Deliverable 1.8

Innovation in the EU Agro-Food Sector

WP1: [STAKEHOLDER INVOLVEMENT IN DATA-DRIVEN ANALYSIS OF THE FOOD SYSTEM IN THE SEARCH FOR NEW SOLUTIONS]

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Executive Summary

In recent decades, innovation has emerged as a fundamental engine of economic, environmental, and social transformation. Confronted with escalating global challenges—including climate change, deepening socio-economic disparities, and intensifying global competition—there is a growing consensus that current models of production, consumption, and societal organization must undergo a profound and systemic shift. Innovation, particularly when directed towards sustainability, holds the potential to drive this transition by fostering more inclusive, resilient, and environmentally sustainable economies (Carrillo-Hermosilla et al., 2009). This builds upon the historical and theoretical foundations that established innovation and technological progress as pivotal forces of long-term economic growth. Contemporary literature has since reaffirmed and expanded these insights, emphasizing innovation's role not only in macroeconomic development but also in enhancing efficiency and value generation on a global scale (Musostova et al., 2023; Yue et al., 2025).

The agri-food sector stands out as one of the most strategically critical domains in which innovation is urgently needed. Faced with the dual challenge of feeding a growing global population and mitigating the adverse effects of climate change and land degradation, innovation in agriculture has become a top policy priority at both the European Union (EU) and United Nations (UN) levels (Finger, 2023; Barth et al., 2017). Technological, organizational, and digital innovations—from precision agriculture and bio-based fertilizers to traceability platforms and circular economy models—have the potential to revolutionize the food system. Yet, realizing this transformation requires supportive public policies, substantial investment in Research and Development, and robust systems for knowledge transfer and capacity-building (Bentivoglio et al., 2016; Latino et al., 2023; Reinhardt, 2023).

Within this broader innovation framework, eco-innovation has gained particular prominence. Defined as innovation that explicitly integrates environmental objectives—enhancing resource efficiency, reducing ecological impact, and promoting sustainable consumption and production patterns—eco-innovation serves as a vital tool for harmonizing economic development with environmental stewardship (Porter, 1991; Bossle et al., 2016). To monitor progress and inform policy in this area, the European Commission has developed several key indicators and benchmarking tools, notably the European Innovation Scoreboard (EIS), Regional Innovation Scoreboard (RIS), and the Eco-Innovation Index (EII). These instruments provide critical data on innovation inputs, activities, and outcomes at both national and regional levels, supporting a place-based policy approach and helping to identify systemic gaps (EC, 2023; EC, 2024)

The deliverable is structured as follows.

First, a systematic literature review is developed on drivers and barriers to innovation in the agrifood sector. Afterwards, a descriptive analysis is conducted for the main innovation indexes at EU level, followed by the main self-produced maps and graphs representing their distribution in the European Union, as well as their evolution in time, and a comment on their main potential meanings and interpretations. The analysis will start with the European Innovation Scoreboard (EIS), followed by the Regional Innovation Scoreboard (RIS) and finally the Eco-Innovation Index (EII). Then, an empirical assessment is developed in the form of an econometric model assessing the effect of domestic investment on innovation, here represented by patents creation at regional level. Finally, the study will provide a micro-economic assessment using firms as units of analysis. All of the above is conducted at EU level, at national and regional (Nuts2) level, with a focus on the four member states that serve as main case studies for the SOSfood Project (Italy, Spain, Greece and Lithuania).

1. Introduction

In the last decades, the relevance of innovation as a catalyst for economic, environmental, and social development has become increasingly known. The intensification of global challenges, such as accelerating climate change, widening social inequalities, and the imperative to remain competitive in an interconnected economy, has increased the need to rethink and renew prevailing models of production, consumption, and behaviour. This transition toward a new paradigm is not only desirable, but necessary. This process can lead to the birth of innovative solutions that support a more inclusive, resilient, and sustainable economy (Carrillo-Hermosilla et al., 2009).

The role of innovation on economic development has been studied for years by many scholars. The first economist to highlight the importance of innovation as a driver of development was Schumpeter in 1934. He stated that competition via innovation is one of the driving forces of economic development and promoted innovation as a critical factor. After Schumpeter, was instead Robert Solow that in 1957 brought innovation into the domain of formal economic growth models. Indeed, one of his main statements was that technological improvements are the main drivers of economic growth and he introduced a model that estimates the fraction of growth due to increase in investments in technological equipment.

Since this first realization, literature on the role of innovation has expanded and nowadays it is demonstrated that innovation contributes significantly to economic growth and development of a national economy, but also at the global level. The effects of innovation lead to substantial advancements in value generation, characterised by notably more efficient outputs (Carrillo-Hermosilla et al., 2009; Musostova et al., 2023; Yue et al., 2025).

