local community or territory. By pooling their resources and using a collective trademark, businesses and individuals in these contexts could work together to promote their products and services and create a sense of identity and community around their work.

An example of a collective trademark related to cultural activities in a rural context is the one protecting “Tonas of Oaxaca” (Cant, 2012). These are artisanal products produced in local woodcarving villages. The indigenous artisans started being challenged by the appearance of cheaper resin figures, which posed a threat not only to the artisans' livelihood but also to Oaxaca's culture and tradition. Hence local authorities, artisans and other actors combined efforts towards developing a collective trademark to flag the authenticity of the local products and help artisans to face market competition better.

The above intuitions have not been analysed in detail in literature so far, and we also lack an empirical assessment of the extent to which collective trademarks are actually used. To fill these gaps, this report offers a **very first exploratory analysis of the potential of collective trademarks to capture creative and cultural activities in non-urban regions for Europe.**

After discussing what collective trademarks are and how they differ from other IPRs, we review the existing literature to offer a thematic analysis of the insights already available. We then present an empirical analysis of all collective trademarks filed at the European Intellectual Property Office (EUIPO) by collectives located across European regions in the period 2011-2019.

1.2. What are collective trademarks?

Collective trademarks are trademarks owned and controlled by a collective entity such as a union, cooperative or other similar organisations (Ghafele & Gibert, 2012). The organisation that owns and manages the trademark has the right to establish specific conditions and standards for the use of the mark and to authorise its members to use the mark only if they meet those requirements for group membership (Gangjee, 2006; Bruch, Vieira & Barbosa, 2014). The organisation owning the collective trademark establishes membership requirements for businesses to be able to use their trademark, hence failure to comply with these requirements results in the denial of permission to use the collective trademark. It is important to note that collective trademarks are indicative of the source of goods and services, similarly to individual trademarks. Their role is to allow consumers to distinguish goods/services from a given source, when such a source is not a single but a collective entity (Gangjee, 2012).

It is useful to understand the differences between certification marks, collective trademarks and geographical indications in relation to individual trademarks owned by single entities (individuals or organisations). Table 1 summarises the key differences in terms of function, duration, ownership, use/licensing and requirements.

Certification marks are trademarks that certify certain characteristics of goods or services, indicating that they meet specific standards set by the owner of the mark. Unlike collective trademarks, there is no requirement for membership in an organisation to use a certification mark. This means that any entity that meets the set standards can use certification mark in their products or services to indicate that their goods or services meet those standards (Song, 2018; EUIPO, 2023). The certification mark owner is solely responsible for monitoring and ensuring that these standards are met and the actual producer or provider of the goods and services does not matter as long as they meet the set standards (EUIPO, 2023).

Geographical indications (GIs) are marks that indicate the specific geographical origin of goods, representing the reputation and qualities associated with goods due to their geographical origin (Gangjee, 2012). Article 22 of the Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS) states that GIs are indications that identify a good as originating from a specific geographical region where a particular quality, reputation or other characteristics of the good are essentially attributable to its geographical origin (TRIPS, 1994). Gangjee (2006) highlights the distinction between GIs and trademarks by noting that while the commercial origin of a trademarked product may change based on various factors, GIs are bound to and embedded in specific geographical regions. Therefore, while the geographical origin of a business that is authorised to use a collective trademark in its products could change, businesses that are allowed to use GI in their product are not permitted to undergo such changes.

At the same time, we should note that these different IPRs may be combined. For instance, individual and collective trademarks can be used simultaneously (Ghafele, 2008). In some cases, a product name may be both protected with a GI and a collective trademark and this has been a contentious matter in some legislations (Josling, 2006). Overall, the legal boundaries between the different IPRs are not as straightforward as one would expect and actual practices of combining IPRs make the boundaries even more fuzzy.

Table 1: Comparison of collective trademarks to similar/related intellectual property rights

Characteristics	Individual trademark	Collective trademark	Certification marks	Geographical Indications
Function	Any sign that identifies the source or origin of goods/services sold in the market	Any sign that identifies the goods or services of members of a particular group	The mark certifies that the products or services meet a certain standard defined by the owner of the mark	Safeguarding the names of products that have specific geographic origins and are recognised for their distinct characteristics or reputation associated with the area of production
Duration	Renewable 10-year periods, until infinite	Renewable 10-year periods, until infinite	Depends, often 5 years	Depends, often infinite

Characteristics	Individual trademark	Collective trademark	Certification marks	Geographical Indications
Ownership	Applicant (individual or company)	The members of the association owning the collective mark	Any natural or legal person, including institutions, authorities and bodies governed by public law	Governments or organisations working with governmental bodies
Use/licensing	The owner of the mark	All entities complying with the conditions for membership of the association	All entities complying with the rules established by the regulations of use of the mark	Local producers and service providers associated with the specific region
Requirements	Use in market requirement, checked by the trademark offices after filing and prior to registration	Use in market requirements by the trademark offices and requirements specified by the association owning the collective trademark	Third party formal assessment of criteria, including different actions	Different ones, depending on the type of geographical indications, but often related to the location of specific parts of the production chain

Source: Authors.

2. Literature review: Research on collective trademarks

2.1. Literature analysis: Methods

Collective trademarks have been the subject of empirical studies since the late 1990s, but a systematic literature review has not been conducted yet. Studies on the use of collective trademarks are scattered across various disciplinary fields. For this reason, we engaged in an **integrative literature review** to connect existing studies and reveal clusters of papers dealing with similar topics. Our specific interest was in collecting literature that would be relevant to understand collective trademarks used by creative and cultural industries (CCIs), especially in non-urban regions. At the same time, we deemed it useful to also search for literature broadly concerned with how collective trademarks are used, with the requirement that studies needed to have an empirical component, either qualitative or quantitative.

Our search process involved several steps that aligned with these objectives. We used Google Scholar as a search engine since we also wanted to include working papers and policy reports. We developed search strings[7] corresponding to our focus on creative and cultural activities in non-urban settings. When reviewing the literature, we noted that collective trademark and collective mark were used interchangeably. Hence, we adapted our search strings accordingly.

For the literature selection step, we reviewed the titles, keywords and abstracts of identified studies and read relevant sections to make inclusion/exclusion decisions. We only included papers where the authors explicitly discussed the role or importance or outcome of the use of collective trademarks and included empirical evidence. We excluded studies that solely focused on legal discussions of collective trademarks. We only included studies written in English.

The analytical step of our literature review consisted of a thematic analysis. Based on categorising topics, we aimed at identifying clusters of studies engaging with similar themes.

Preliminary to the thematic analysis, we provide a descriptive overview of the selected literature.

2.2. Literature analysis: Descriptive results

The search step resulted in an initial set of around 500 publications. The selection step resulted in 52 studies from 47 authors being included as selected literature for our review. Most studies are peer-reviewed articles, but we also included conference proceedings, doctoral as well as master theses, reports, book chapters and working papers. In terms of research methods: qualitative, quantitative and mixed methods are all represented.

[7] The search strings we have utilised are: “Collective trademark“; “Collective trademark“ AND “rural“; “Collective trademark“ AND “urban“; “Collective trademark“ AND “art“; “collective trademark'' AND ''regions''; “collective trademark'' AND ''culture'' AND ''creative'' AND ''art''; “collective trademark'' AND ''Europe'' AND ''region''; “tourism'' AND ''collective trademark'', “collective trademark'' AND ''differences'', “creative industries'' AND ''collective mark'' AND ''cultural''; “collective trademark” AND “heritage”, “Art” AND “collective trademark” AND creativ*, “Art” AND “collective trademark” AND “village”, “collective trademark” AND “village” AND “culture”, “collective trademark” AND “rural” AND “handicraft”; “collective trademark” AND “intellectual property”, “collective trademark” AND creativ*; “collective trademark” AND effect; “Collective trademark” AND “creative industries”, “Collective trademark” AND “Social capital”; “Collective trademark” AND “SME; “collective trademark” AND cultur*.
Since “collective trademark” and “collective mark” are interchangeably used, we conducted our search by using two both terms. Hence, every keyword that came after “collective trademark” was also employed for “collective mark”.

The literature is scattered across different disciplines. Tourism studies, food studies and business studies are three key fields. Overall, we note a large variety of publication outlets: the articles included in the final selection are published in 30 different journals[8].

The earliest study in our review was published in 1999, and the latest in 2022. Although several studies were conducted in the 1999-2010 period (15), the majority of studies were published after 2010 (37).

Figure 1 shows the distribution of studies by geography. Thirty countries are represented: they correspond to the geography of the research area of the empirical analysis of the papers. The studies are slightly more on collective trademarks in European countries, but other continents are also represented.

More than half of the studies are explicitly focused on rural areas, while a quarter of all studies focus on urban areas.