Among the sectors where innovation is most urgently needed is agriculture and food production. Indeed, innovation adoption and diffusion in the agri-food sector lately has been seen by scholars and policymakers as a priority. Food production is expected to face a 70% increase by 2050, by being at the same time under strong pressure due to climate change and soil degradation (Finger, 2023). Considering this, both the EU and the UN are putting research and innovation on food security and sustainable agriculture as a top priority, because the aim is to make the world's agricultural system become more productive, more resource-efficient, more resilient, and less wasteful (Barth et al., 2017).

Innovation in the agri-food sector is therefore not a luxury, it is a necessity. From precision farming to bio-based fertilizers, from circular economy models to digital platforms for traceability, the diffusion of new technologies and organizational models has the potential to transform how food is produced, distributed, and consumed. However, for innovation to be effective and inclusive, it must be supported by appropriate policies, investments in research and development, and effective knowledge transfer systems (Bentivoglio et al., 2016; Latino et al., 2023; Reinhardt, 2023)

In this context, the concept of eco-innovation has gained prominence. Eco-innovation refers to all forms of innovation (technological, organizational, or social) that contribute to a reduction of environmental impacts, enhance resource efficiency, or lead to more sustainable patterns of production and consumption. Unlike traditional innovation, which may focus solely on productivity or profitability, eco-innovation explicitly integrates environmental objectives, making it a powerful instrument for aligning economic development with ecological sustainability (Bossle et al., 2016).

To monitor the performance of innovation systems, especially in relation to sustainability, several tools have been developed at the European level. The European Innovation Scoreboard (EIS) provides a comparative assessment of the research and innovation capabilities of EU Member States and selected non-EU countries. It is a strategic tool for identifying each country's strengths and weaknesses, helping policymakers set priorities and design effective innovation strategies. The Regional Innovation Scoreboard (RIS) complements the EIS by offering a more granular analysis at the regional level, enabling a place-based perspective on innovation performance (European Commission, 2023).

Moreover, the Eco-Innovation Index, developed to assess Member States' performance in promoting and implementing eco-innovation, plays a crucial role in evaluating how innovation contributes to environmental objectives. Covering the period from 2014 to 2024, this index captures key dimensions such as eco-innovation inputs (e.g., R&D expenditure), eco-innovation activities (e.g., adoption of green technologies), and socio-economic outcomes (e.g., employment in eco-industries). These indicators not only provide an overview of the progress achieved but also help highlight persistent gaps and policy needs (EC, 2024).

2. Literature Review

Innovation is considered a critical component of the European Union's (EU) strategy for achieving a sustainable, resilient, and competitive agro-food sector (Singh et al., 2014; Borrello et al., 2016). The main two EU policy frameworks, namely the EU Green Deal and the Farm-to-Fork (F2F) strategy, underscore the role of innovation in transitioning toward sustainable food systems. However, despite the clear policy momentum, the adoption of innovative practices, and in particular eco-innovation, is uneven across the food supply chain, considering both farms and firms in the sector. Financial constraints, regulatory uncertainty, and knowledge gaps often hinder innovative efforts, especially among smallholder farmers and SMEs (Dicecca et al., 2016).

The innovations that are considered in this context are not only technological, but also organizational and social. Those all support the EU's twin aims of climate neutrality and food system sustainability, as outlined in the Green Deal and F2F strategy. These policies promote a series of actions, such as the reduction of pesticide use, conservation of biodiversity, and application of organic farming, with precision agriculture, biotechnologies, and digital tools serving as enablers (Bentivoglio et al., 2016; Latino et al., 2023; Reinhardt, 2023).

Public incentives such as the ones promoted with the new CAP 2023-2027, and consumer-driven demand for sustainable products, reinforce innovation throughout the agro-food supply chain. Additionally, cooperative networks and partnerships play a critical role in disseminating knowledge to foster resilience, especially for SMEs (Viaggi & Cuming, 2012; Borrello et al., 2016; Ryan et al., 2016).

Ultimately, innovation is both a policy target and a practical means to transition toward a climate-neutral and economically viable food system in Europe.

This literature review summarizes findings from a literature review that investigates drivers and barriers to innovation adoption in the EU agro-food sector. It focuses on innovation across the whole supply chain, distinguishing between the different experiences of farms and firms, offering comparative insights that can foster academic understanding and inform policymakers.

The literature review was conducted following the Structured Literature Review (SRL) framework introduced by Dumay and Cai (2014) and refined by Massaro et al. (2015). The approach used in this study is based on the systematic review of peer-reviewed papers, retrieved from the Scopus database. Two separate searches were conducted: one for farms, and one for firms, using a combination of keywords that refer to the agro-food sector, innovation, and specifically eco-innovation. The scope was to limit the search to EU countries, and to exclude non-peer reviewed and off-topic disciplines papers (e.g., medical or pharmaceutical studies). Out of a first finding of 165 papers, the final selection included 25 papers focusing on farms and 33 on firms.

The approach aims at answering some key consecutive and interconnected research questions (RQs): (1) How has the literature evolved over time? (2) What are the main drivers and barriers to innovation? (3) What are the implications for policy and practice? (4) What are the gaps and directions for future research?

To address the RQs the review provides a quantitative mapping of the literature's evolution over time, source journals, key contributing countries, and thematic trends. The results of this analysis served to contextualize the field's development and guide the in-depth examination of the specific drivers and barriers to innovation across farms and firms.

2.1 Drivers and Barriers for Innovation Adoption in Farms and Firms

The analysis provides an overview of the evolution and structure of the literature. It reveals an increasing number of publications over the last decade, with significant peaks after the launch of the EU Green Deal and the F2F strategy. Key contributing countries include Italy and Spain. The literature predominantly clusters around thematic areas such as sustainability transitions, digital transformation in agri-food systems, innovation policy, circular economy, and knowledge transfer mechanisms. Thematic and conceptual maps show strong linkages between innovation, sustainability, digitalization, and EU policy frameworks, underscoring the growing interdisciplinary focus of research in the agro-food sector.

Building on this general overview, the following sections delve deeper into the drivers and barriers to innovation adoption in farms and firms.

2.1.1 Farms

Farms, positioned at the downstream end of the agro-food supply chain, exhibit specific patterns in innovation adoption influenced by their production-focused role.

2.1.1.1 Drivers

Farm-level innovation is mostly driven by external policy frameworks and the growing societal demand for sustainable products and practices. EU-level strategies such as the Green Deal and the F2F strategy create strong incentives for adopting eco-innovative solutions. Other policy instruments like the CAP or the Life Cycle Assessment (LCA) methodologies, instead, provide financial and technical support for the sustainable transformation of farms (Borrello et al., 2016; Gambelli et al., 2021; Paolotti et al., 2023). Moreover, technological innovation, particularly in precision agriculture, further enhances resource efficiency and productivity (Marchiol, 2019; Parra-López et al., 2021; Finger, 2023). Another important driver relies on cooperation with public institutions, participation in cooperative networks, and access to advisory services. These three aspects act as important enablers for farms seeking to innovate, especially in contexts with limited resources (Viaggi & Cuming, 2012; García-Cortijo et al., 2019).

2.1.1.2 Barriers

Despite the presence of incentives, farms also face several obstacles in the adoption of innovation. Financial constraints remain one of the main constraints and the most frequently cited barrier, especially for smallholder farms. The high cost of adopting advanced technologies, combined with the uncertainty of the economic returns, often prevents farmers from investing in innovations (Bentivoglio et al., 2021; Ribašauskienė et al., 2024). Regulatory and policy uncertainties, and particularly the instability of subsidy regimes or inconsistent environmental requirements, discourage farmers to adopt long-term strategies in this context (Reinhardt, 2023). Additionally, limited access to knowledge and technical training creates a persistent skills gap, which hinders the uptake and effective introduction of new practices (Lamprinopoulou et al., 2014; Dicecca et al., 2016).

2.1.2 Firms

Firms operate at the downstream end of the agro-food supply chain, transforming raw agricultural inputs into processed goods and distributing them through wholesale and retail channels.

2.1.2.1 Drivers

For firms, innovation is strongly market-driven. The growing consumer demand for high quality and sustainable food products encourages the development of new processes and the creation of new products (Petridis et al., 2020; Zarbà et al., 2022). Firms also benefit from the increasing digitalization process of the supply chains: e-commerce, blockchain, online configurators, and other digital tools allow for improved customization, logistics, and product traceability (López-Becerra et al., 2016; Crisp et al., 2021). Moreover, knowledge networks and partnerships, particularly those involving research institutions and innovation intermediaries, often facilitate information exchange and collaboration in developing innovations (De Martino and Magnotti, 2018; Val and Harris, 2018); Germundsson et al., 2021). Lastly, public funding and investment mechanisms tailored to SMEs further boost the capacity of firms to engage in innovation, especially in regions where cluster development and innovation ecosystems are supported (Alarcón and Arias, 2019; Paoloni et al., 2023).