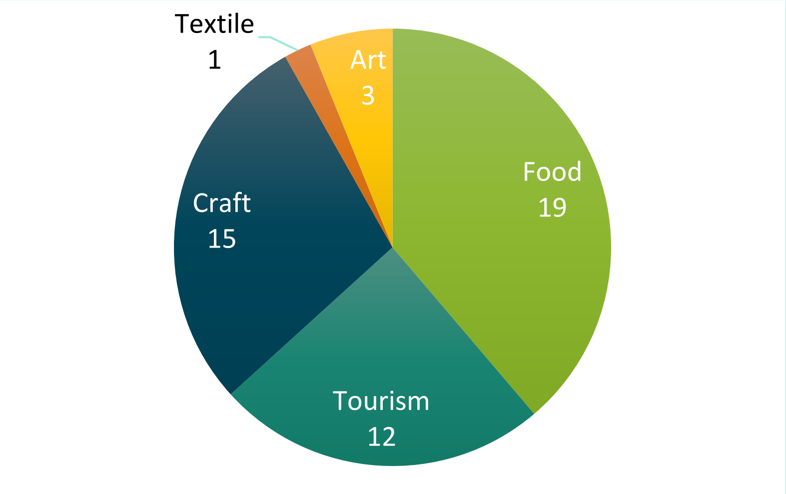
Figure 2 displays the distribution of sectors in our review. The main sector is food, while tourism and craft industries also have significant shares.

[8] In alphabetical order: *Agriculture; Annals of Tourism Research; Aquaculture Economics and Management; Art Antiquity; Asia-pacific journal on human rights and the Law; Business History; Cogent Food & Agriculture; Ecological Economics; Economia Agro-Alimentare; Food Policy; Hue University Journal of Science and Development; Indonesia Law Review; International Centre for Research on the Economics of Culture, Institutions, and Creativity; International Institute for Environment and Development; International Journey of Cultural policy; International Journal of Cultural Property; Journal of Dairy Science; Journal of Development Studies; Journal of Intellectual Property Law & Practice; Journal of Intellectual Property Rights; Journal of Royal Anthropology Institute; Journal of Law; Netherland and France; økonomisk Fiskeriforskning; Oñati Socio-Legal Series; Regional Studies; System Dynamics and Innovation in Food Networks; The International Journal of Engineering and Science; The Oxford Handbook of International Cultural Heritage Law; Tourism Management; Tourism, Creativity and Development; Tropical Conservation Science*.

Figure 1: Distribution of reviewed studies by geography

Source: Authors.

Figure 2: Distribution of reviewed studies by activity/industry

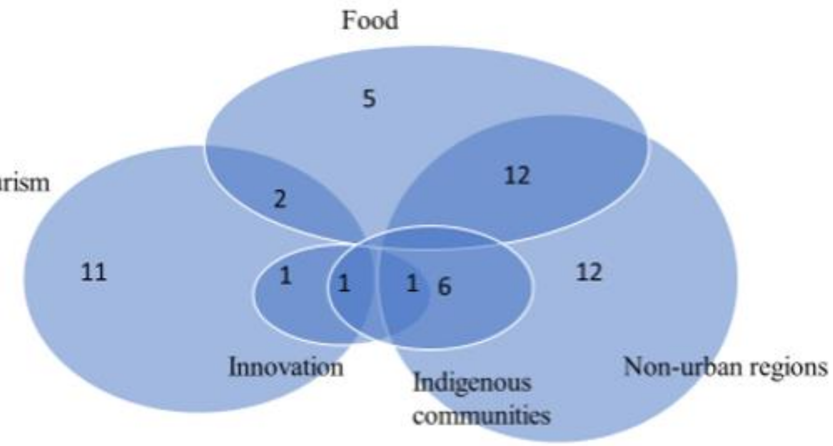


Source: Authors.

2.3. Literature analysis: Thematic analysis

Based on categorising topics, we identified five thematic clusters: collective trademarks and (1) tourism, (2) food, (3) rural regions, (4) indigenous communities and (5) innovation. The clusters are overlapping, as several studies covered more than one theme. Figure 3 depicts the connections and size of the five thematic clusters.

Figure 3: Thematic clusters emerging from the literature review



Source: Authors.

2.3.1. Collective trademarks and tourism

A substantial body of literature has investigated how collective trademarks are used to promote tourism in urban regions (Ghafele & Santagata, 2006; Santagata, 2006; Santagata, Russo & Segre, 2007; Russo & Segre, 2007; Cuccia, Marrelli & Santagata, 2008; Bertacchini, Saccone & Santagata, 2009, 2010, 2011; Ghafele, 2009; Ghafele & Gibert, 2012; Mady, 2015).

Cuccia, Marrelli & Santagata (2008) and Ghafele & Santagata (2006) argue that collective trademarks play two critical functions. The first is an information function: collective trademarks distinguish and safeguard original products from illegal copies. This function serves to protect customers by preventing the production of counterfeit goods, services, ideas, labels and logos (Cuccia, Marrelli & Santagata, 2008). This role of collective trademarks is expected to decrease consumers' search costs (Ghafele & Santagata, 2006, p. 6). These trademarks provide customers with the assurance that the products adhere to certain quality standards. In situations where customers have insufficient prior knowledge and experience regarding the quality and value of products, collective trademarks can serve as a valuable source of information to aid in making informed decisions. In doing so, it is acknowledged that collective trademarks can enhance the value of products and empower producers in the cluster to impose a premium on their goods (Santagata, 2006).

A second function relates to collective trademarks being reputational assets. They are crucial in enabling producers within clusters to invest and manage the reputation and value of their distinctive resources (Bertacchini, Saccone & Santagata, 2009, 2010, 2011). This second function of collective trademarks pertains to the managerial function as considered by Cuccia et al. (2008)'s study. This function entails certifying standard quality and other managerial mechanisms that reinforce and safeguard the reputation of the cluster. These two functions align with the overall functions of trademarks (Castaldi, 2020), but in a collective setting.

Several studies have highlighted the collective nature of these IPRs. Ghafele (2008) notes that collective trademarks are not only a complementary tool for regions' branding activities but also an institutional tool for protecting a community's intangible capital and encouraging social cohesion. By facilitating the establishment of the legal structure of cluster formation and encouraging collective action, collective trademarks can be an effective instrument for businesses with shared economic goals to form clusters (Ghafele, 2009). As the mark is collectively owned, this aspect fosters social cohesion, collaboration and cooperation among the actors in the same cluster. Additionally, the mark can act as an incentive for local businesses in the same region to promote a joint identity and community entrepreneurship (Ghafele, 2009). In line with this, collective trademarks can help local actors enhance their market position and engage in activities to increase their cluster's reputation.

Overall, the literature suggests that collective trademarks are a promising tool for creating clusters and fostering regional economies (Santagata, 2006; Ghafele, 2009; Ghafele & Gibert, 2012). Furthermore, the use of collective trademarks is not limited to urban areas.

2.3.2. Collective trademarks and food

As suggested by the sectoral distribution of the selected studies, the relationship between collective trademarks and food has been investigated in several studies (Norberg, 2000; Girard & Mariojouls, 2003; Stanziani, 2009; Ohe & Kurihara, 2013; Vanhove & Van Damme, 2013; Bruch, Vieira & Barbosa, 2014; van den Eeckhout, Luján Sánchez & Ugas, 2014; Crespo, Réquier-Desjardins & Vicente, 2014; Rios, Russo & Siles, 2015; Jatib, Muncha & Bentivegna, 2015; Kranjac et al., 2015; Chiffoleau, Millet-Amrani & Canard, 2016; González-Córdova et al., 2016; Enriquez-Sanchez et al., 2017; Loc & Nghi, 2018; Defrancesco & Kimura, 2018; Kalauni, Joshi & Joshi, 2020; Starobin, 2021; Santeramo et al., 2022).

Many studies in this thematic cluster view collective trademarks as functional tools for promoting and differentiating agricultural products (food but also wine and other liquors), primarily by signalling the region of origins and the distinctive features of products (Girard & Mariojouls, 2003; Jatib, Muncha & Bentivegna, 2015; Kranjac et al., 2015). Through product differentiation, producers seek the opportunity to advance their market integration and improve product positioning in the existing sales channels (van den Eeckhout, Luján Sánchez & Ugas, 2014). Product differentiation through collective trademarks can be supported by public policies as well. Jatib, Muncha & Bentivegna (2015) discuss how collective trademark strategies can be implemented by governmental bodies. The authors note that building a collective trademark through a planned differentiation strategy supported by the government added value to products and resulted in better market economic performance. Interestingly, the program enhanced local producers' social capital accumulation as well. Likewise, Chiffoleau, Millet-Amrani & Canard (2016)'s study captures the societal aspect of forming collective trademarks. In the case that this study discusses, a free collective trademark was introduced in urban food networks through the ownership structure, including various stakeholders. The mark eventually encouraged several actors to be a part of sustainable production and was used for expressing the ideas supporting a food democracy movement.

Another insight from this literature is that collective trademarks can help small-scale businesses to enter national and international markets (Jatib, Muncha & Bentivegna, 2015; Starobin, 2021). The opportunities for market access are essential for small-scale producers, particularly in developing countries. Collective trademarks enable these producers to promote territorial assets that are strategically important for rural communities. Hence, collective trademarks are presented as supportive instrument for designing rural development strategies (Stanziani, 2009).