2.1.2.2 Barriers

Nonetheless, firms face several structural and strategic barriers. For instance, access to capital for innovation projects is not always guaranteed, especially for SMEs that lack a credit history (Riandita, 2022). Also, the costs associated with product certification, food safety compliance, and international trade regulations can significantly increase the burden of innovation (Kühne et al., 2010). Important is also to address the problem of internal capacity limitations, including the absence of dedicated innovation management, the often-fragmented coordination across departments, or the low absorptive capacity. These further hinder the successful integration of new practices or technologies. These constraints are particularly present in firms operating in more traditional and rural settings (Jack et al., 2014; Bjerke and Johansson, 2022).

2.2 Comparative Analysis of Farms and Firms

The comparative analysis of farms and firms reveals diverse shared and divergent patterns for both drivers and barriers to innovation adoption. Both actors are highly responsive to sustainability goals and policy incentives, demonstrating that top-down policies could help shaping innovation agendas.

Another shared driver is the digital transformation, with both precision agriculture and ICT tools central in farms, and e-commerce and customization tools prevalent among firms.

However, while financial barriers exist across both categories, farms, and especially smaller ones, face serious challenges in securing capital. In contrast, firms have access to a broader range of funding channels, including private investments. For what concerns regulatory uncertainty, it affects both, but the nature of the constraints differs. In particular, for farms, unclear environmental standards are a deterrent; for firms, on the other hand, the challenge lies more in navigating the complexity of the rules on food safety and international trade standards.

Another common theme is the knowledge gap, yet the manifestation differs also in this case: farms mostly struggle with technical know-how and advisory support, whereas firms face difficulties in strategic innovation management and coordination across the different internal departments.

Finally, both sectors benefit significantly from participation in cooperative networks, public-private partnerships, and regional innovation clusters, suggesting that horizontal collaboration is a vital enabler for innovation.

2.3 Conclusion

This literature review shows that innovation and eco-innovation in the agro-food sector are influenced by interrelated technological, institutional, financial, and behavioural factors. In particular, the role of public policy is both enabling and constraining, depending on how clear, consistent and accessible it is. To foster innovation adoption and close the gap between its potential and its implementation, tailored support mechanisms, an improved access to finance, and a stronger capacity-building effort are needed.

Future research on the topic should focus on developing innovative financing models like cooperative funding and microfinancing. Other types of studies should focus on the analysis of policy evaluation using counterfactual methods. Finally, it could be important to focus on consumer-market dynamics influencing eco-innovation uptake. Comparative analyses across EU regions could also shed light on context-specific barriers and opportunities.

3. Descriptive Analysis

3.1 European Innovation Scoreboard

Innovation is a crucial driver of progress. Therefore, the European Union (EU) has developed an indicator aimed at understanding how innovation and the propensity towards it is distributed in space and time within its borders. The Scoreboard's outcome is broadly represented by a Summary Innovation Index, made up of a total of 32 indicators, grouped into 12 dimensions, further divided into 4 categories. From a computational perspective, the basis of the scoreboard is represented by the 32 indicators, mainly coming from institutional data from EU member states. These have been directly reported at national level by the authors of the report. Of course, all of them are either percentages or adapted on a per capita basis to allow comparisons among countries. The 12 dimensions are merely groups of two or three indicators and are calculated as a non-weighted average of the indicators, that are previously normalised to assure the same scale of values (from 0 to 1), to allow a proper comparison. The purpose of the dimensions is therefore merely one of descriptive facilitation. They are not elaborations of the indicators, and they don't add information which is not available from them. Their reduced number (from 32 indicators to 12 dimensions) serves the purpose to simplify the picture of the scoreboard, preventing the reader from the need to study 32 different graphs and units of measurement. The exercise is then repeated by the report to move from the 12 dimensions to the 4 categories. Even in this case, the categories are no more than an arithmetic average of the 12 dimensions, that are divided into 4 groups of three dimensions each and further simplify the overall picture (European Commission, 2024). The simple graph below (table 3.1) provides a simplified structure of the scoreboard, that can therefore be analysed by indicators, dimensions or categories at the analyst's discretion. Indicators are the best choice when there are no time or human resources constraints, as they provide a more detailed picture, while categories are a broader picture but easier to analyse.

Type of Index	Number of Variables	Aggregation Level	Time Expenditure	Precision
Categories	4	High	Low	Low
Dimensions	12	Medium	Medium	Medium

Type of Index	Number of Variables	Aggregation Level	Time Expenditure	Precision
Indicators	32	Low	High	High

Table 3.1 - Overview of parameters used as part of EIS. Source: Own elaboration from European Commission (2023).

Table 3.2 below provides a full picture of the indicators, dimensions and categories composing the scoreboard. As anticipated above, indicators are essentially units of measurements that have then been used to further directly calculate dimensions (and indirectly categories). Therefore, there is no specific name for the indicators, as they are directly named after the unit of measurement they represent. It is here anticipated that given the considerations provided here and given the structure of the scoreboard, the authors have chosen to base the present paper and related analysis at the dimensions level. It is here believed they represent the best compromise between a very specific (and time consuming) analysis and an oversimplified picture. Therefore, maps and the related description will be based on the 12 dimensions, provided in the central column of Table 3.2 below, with a specification of the indicators they are formed by and the categories they are part of.