A few studies examined the complex factors affecting the success of collective trademarks. Loc & Nghi (2018) identify the conditions required for collective trademark ownership. The willingness to own a collective trademark is connected to the financial and social conditions of producers. Crespo, Réquier-Desjardins & Vicente (2014) emphasise the necessary collective action needed to develop a collective trademark. In their case study, cheese producers in Mexico received government funding and other support to develop regional collective trademarks. Yet, the project failed to attract cheese producers due to various reasons, including lack of trust and commitment to the project. Vanhove & Van Damme (2013)'s study is another example portraying the vulnerability of collective trademark projects. They investigated a native fruit protected under a collective trademark, and found out that poor management of the mark and a lack of monitoring of the producers downgraded the quality of the underlying value chains. In sum, these studies warn that the benefits of collective trademark strategies can only materialise when there is a shared commitment and solid organisational support.

A set of studies within this thematic cluster investigates how collective trademarks influence consumer experiences and attitudes, drawing insights from consumer behaviour and marketing studies. This research direction questions how a collective trademark adds value to a product and to what extent a collective trademark actually influences consumer behaviour. In an early study of Norway, Norberg (2000) finds that collective trademarks may grab consumers' attention and influence their purchasing decision if certain conditions are met. Those conditions are the perceived credibility of the mark owner, the familiarity of consumers with the mark, and the relevance of attributes promoted by the mark. In other words, collective trademarks stimulate consumers' purchase decisions if consumers have a certain level of knowledge about the mark, trust the mark owner in terms of monitoring and ensuring the quality of products having the mark, and find the attributes of the collective mark relevant for their decision-making process. Several authors note low levels of awareness of collective trademarks among consumers (Bruch, Vieira & Barbosa, 2014; Santeramo et al., 2022). However, other studies do find evidence that consumers are willing to pay up to 30 per cent more if they identify the benefits of collective trademark or other intellectual property rights (Bruch, Vieira & Barbosa, 2014). Overall, this positive view on the effectiveness of collective trademarks to support collective promotion and marketing of food products exists next to more critical views on the challenges to mobilise resources and commitments in collective way.

2.3.3. Collective trademarks and rural regions

We identified a good number of studies focused on the use of collective trademarks in rural contexts (Aguilera, 2007; Verma, 2010; Lorenzini, Calzati & Giudici, 2011; Silva & Peralta, 2011; Newcity, 2012; Cant, 2012, 2015; Argumedo, 2013; Ohe & Kurihara, 2013; Sardjono, Prastyo & Larasati, 2013; Vanhove & Van Damme, 2013; van den Eeckhout, Luján Sánchez & Ugas, 2014; Crespo, Réquier-Desjardins & Vicente, 2014; Ibarra Rojas, 2015, 2016; Jatib, Muncha & Bentivegna, 2015; Phochanthilath, 2015; Rios, Russo & Siles, 2015; González-Córdova et al., 2016; Enriquez-Sanchez et al., 2017; Loc & Nghi, 2018; Mattila, 2018; Defrancesco & Kimura, 2018; Burri, 2019; Phuc & Linh, 2019; Gorda & Anggreni, 2020; Starobin, 2021; Jimenez et al., 2022; Musiza, 2022; Santeramo et al., 2022; Chuma-Okoro, 2022)

These studies investigate the role of collective trademarks in economic activities of small-scale producers or artists in non-urban regions. According to these studies, ownership and use of collective trademarks benefit actors in numerous ways. First, collective trademarks can be used for identifying unique and specialised techniques that are associated with particular regions, often connected to history and local culture and traditions. For instance, Cant (2015) indicates that Mexican artists initiated legal actions for collective trademark ownership to highlight the aesthetic and unique value of their products through a jointly owned collective trademark. They did so to signal the cultural value and local artisanship, more than for purely economic reasons. Collective trademarks can help to preserve and protect local heritage by differentiating local artists from mass production and industrial replicas. Among all other IPRs, they offer an opportunity to protect traditional cultural expressions against cultural appropriation efforts (Aguilera, 2007; Chuma-Okoro, 2022; Musiza, 2022).

At the same time, small rural producers can also economically benefit from collective trademarks, since they can leverage them to access broader markets. For example, Aguilera (2007) proves that use of collective trademarks aided Guatemalan artisanal businesses to become active beyond local markets. Studies conducted in Vietnam and Nigeria and South Africa also support this claim. Phuc &

Linh (2019)'s research even suggests that the ownership of a collective trademark could trigger competitiveness among local producers. Hence, a link is made between collective trademarks and rural development.

However, there are also studies that warn about negative aspects of collective trademarks. For instance, collective trademarks can discourage competition by associating the quality of products with an focal organisation. Ibarra Rojas (2015)'s work investigates the dual nature of the collective trademark project in protecting culture and artisanship. Her study stresses several problems with local collective trademark projects, including instabilities in policymaking, exclusion of certain artist groups from the organisation owning the collective trademark, poor management of the organisation and trademark, inadequate training of the artists on the use of the collective trademark, unsatisfactory efforts for the continuation of the project, and a general lack of knowledge on collective trademarks. Hence, also in this thematic cluster one finds evidence of positive and negative aspects of the use of collective trademarks.

2.3.4. Collective trademarks and indigenous communities

A small group of studies investigated collective trademarks in relation to the protection of heritage of indigenous communities (Verma, 2010; Newcity, 2012; Argumedo, 2013; Ibarra Rojas, 2016; Mattila, 2018; Burri, 2019; Jimenez et al., 2022). Mattila (2018) discusses the different kinds of legal instruments that were considered in the attempt to preserve the Finnish Sami's cultural heritage against violations. Traditional Duoji handcrafts, with which many Sami artists make their living, are at stake against cheap industrial replicas or non-Sami handicrafts in the marketplace. While there is an already registered Sami duodji trademark in Sweden for guaranteeing the authenticity of the goods, it has not been implemented in Finland yet. The author considers that the newly suggested Sami collective trademark could help differentiate products of Sami origin. At the same time, local authorities claim that the trademark serves only commercial purposes and neglects other community values.

However, collective trademarks can also align with the cultural values of indigenous communities. For example, the collective trademark effectively represents the goods from indigenous communities-led Potato Park in Peru (Jimenez et al., 2022). By considering Buen Vivir's emphasis on community and collectivism, the collective trademark was built to promote collective and traditional knowledge of indigenous communities and challenge the existing individual rights-oriented IPR system. On the other hand, Argumedo (2013)'s study notes the complexities of using collective trademarks in Potato Park. Even though a collective trademark was implemented for differentiating the products, enhancing social cohesion among the community, establishing specific standards in the production, differentiating the products and integrating the market more effectively, bureaucratic and legal challenges prevented the indigenous communities from registering their market formally and secure protection under existing intellectual property rights system. According to the author, the complex, expensive and slow-moving process of collective trademark registration resulted in the informal use of collective trademarks and put indigenous-led marks and products in a vulnerable position against misuse and various violations.

In sum, this small thematic cluster started to engage with the potential benefits of collective trademarks for protecting heritage of indigenous communities, but questions remain open on the actual applicability and effectiveness of these strategies.

2.3.5. Collective trademarks and innovation

A handful of academic studies has examined the relationship between collective trademarks and regional innovation (Ghafele & Gibert, 2012; van den Eeckhout, Luján Sánchez & Ugas, 2014; Kranjac et al., 2015; Block et al., 2022; Jimenez et al., 2022).

Jimenez et al. (2022) presented collective trademarks as an alternative approach to individual IPRs that prioritises collective rights over individual rights. They argue that using collective trademarks for protecting the products of indigenous communities, such as the Buen Vivir philosophy-driven Potato Park in Peru, is a strategy for acknowledging the cultural values and needs of these communities. It aligns with a broader notion of innovation which encompasses social innovation and collective innovation processes.

Other studies, like Kranjac et al. (2015) and Ghafele & Gibert (2012), also suggest that collective trademarks can stimulate the economic achievements and innovative performance of clusters. Van den Eeckhout, Luján & Ugas (2014) point to the incentives towards value chain innovation that collective trademarks might support: they discuss a policy proposal to make a community of organic smallholder producers aware of the opportunities and challenges of using collective trademarks to align to their innovative practices of collective production.

A recent study by Block et al. (2022) identified a link between trademarks and regional innovation activities for Japan, where a system of regional collective trademarks has been developed since 2006. Such a system led to many new trademarks being filed in relation to regional specialties and regional brands. Their study leveraged a systematic analysis of trademark filings and regional growth, but did not distinguish between individual and collective trademarks in the empirical analysis.

Overall, this small set of studies points to an emerging interest in considering collective trademarks as protecting organisational, social and collective innovation. At the same time, the original intuitions have not led to any systematic assessment of the opportunities and pitfalls of using collective trademarks to capture innovative economic activities.

2.4. Literature review: Summary of key insights

The descriptive overview and the thematic analysis offered an integrative assessment of current empirical research on collective trademarks. As discussed, the insights are scattered across journals and disciplines, but key disciplinary fields emerged. Table 2 summarises the main disciplinary fields that characterise each thematic cluster. Rural studies and cultural studies are academic fields where efforts to understand the potential benefits and unexpected challenges of collective trademarks have concentrated. This is a result that aligns with the two intuitions that originally prompted the development of Task 1.2.

Table 2: Thematic clusters and disciplinary fields

Thematic cluster	Main disciplinary fields
Collective trademarks and tourism	Tourism studies Cultural studies
Collective trademarks and food	Marketing studies Rural studies
Collective trademarks and rural regions	Rural studies Cultural studies
Collective trademarks and indigenous communities	Development studies Rural studies
Collective trademarks and innovation	Innovation studies Regional studies

The emerging themes linked to specific sectors (food and tourism) and specific geographical references (rural and indigenous communities). The studies made clear that collective trademarks capture, on one hand, **economic** activities of promotion, commercialisation and market expansion, and, on the other hand, **social** processes of community building around collectively owned resources, like heritage, cultural assets and indigenous knowledge. The literature review also made it clear that there are several potential benefits of developing collective trademarks but these benefits might fail to realise because of organisational, strategic or legal challenges.

The theme of how collective trademarks might relate to innovation was the most heterogenous and also the smallest. There are two clear gaps there. The first gap is a theoretical/conceptual one: studies have not yet articulated the theoretical mechanisms behind a link between collective trademarks and innovation in a systematic way. This partly relates to the very challenges of broadening the notion of innovation to better fit the activities of creative and cultural industries (see the seminal work of Stoneman, 2010). The second gap is an empirical one: there is no study that offers large-scale empirical evidence about the proposed link. The available empirical evidence relies on regional or national case studies only, which is already informative but does not provide a comparative assessment of patterns of use and outcomes of collective trademarks in relation to innovation.

In sum, the literature review results showed emerging themes indicating a clear interest in exploring collective trademarks further, both theoretically and empirically. The original intuitions that collective trademarks could reveal hidden elements of the economic and innovative contribution of creative and cultural activities in non-urban regions appears partly supported. Yet, further research will be needed to follow up on the seminal studies that opened the way to this new research topic. Within this report we complement the insights from this literature review with a first empirical analysis of all collective trademarks filed at EUIPO. Such an analysis offers a first step in the direction of providing more systematic empirical evidence on the actual use of collective trademarks in European regions.

3. Empirical analysis

3.1. The construction of a regionalised EUIPO collective trademark database

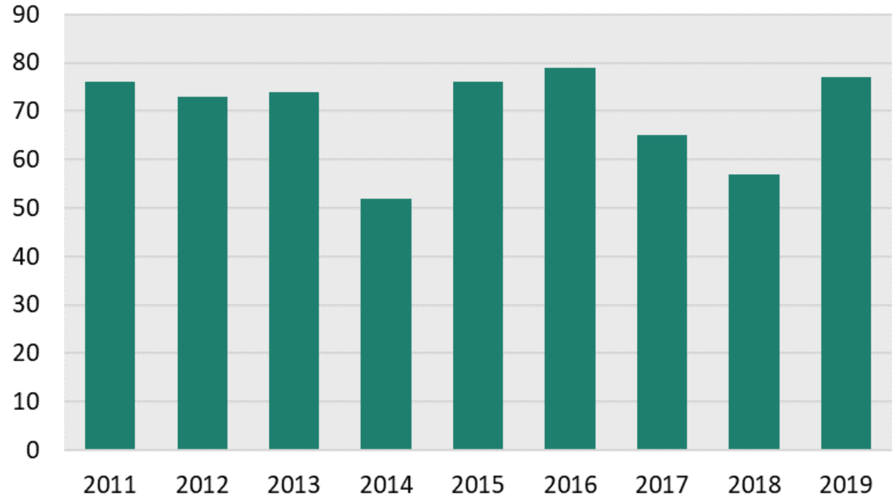
We used the same trademark data source as in Task 1.1, namely the open data of EUIPO. From the overall trademark database, which we already regionalised, we selected all collective trademarks (indicated by the variable trademark type: individual/collective). For each collective trademark we have the same information as for individual trademarks.

For our purposes here, we make use of the location of the owner, the Nice classes where the collective trademark is filed, the year of filing and the goods and service description. This last information is a short text describing the good/service covered by the trademark (Castaldi, 2020) and can be leveraged to understand the extent to which collective trademarks relate to creative and cultural assets or activities.

In the period 2011 to 2019, an average of 70 collective trademark applications per year were filed in total in the countries analysed. We collected data for all 27 EU Member countries, 4 EFTA countries and UK. For 24 of these countries we found at least one application of collective trademarks and our analysis will focus on these countries only.

Figure 4 shows how the total number of filings of collective trademarks changed over time. The numbers are rather stable, except for a drop in 2014. Overall, filings of collective trademarks remain a small proportion of all trademarks filed at EUIPO.

Figure 4: Collective trademarks fillings per year



Source: Authors based on EUIPO.

Table 3 shows the numbers of collective trademark applications by country. Italy ranks first with a total of 170 collective trademarks accumulated over the period from 2011 to 2019, followed by Germany, France and Spain, which are the only countries with more than 75 collective trademarks accumulated in the analysis period.

Table 3: Absolute counts of collective trademarks by country and year (2011-2019)

Country	2011	2012	2013	2014	2015	2016	2017	2018	2019	Total (2011-2019)
IT	12	20	17	19	21	28	16	21	16	170
DE	21	21	20	10	9	7	11	12	12	123
FR	17	13	4	5	15	17	11	4	14	100
ES	2	3	7	5	11	10	16	7	14	75
BE	4	4	9	4	4	3	2	4	6	40
UK	6	2	8	3	3	5	2	3	5	37
NL	3	2	2	1	7					15
AT		3		1	1	1			4	10
CH	1	1				1	2	1	1	7
PT	2			1	1	1		2		7
DK	4	2				1				7

Country	2011	2012	2013	2014	2015	2016	2017	2018	2019	Total (2011-2019)
EL	3	1							2	6
SE			2		1	3				6
PL			1	2				1		4
LU	1				1		1		1	4
IE						1		2		3
MT		1	1			1				3
CY			2	1						3
FI			1				1		1	3
SI							3			3
BG					1					1
LV					1					1
HR									1	1
LT									1	1

Source: Authors based on EUIPO.

We note that there is a strong concentration of collective trademark applications in some countries and also sporadic applications in others. The first four countries mentioned above account for 74.3% of the total number of collective trademark filings in the period. In sequence, another 4 countries (Belgium, United Kingdom, Netherlands and Austria) have between 10 and 40 applications in the period, representing 16.2% of the total applications in the period. Another 16 countries have no more than 10 collective trademarks in the entire period (accounting for 9.5% of the total).

In the next section, we focus on the regional distribution of collective trademarks.

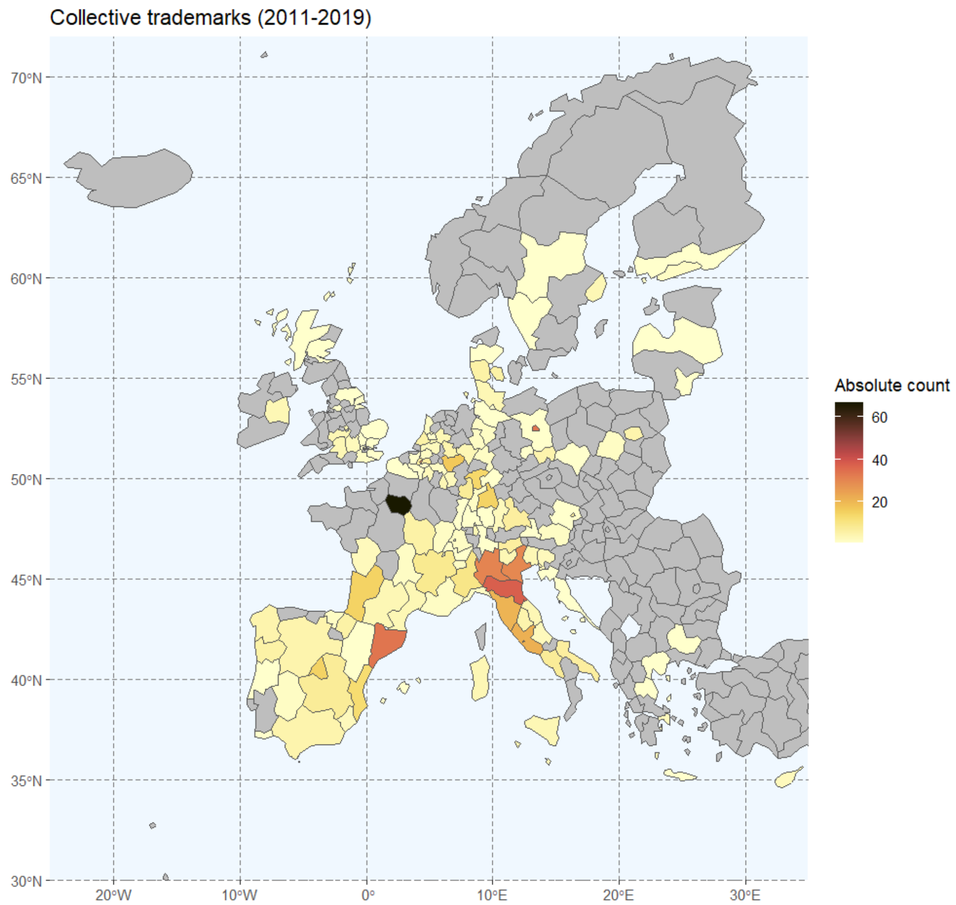
3.2. Regional distribution of EUIPO collective trademarks

Figure 5 shows the regional distribution of the absolute number of collective trademarks found in the period 2011 to 2019 at the level of NUTS level 2 regions.