Category	Dimension	Unit of Measurement (Indicator)
Framework Conditions	**Human Resources**	New doctorate graduates in science, technology, engineering, and mathematics (STEM) per 1000 population aged 25-34
		Percentage population aged 25-34 having completed tertiary education
		Percentage population aged 25-64 participating in lifelong learning

Category	Dimension	Unit of Measurement (Indicator)
	Attractive Research Systems	International scientific co-publications per million population
		Scientific publications among the top-10% most cited publications worldwide as percentage of total scientific publications of the country
		Foreign doctorate students as a percentage of all doctorate students
	Digitalisation	Number of enterprises with a maximum contracted download speed of the fastest fixed internet connection of at least 100 Mb/s over total enterprises
		Individuals who have above basic overall digital skills (% share)
Investments	**Finance and Support**	R&D expenditure in the public sector (percentage of GDP)
		Venture capital (percentage of GDP)

Category	Dimension	Unit of Measurement (Indicator)
		Direct government funding and government tax support for business R&D (percentage of GDP)
	Firm Investments	R&D expenditure in the business sector (percentage of GDP)
		Non-R&D innovation expenditures (percentage of turnover)
		Innovation expenditures per person employed
	Use of Information Technologies	Enterprises providing training to develop or upgrade ICT skills of their personnel over total enterprises
		ICT specialists (as a percentage of total employment)
Innovation Activities	**Innovators**	SMEs introducing product innovations (percentage of SMEs)

Category	Dimension	Unit of Measurement (Indicator)
		SMEs introducing business process innovations (percentage of SMEs))
	Linkages	Innovative SMEs collaborating with others (percentage of SMEs)
		Public-private co publications per million population
		Job-to-job mobility of Human Resources in Science & Technology as a percentage of the working age population aged 25 to 64
	Intellectuals' assets	PCT patent applications per billion GDP (in PPS)
		Trademarks applications per billion GDP (in PPS)
		Designs applications per billion GDP (in PPS)

Category	Dimension	Unit of Measurement (Indicator)
Impacts	**Employment impacts**	Employment in knowledge-intensive activities (percentage of total employment)
		Employment in innovative enterprises over total employment in enterprises with more than 10 employees
	Sales Impacts	Exports of medium and high technology products as a share of total product exports over total value of all product exports
		Knowledge-intensive services exports as percentage of total services exports
		Sales of new-to market and new-to enterprise innovations as percentage of turnover
	Environmental Sustainability	Resource productivity expressed by the amount of GDP (in Purchasing Power Standard (PPS) generated per unit of direct material consumed (in kilograms)
		Air emissions by fine particulate matter (PM2.5) in the Manufacturing sector in Tonnes over value added in the Manufacturing sector - Chain linked volumes (2010), million euro

Category	Dimension	Unit of Measurement (Indicator)
		Development of environment-related technologies, percentage of all technologies

Table 3.2 - Indicators' grouping and distribution within the European Innovation Index (source: European Commission, 2024). Source: Own elaboration from European Commission (2023).

For simplicity purposes and given the consistent number of dimensions to be potentially considered, the present paragraph will only present the two dimensions that might be most coherent for the purposes of the Project, hence the Summary Innovation Index as a whole (theoretically representative of general innovation with no further specification) and the 12th dimension, hence representative of environmental sustainability. As shown by Table 3.2, while the total Summary Innovation Index is essentially an average of all dimensions, environmental sustainability is a dimension that averages resource productivity (efficiency), particulate matter (air pollutants) emissions, and environment-related technologies. The other 11 dimensions are then listed in Annex 1[1].

3.1.1 Summary Innovation Index (General)

Figures 3.1 from a) to d) show the Summary Innovation Index for all EU countries. It must be immediately noted here that Index values are not to be seen as absolute values, but have a comparative nature that facilitates comparisons among different countries. This is particularly useful in this case, as the Summary Innovation Index is not just one specific indicator, but is indeed an average of many different indicators, which makes the use of an absolute value potentially confusing. Here, fig. 3.1a) sets the average outcome of the index for the European Union at a value of 100, while the values for all other countries are comparatively adapted accordingly. Here, following the categories proposed by the European Union report, countries are distributed among 4 groups. The first group (lightest colour) of countries presents a value which is below 70% of the EU average (emerging innovators). Moving up, the second group presents a value included between 70% of the EU average and the EU average (moderate innovators), followed by the third group presenting a value between the average and 125% of it (strong innovators). Finally, the fourth group presents the highest value above 125% of the EU average (leader innovators).