The darkest point on the map indicates the French region Île-de-France, and there is a concentration of applications in the Southern regions of France. In Italy, Northern regions stand out, like Emilia-Romagna, Veneto and Lombardia, together with other regions in the central area of the country. In Spain, Cataluña stands out in relation to the rest of the country. The Berlin region stands out in Germany, followed by other regions such as Köln, Stuttgart and Darmstadt.

The grey areas indicate those regions where no collective trademark applications were found in the period.

Figure 5: Collective trademarks total between 2011-2019

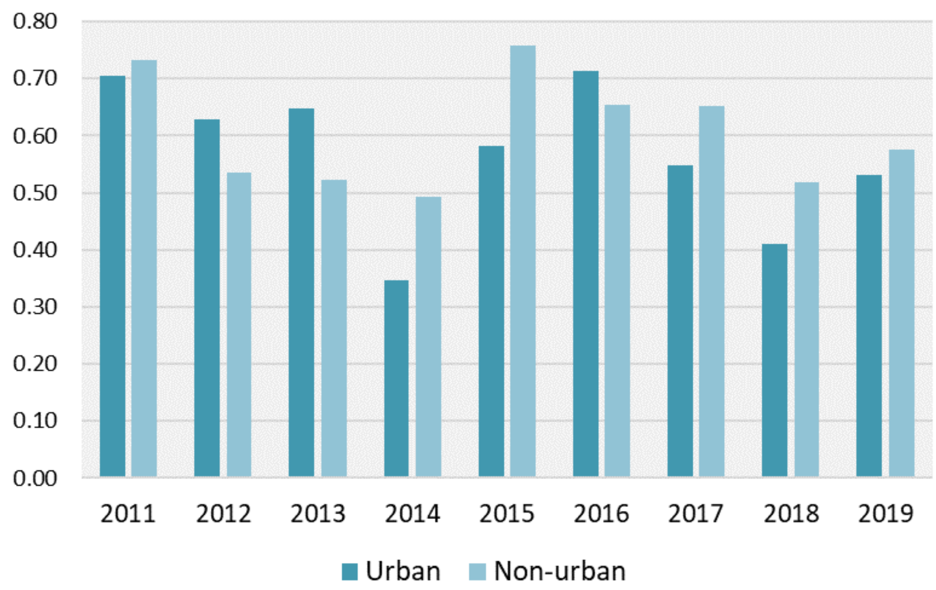


Source: Authors based on EUIPO.

Figure 6 shows the amount of applications per million inhabitants for urban and non-urban regions. We are using the same methodology to classify regions by urbanisation type as we did in Task 1.1.

In two thirds of the time period, non-urban regions had more applications by million inhabitants than urban regions. In 2019, the difference was 8.5% more applications in favour of non-urban regions. It is interesting to note that even in the two years with the lowest number of applications (2014 and 2018), non-urban regions registered proportionally more applications per million inhabitants than urban regions.

Figure 6: Collective trademarks by urban vs non-urban regions (per million inhabitants)



Source: Authors based on EUIPO.

Table 4 shows the absolute number of applications for the three types of regions by degree of urbanisation (urban, intermediate and rural). The number of collective trademarks is negatively associated with the degree of urbanisation for most years. There was a 26.5% growth in the number of applications originating in urban regions between 2011 and 2019. However, the non-urban regions – including rural and intermediate regions – have almost the same number of trademarks as the urban regions.

Note that the rural regions showed the largest variation in the total number of applications over the period.

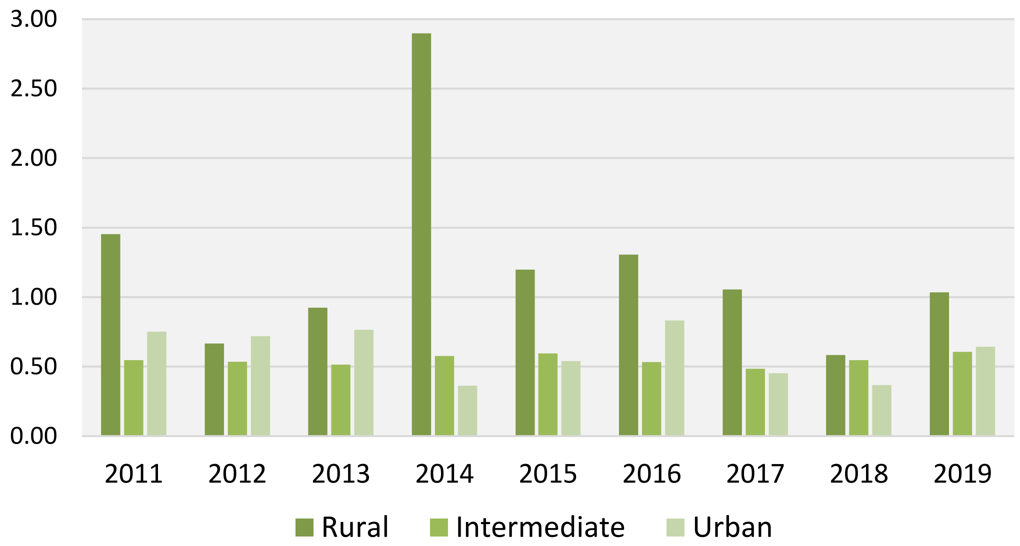
Table 4: Absolute number of collective trademarks by degree of urbanisation

Degree of urbanisation	2011	2012	2013	2014	2015	2016	2017	2018	2019	Total
Urban	34	42	48	25	45	50	37	31	43	**355**
Intermediate	23	22	19	24	13	16	16	22	21	**176**
Rural	19	9	7	3	18	13	12	4	13	**98**
Total	**76**	**73**	**74**	**52**	**76**	**79**	**65**	**57**	**77**	**629**

Source: Authors based on EUIPO.

Although rural regions filed fewer collective trademarks than the other regions in absolute terms (Table 4), they had the highest intensity of collective trademarks per capita (Figure 7) in all years.

Figure 7: Collective trademarks per million inhabitants, by degree of urbanisation and year



Source: Authors based on EUIPO.

3.3. Thematic analysis

Trademark applications include, among other information, two pieces of information that offer opportunities for a qualitative analysis of the products and services protected by trademarks: (1) Nice classes and (2) a goods and services description.

The Nice Classification is the standard international classification that lists all possible markets where trademark filers plan to use their trademarks. The 45 Nice classes describe, in general terms, the nature of the goods or services covered the trademark application. The classification includes 34 classes of goods (codes 01 to 34) and 11 classes of services (codes 35 to 45). Appendix B lists all Nice classes with their brief description.

Since each Nice class is quite broad and covers many different goods or services, trademark applicants also include a brief textual description that further specifies their product. Hence, this text provides additional and more specific information that complements the Nice classes (Castaldi, 2020).

Table 5 presents the distribution (total and percentage) of Nice classes in the first and last year analysed, indicating with more intense colours the classes where most collective trademarks were filed in each year. An application can refer to more than one Nice class. For this report we adopted whole counting and counted trademarks filed in more classes as filings for each class.

Classes 41, 35 and 42 are the three classes that appear most frequently in both years, representing between about 5% and 8% of the classes most indicated by collective trademarks in 2019. They correspond to three groups of services: education, training and entertainment (42)[9]; advertising and business management (35)[10]; and scientific and technological services (41)[11].

Within the list of product classes, in 2019 the most frequently cited classes were 33, 29, 30, 31 and 16, representing between 2.7% and 5.5% of Nice class indications in collective trademarks in that year. They include: alcoholic beverages, except beers (33)[12]; food like meat, jam, cheese, milk products, among others (29)[13]; coffee, tea, pastries, spices, among others (30)[14]; and raw and unprocessed agricultural products and flowers (31)[15].

The other collective trademarks are scattered across many other classes, with several classes of services appearing among the most frequent.

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[9] Education; providing of training; entertainment; sporting and cultural activities.

[10] Advertising; business management; business administration; office functions.

[11] Scientific and technological services and research and design relating thereto; industrial analysis and industrial research services; design and development of computer hardware and software.

[12] Alcoholic beverages, except beers; alcoholic preparations for making beverages.

[13] 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.

[14] 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).

[15] 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.

Table 5: Distribution across Nice classes (counts and shares of all collective trademarks)

NICE Class	2011	2019	2011 (%)	2019 (%)
1	7	6	2.3	1.4
2	2	4	0.7	1.0
3	2	5	0.7	1.2
4	6	4	2.0	1.0
5	6	6	2.0	1.4
6	6	8	2.0	1.9
7	6	6	2.0	1.4
8	2	4	0.7	1.0
9	10	10	3.4	2.4
10	2	5	0.7	1.2
11	6	4	2.0	1.0
12	5	4	1.7	1.0
13	0	3	0.0	0.7
14	1	6	0.3	1.4
15	0	3	0.0	0.7
16	15	11	5.0	2.7
17	7	5	2.3	1.2
18	3	5	1.0	1.2
19	8	7	2.7	1.7
20	7	6	2.3	1.4
21	6	9	2.0	2.2
22	3	5	1.0	1.2
23	0	4	0.0	1.0
24	5	5	1.7	1.2
25	3	6	1.0	1.4
26	0	3	0.0	0.7
27	2	5	0.7	1.2
28	3	5	1.0	1.2
29	12	21	4.0	5.1
30	5	16	1.7	3.9
31	8	14	2.7	3.4
32	4	11	1.3	2.7
33	9	23	3.0	5.5
34	2	4	0.7	1.0
35	22	31	7.4	7.5
36	9	12	3.0	2.9
37	10	7	3.4	1.7
38	9	11	3.0	2.7
39	10	15	3.4	3.6
40	11	8	3.7	1.9
41	24	31	8.1	7.5
42	19	22	6.4	5.3

NICE Class	2011	2019	2011 (%)	2019 (%)
43	6	14	2.0	3.4
44	5	10	1.7	2.4
45	10	11	3.4	2.7

Source: Authors based on EUIPO.

The results based on Nice class appear to align with the insights from the literature review. We find extensive use of collective trademarks in relation to food and tourism, but also in relation to creative and cultural activities (advertising, entertainment, business promotion).

To complement the analysis based on Nice classes, we also analysed the information from the goods and services description. We did so with a keyword analysis of the additional textual information. We present the results in the form of word clouds, to visualise which keywords appear more frequently in collective trademark applications.

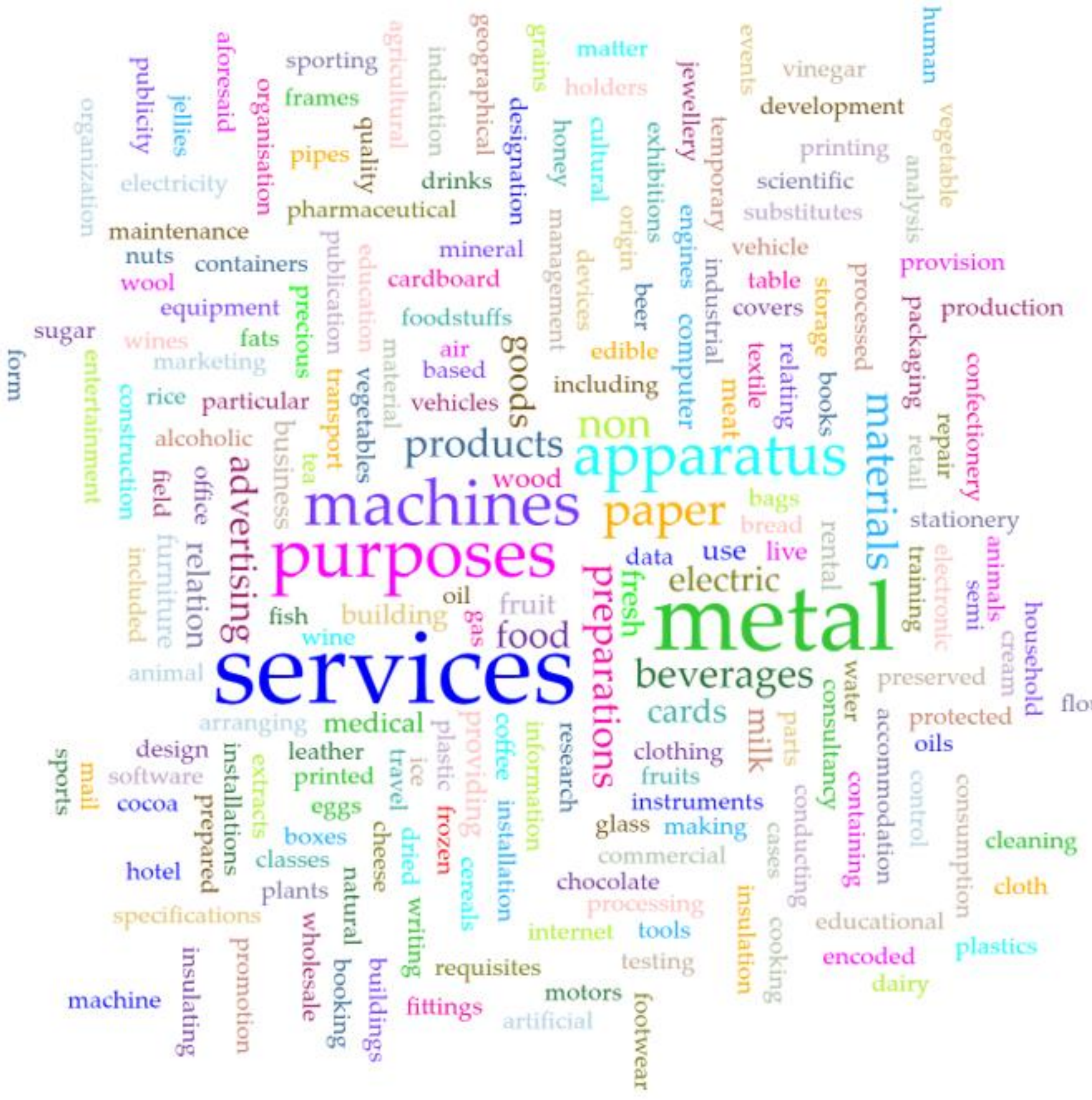
Figure 8 illustrates a word cloud drawn from all goods and services descriptions in the period from 2011 to 2019. As service classes are among the most cited in the set of collective trademarks, it was expected that the word *services* would appear prominently (3,173 events) in the description as well. Other featured terms are: *metal* (1,749); *purposes* (1,484); *apparatus* (1,012); and *advertising* (942). The term *metal* is often related to precious metals, advertising (of metal products), pipelines, and machine tools, and also specifying non-metal products.

Figure 8: Word cloud based on the goods and service descriptions of all collective trademarks, 2011 to 2019

Source: Authors based on EUIPO.

We also created clouds of words to regions by degree of urbanisation to verify if there are differences between them. First, Figure 9 presents the image for **non-urban regions** (2011-2019). The prevalence of *services* (1,487); *metal* (1,301); *purposes* (757); *machines* (661); and *apparatus* (642) is evident. The difference in relation to the previous figure, which comprises all collective trademarks, is that in non-urban regions the term *machines* is now among the most cited (replacing *advertising*).

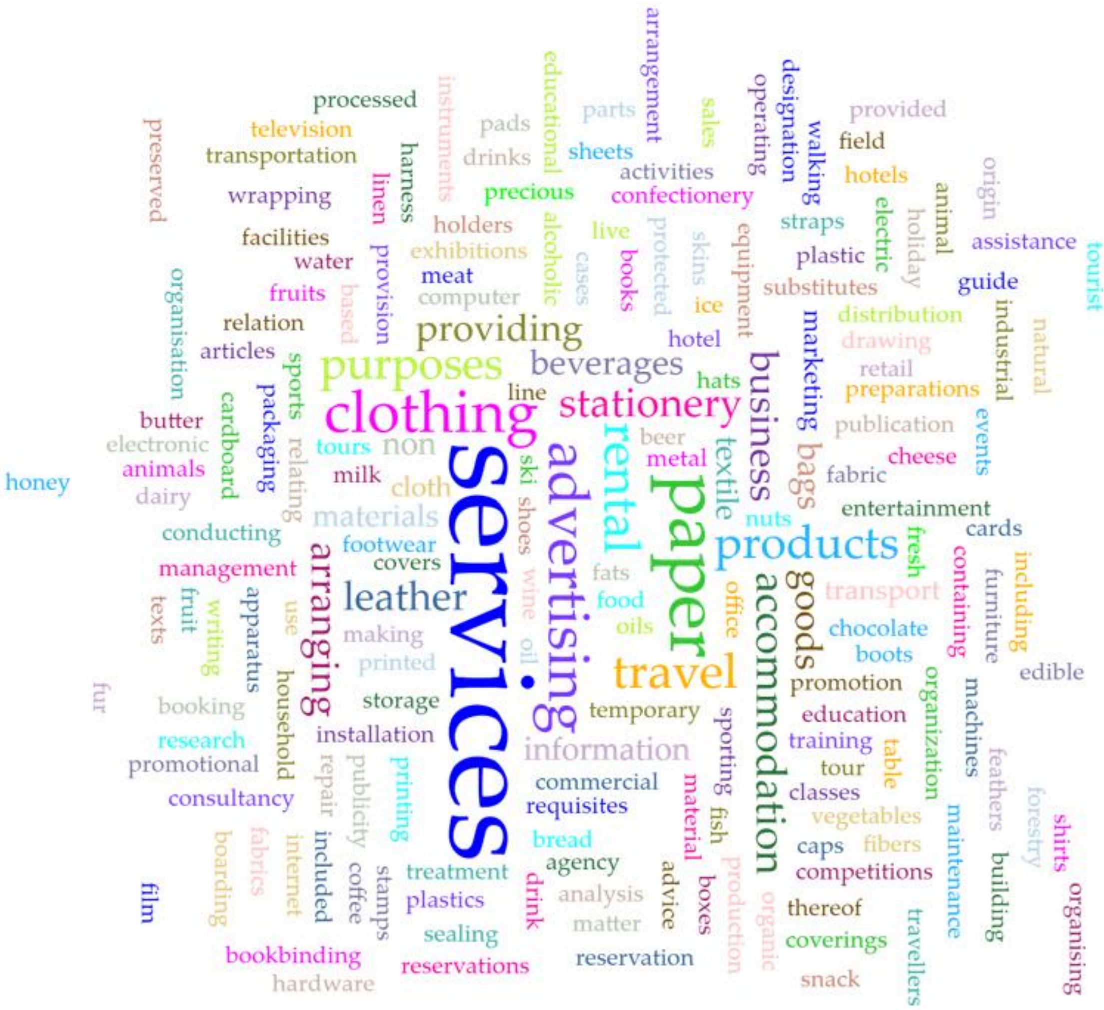
*Figure 9: Word cloud based on collective trademarks from **non-urban regions**, 2011 to 2019*



Source: Authors based on EUIPO.