Fig. 3.1b) uses the same categories, using 2017 as a baseline. This means that increases in the value of the Index (which has been generally increasing in time) are not accompanied by a recalculation of the EU average, which remains 100, hence the average value in 2017. This can be useful to focus on

[1] All graphs below have been developed using the Geoda software based on the raw data made available by the European Commission (2024).

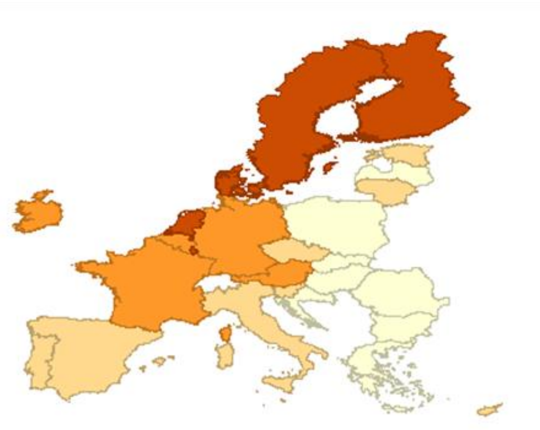
the improvements (or lack of) that countries have made between 2017 and 2024, and how they position now in the four categories, based on 2017 standards.

Fig. 3.1c) is still presenting the distribution of the Index for 2024, but this time recalculating the new EU average, based on 2024 values. This helps understand how the EU has performed as a whole in the analysed period, as well as how the comparative positions among countries have changed throughout time between 2017 and 2024, and therefore if there are regional clusters that have improved more than others based on the four categories' distribution.

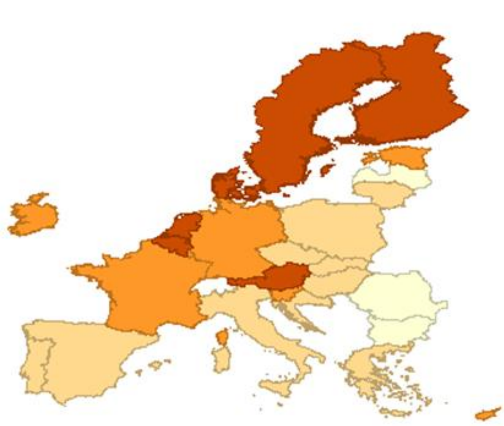
Based on the above explanation, figures 3.1 from a) to d) show the innovation index has overall increased in the European Union in the considered timeframe, with particular regards to the East. While the west has seen no consistent variations in terms of the grouping of the countries of interest (Luxembourg has downgraded from leader to strong innovator, while Belgium has improved from strong to leader), the East has seen several countries improving, from moderate to strong innovators (Cyprus and Estonia) and especially from emerging to moderate (Croatia, Greece, Hungary, Slovakia, Czechia, Poland).When focusing on the four case studies subject to the Project, the line chart shows all of them have experienced an increase in the Summary Innovation Index in the considered timeframe, as also shown in fig.3.1d). While eastern countries (Lithuania and Greece) have shown a comparatively greater increase (Greece upgrading from emerging to moderate innovator), Italy and Spain stick to slightly higher values and get very close to upgrading to strong innovators, considering 2017 thresholds.

However, 3.1c) shows that the comparative distribution of the Index among countries in 2024 hasn't consistently changed. The map still shows consistent differences through the east-west axis, as well as the north-south one. Northern and western countries are still performing comparatively better than eastern and southern countries, showing that the comparatively higher improvement registered especially in the east in the analysed period has not been enough to cover the head start that more advanced regions had in 2017.

Annex 1 shows the same figures for the first 11 dimensions proposed in Table 3.2, except for Environmental Sustainability, which is presented here below because of the particular attention paid to it by the present report and related Project.



a)