Figure 10 shows the word cloud for collective trademarks from **rural regions** (2011-2019). The most frequently appearing terms besides *services* (434) are *paper* (183); *clothing* (147); *advertising* (144); and *rental* (126). The term *clothing* is often associated with leather and footwear. In the case of *rental*, its occurrence is associated with sports.

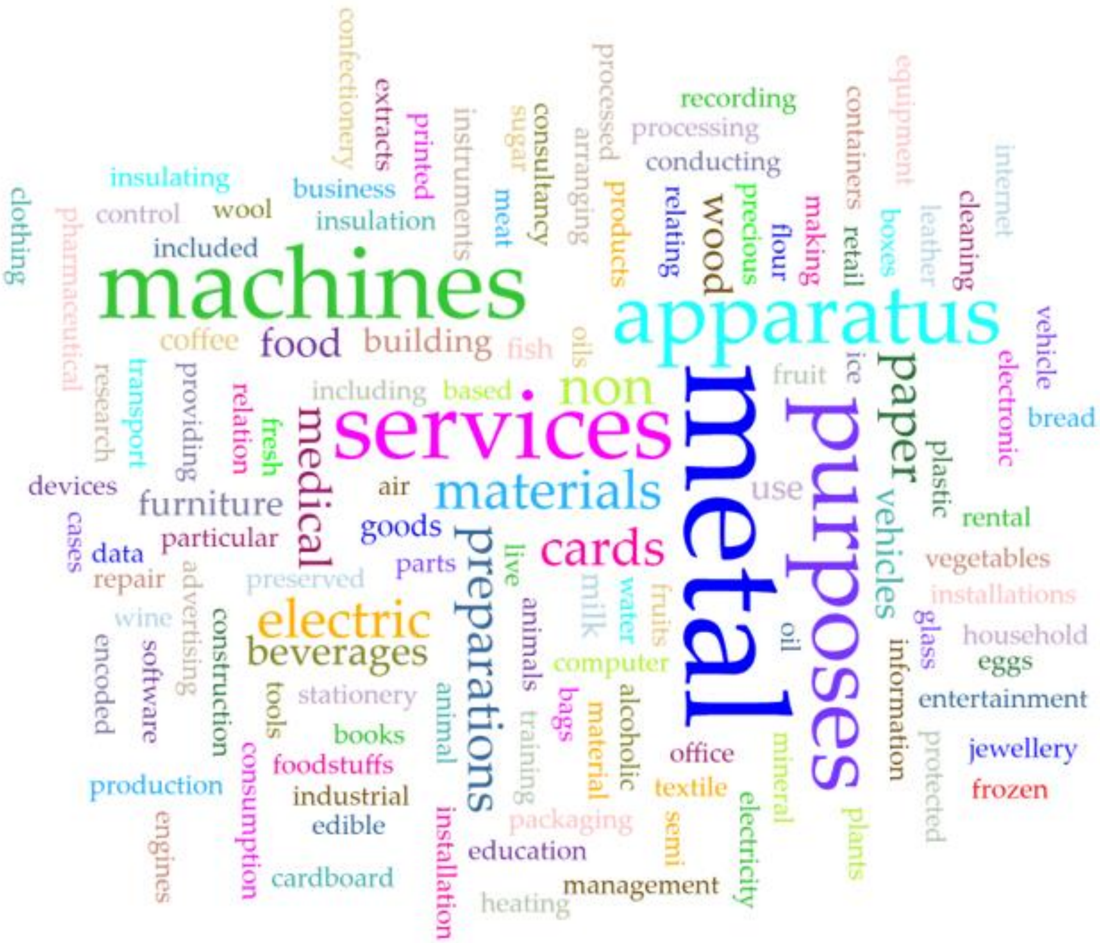
*Figure 10: Word clouds based on collective trademarks from **rural regions**, 2011 to 2019*



Source: Authors based on EUIPO.

The terms most frequent to **intermediate regions** (Figure 11) are *metal* (1,161); *services* (603); *machine* (600); *purposes* (577); and *apparatus* (508). In addition to these, the terms *electric*, *materials* and *cards* are also highlighted in the Figure 11, so goods related to electrical equipment are the most related to collective trademarks in intermediate regions.

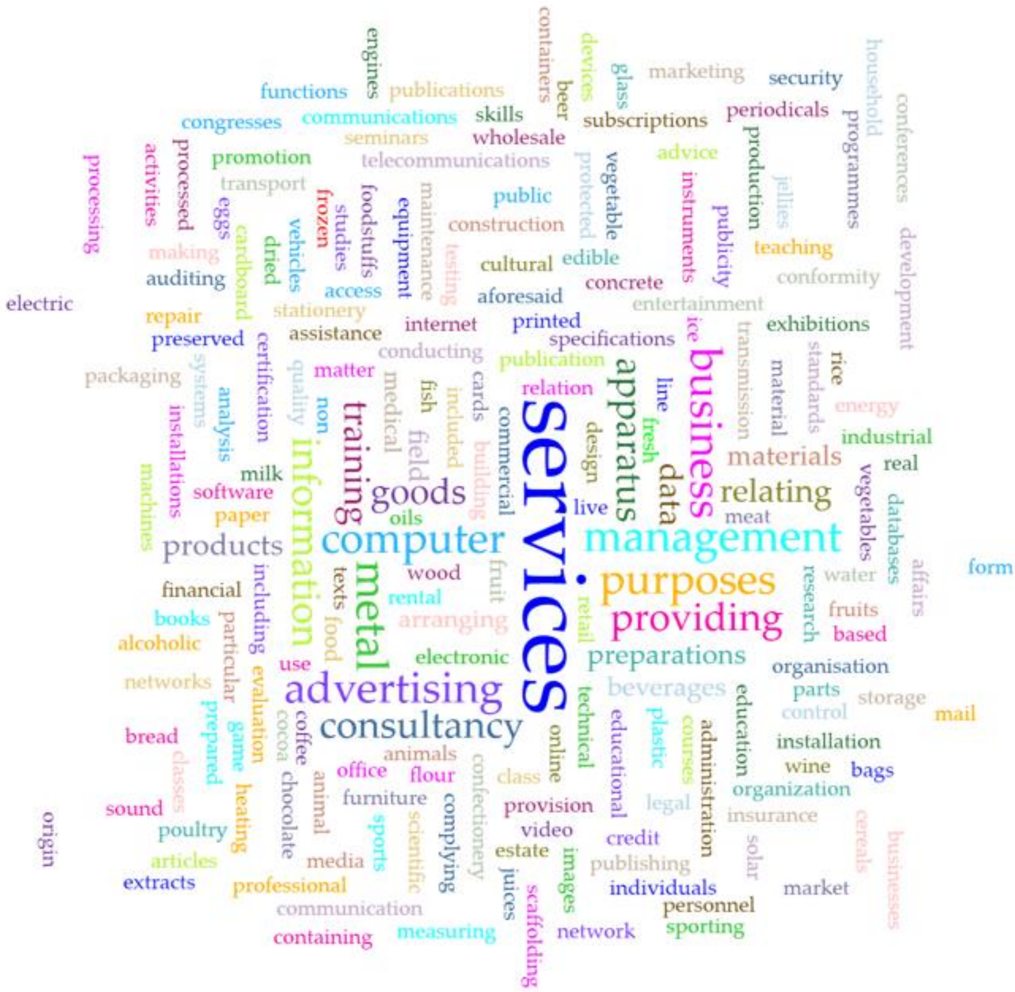
Figure 11: Word clouds based on collective trademarks from ***intermediate regions****, 2011 to 2019*



Source: Authors based on EUIPO.

We also produced the word cloud for **urban regions**. The results show that the most frequently cited terms here were *services* (1,546); *advertising* (518); *metal* (507); *business* (505); and *purposes* (476). Other frequent terms were *computer* (470), *management* (464) and *information* (457); therefore, in urban regions we noticed that there is a stronger association with terms related to technological services.

*Figure 12: Word clouds based on collective trademarks from **urban regions**, 2011 to 2019*



Source: Authors based on EUIPO.

Overall, the different word clouds show that collective trademarks cover specific goods and services in different groups of regions. This exploratory analysis suggests interesting patterns that one could further investigate. We discuss options in the next section.

4. Discussion and conclusion

Within this exploratory task, we aimed to investigate collective trademarks as a potential new source of data to capture the socio-economic and innovative contribution of creative and cultural activities in non-urban regions. The literature review and the exploratory empirical analysis indicate a number of interesting and novel insights.