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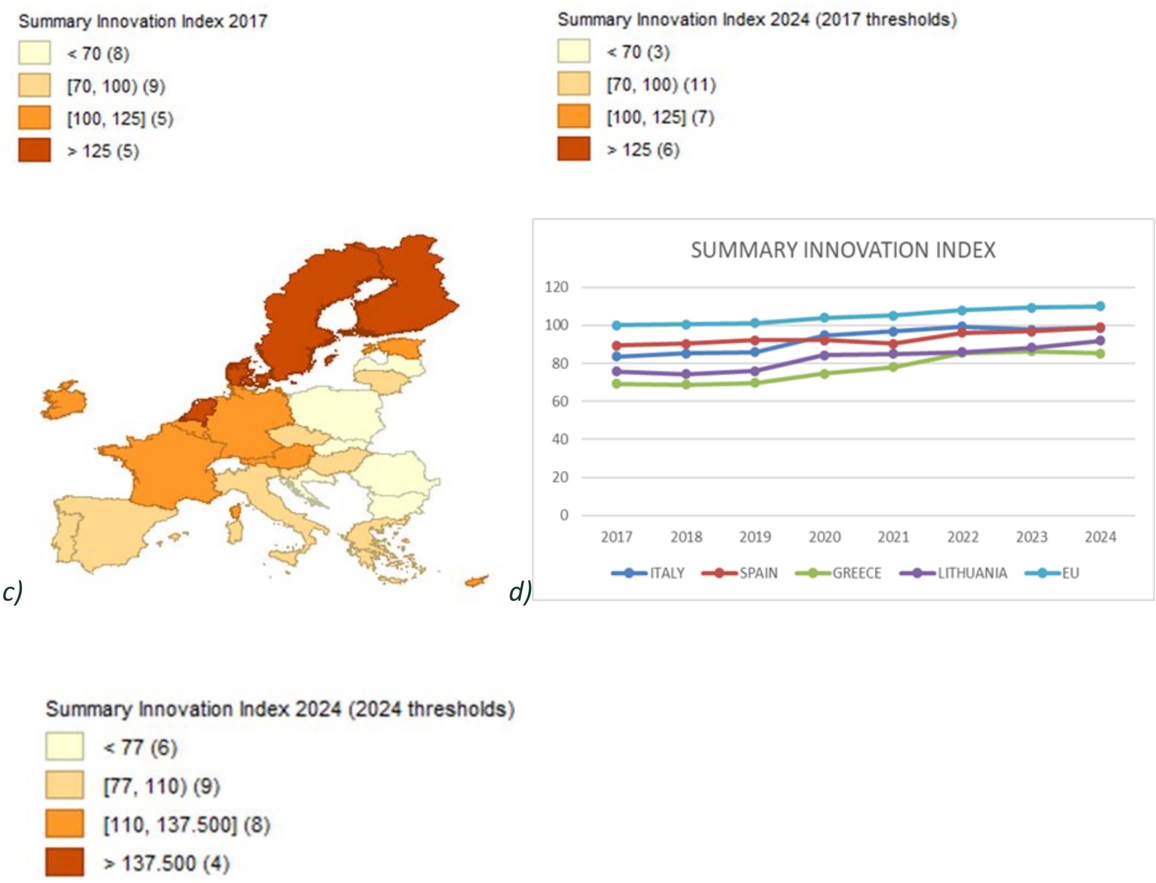
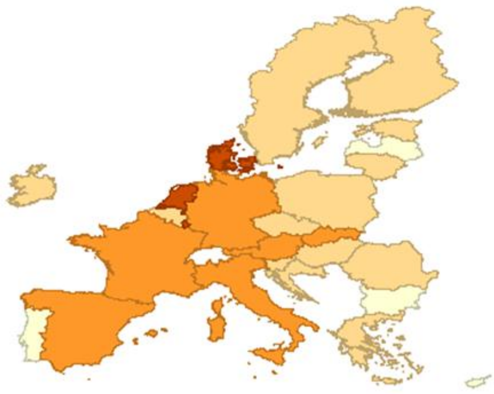


Figure 3.1. a) Summary Innovation Index 2017. b) Summary Innovation Index 2024 (2017 thresholds). c) Summary Innovation Index 2024 (2024 thresholds). d) Summary Innovation Index line chart (2017-2024). Source: Own elaboration from European Commission (2023) through the Geoda software.

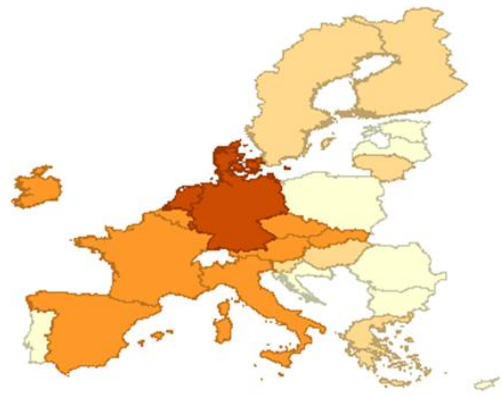
3.1.2 Environmental sustainability

Results on the outcome of the environmental sustainability dimension show that, despite the general increase in the Index shown in all fig. 3.1, the environmental performance of the European Union (provided the specific indicators adopted for the calculation of the dimension) has only very slightly improved, but only in some countries. Indeed, with the exceptions of Germany and Belgium, no countries have scaled up by category status on a 2017 baseline, while several eastern European countries have even downgraded (fig. 3.2a) and 3.2b)). When it comes to the main four case studies of the SOSfood Project, Spain has registered a visible reduction of its performance in the analysed timeframe, while Italy, Greece and Lithuania have kept the same performance level (fig. 3.2d)). When readapting categories' distribution to the new EU average levels in 2024, fig. 3.2c) shows that there are currently no leader innovators, with most eastern Europe down to emerging innovators and most of the west showing strong innovation values.