A first insight is that collective trademarks appear related to activities that leverage territorial assets associated with heritage, culture and community. In this sense, we see a stronger link with the **cultural** element rather than the creative one.

A second insight is that collective trademarks seem particularly interesting to use for **non-urban regions**. This might be related to the type of goods and services that they protect, particularly in the case of food and heritage promotion, but we see a range of different products related to other economic activities too. It might also be the case that the collective nature of this IPR suits rural contexts better, as suggested by some scholars (Jimenez et al., 2022).

A third insight is that **collective trademarks filed at EUIPO are only a very small share of all trademark filings** and several regions in Europe never filed such a collective trademark. Here we should note the limitation that we are only considering EUIPO filings and not filings at national trademark offices. Further research efforts could be directed towards developing a complete database of collective trademarks filed at both international and national offices. However, this is a challenge because such offices differ significantly regarding online data availability, and there might also be different practices when it comes to preferring national vs. supranational filings.

Overall, this report suggests a potential for further exploring this particular intellectual property right.

Conceptually, further research could develop an understanding of how collective trademarks might offer an **inclusive IPR.** Under 'inclusive' one could consider: (1) a social dimension: to what extent do collective trademarks benefit more actors simultaneously and also groups of actors with otherwise weaker opportunities to economic returns?; (2) a geographical dimension: how can collective trademarks offer a viable alternative for peripheral regions and rural regions? These regions might suffer from 'liabilities of distance' that results in lower ownership of standard IPRs.

Empirically, there are many ways in which one could go beyond the first step that we took within this report. Next to including national filings, the thematic analysis of collective trademarks could be refined using more advanced techniques of textual analysis. For example, our word clouds were only based on single word keywords, but keywords with multiple words are able to capture more meaningful expressions. Identifying collective trademarks related to specific industries, like creative and cultural activities, would need to rely on standardised lists of terms that capture such activities.

Possibly those lists could be made based on extracting keywords from both industry-based and occupation-based classification of these activities. Such efforts could offer a next step in mapping creative and cultural activities, in line with what we already discussed in the conclusions to Task 1.1.

To conclude, the conceptual and empirical lines of research show significant potential. They also appear strongly needed before one can draw solid implications for policymakers or other economic actors wishing to include collective trademarks in their toolbox of data and metrics.

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Appendices (Task 1.2)

Appendix A: Database on collective trademarks by regions NUTS level 2 for the period 2011 to 2019

NUTS 2	2011	2012	2013	2014	2015	2016	2017	2018	2019	Total (2011-2019)
FR10	10	10	1	4	5	11	5	3	8	57
DE30	5	6	12	1	1	4	2		1	32
ITH5		4	3	1	3	5	7	6	2	31
ITH3		1	3	6	2	7	2	6	1	28
BE10		4	7	2	4	2	2	1	3	25
ES51			1		4	5	3	2	8	23
ITC4	3	2	3	5		2	1	2	2	20
ITI4		1	2	2	7	3	2	1	1	19
ITI1		1			5	3	1	2	5	17
DEA2	4	3		1	2	1	2	1	3	17
FRI1			2		5	2		1	4	14
DE11	3	3		1	1		3	1		12
ES30		2	2	1	1		2	2	2	12
DE71	1	5	1		3	1		1		12
ES52		1		1	2	4	2		1	11
UKI3	1		3		2	2	1	2		11
ITC1	2	4			1	1			2	10
FRK2	7	1								8
DEB3	1	1	4	1			1			8
AT13		3		1					3	7
ITF4		2	1	2			2			7
ITH1			1	1	2	2			1	7
DE21				1				6		7
ITF3		1	1		1	2		1		6
ES42			2		2		1	1		6
DK03	4	2								6
NL33	1		2		3					6
FRC1					4	2				6
BE24	2					1		1	1	5
PT11	1				1	1		2		5
DED2	1		2		1				1	5
DEA1		1			1		1		2	5
ES41			1	2			1		1	5

NUTS 2	2011	2012	2013	2014	2015	2016	2017	2018	2019	Total (2011-2019)
ES61			1	1				2		4
ES11							4			4
DEF0	1								3	4
ITH2	2					2				4
LU00	1				1		1		1	4
UKG1	1		2			1				4
SE11			1			3				4
DEA5				1				2	1	4
NL22					4					4
FRJ2							4			4
UKK1									4	4
ES22							2		1	3
ITI2	2							1		3
CH04	1						1	1		3
ITH4	1	1		1						3
ITI3	1		1	1						3
ITG1			2					1		3
IE06						1		2		3
EL30	3									3
NL41	2	1								3
UKI4	1	1						1		3
ITF1		2					1			3
MT00		1	1			1				3
BE35			1					1	1	3
CY00			2	1						3
DEB2				2		1				3
UKJ1				3						3
SI04							3			3
ITG2		1							1	2
FRJ1						1	1			2
BE21	2									2
DE12	2									2
DE73	1	1								2
ES21	1								1	2
ITC2	1					1				2
UKJ2	1	1								2
DE92		1		1						2
FRC2		1	1							2
NL32		1		1						2
BE33			1					1		2

NUTS 2	2011	2012	2013	2014	2015	2016	2017	2018	2019	Total (2011-2019)
FRL0				1					1	2
PL71				1				1		2
CH02						1			1	2
FRK1						1	1			2
FI1B							1		1	2
ITC3								1	1	2
PL91			1							1
ES62	1									1
DE27			1							1
FRI3					1					1
ES70						1				1
ES43							1			1
AT22									1	1
DE40	1									1
DE93	1									1
PT16	1									1
UKD3	1									1
UKM7	1									1
CH01		1								1
EL43		1								1
FRF1		1								1
FI1C			1							1
SE23			1							1
UKE2			1							1
UKH2			1							1
UKI7			1							1
BE23				1						1
BE31				1						1
DE13				1						1
PL51				1						1
PT15				1						1
AT12					1					1
BG42					1					1
ES24					1					1
ES53					1					1
LV00					1					1
SE31					1					1
UKH3					1					1
AT32						1				1
DK04						1				1

NUTS 2	2011	2012	2013	2014	2015	2016	2017	2018	2019	Total (2011-2019)
UKH1						1				1
UKJ4						1				1
CH05							1			1
DE26							1			1
DED5							1			1
UKM6							1			1
DE60								1		1
BE32									1	1
DE14									1	1
EL52									1	1
EL61									1	1
FRE1									1	1
HR03									1	1
UKE1									1	1
LT01									1	1

Source: Authors based on EUIPO.

Appendix B: Nice Classification descriptions

Nice Class	Description
1	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 preparxations; 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	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	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	Industrial oils and greases, wax; lubricants; dust absorbing, wetting and binding compositions; fuels and illuminants; candles and wicks for lighting.
5	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	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	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	Hand tools and implements, hand-operated; cutlery; side arms, except firearms; razors.
9	Scientific, research, navigation, surveying, photographic, cinematographic, audiovisual, optical, weighing, measuring, signalling, 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	Description
10	Surgical, medical, dental and veterinary apparatus and instruments; artificial limbs, eyes and teeth; orthopaedic 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	Apparatus and installations for lighting, heating, cooling, steam generating, cooking, drying, ventilating, water supply and sanitary purposes.
12	Vehicles; apparatus for locomotion by land, air or water.
13	Firearms; ammunition and projectiles; explosives; fireworks.
14	Precious metals and their alloys; jewellery, precious and semi-precious stones; horological and chronometric instruments.
15	Musical instruments; music stands and stands for musical instruments; conductors' batons.
16	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	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	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	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	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	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	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	Yarns and threads for textile use.
24	Textiles and substitutes for textiles; household linen; curtains of textile or plastic.
25	Clothing, footwear, headwear.

Nice Class	Description
26	Lace, braid and embroidery, and haberdashery ribbons and bows; buttons, hooks and eyes, pins and needles; artificial flowers; hair decorations; false hair.
27	Carpets, rugs, mats and matting, linoleum and other materials for covering existing floors; wall hangings, not of textile.
28	Games, toys and playthings; video game apparatus; gymnastic and sporting articles; decorations for Christmas trees.
29	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	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	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	Beers; non-alcoholic beverages; mineral and aerated waters; fruit beverages and fruit juices; syrups and other non-alcoholic preparations for making beverages.
33	Alcoholic beverages, except beers; alcoholic preparations for making beverages.
34	Tobacco and tobacco substitutes; cigarettes and cigars; electronic cigarettes and oral vaporizers for smokers; smokers' articles; matches.
35	Advertising; business management; business administration; office functions.
36	Insurance; financial affairs; monetary affairs; real estate affairs.
37	Building construction; repair; installation services.
38	Telecommunications.
39	Transport; packaging and storage of goods; travel arrangement.
40	Treatment of materials.
41	Education; providing of training; entertainment; sporting and cultural activities.
42	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	Services for providing food and drink; temporary accommodation.
44	Medical services; veterinary services; hygienic and beauty care for human beings or animals; agriculture, horticulture and forestry services.
45	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.

Note: Blue indicates goods classes and yellow indicates services classes.

Source: EUIPO.