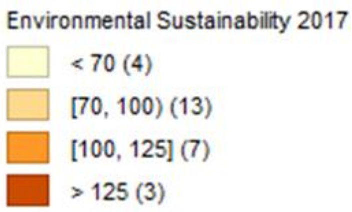
This not particularly optimistic outcome has multiple possible interpretations. At first glance, it shows a weak performance increase in environmental sustainability in the EU. It might well be though very dependent on the specific adopted indicators, that might not be perfectly representative of all environmental sustainability. The adoption of different criteria (e.g. waste recycling, CO2 emissions) might provide a different outcome.



a)



b)



c)

d)

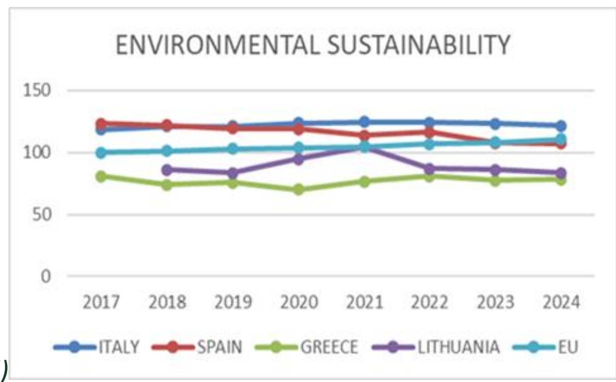


Figure 3.2 a) Environmental Sustainability 2017. b) Environmental Sustainability 2024 (2017 thresholds). c) Environmental Sustainability 2024 (2024 thresholds). d) Environmental Sustainability

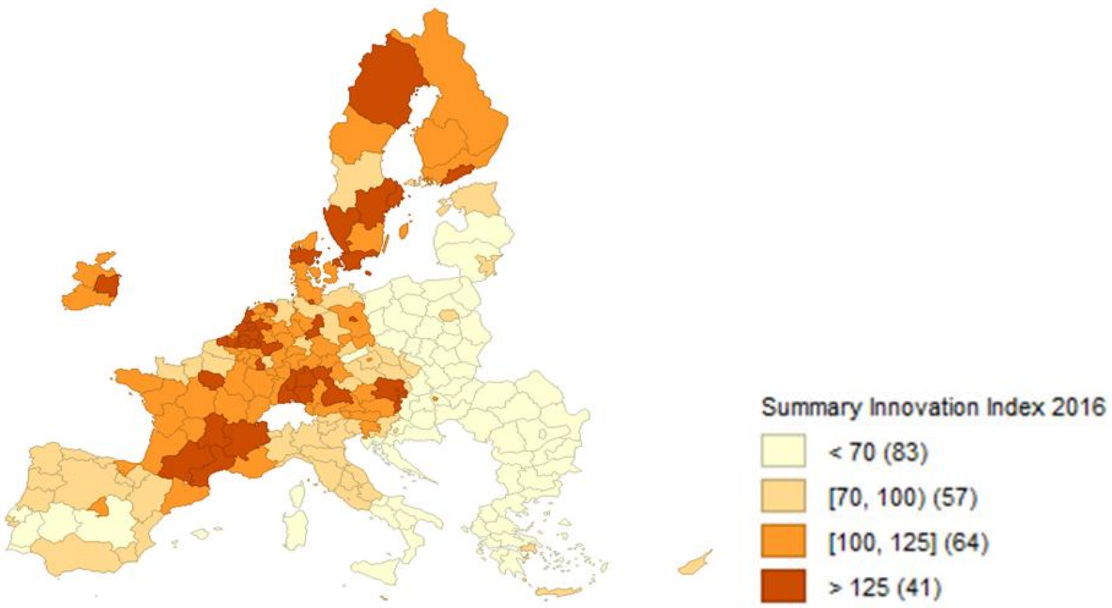
line chart (2017-2024). Source: Own elaboration from European Commission (2023) through the Geoda software.

3.2 Regional Innovation Scoreboard

The Regional Innovation Scoreboard (RIS) proposes the same scheme and descriptive information provided by the European Innovation Scoreboard at regional (NUTS-2) level. As explained in the related European Commission's report, the lack of data for some regions made it necessary for the authors to aggregate some regions into forming NUTS-1 macro-regions. This required some manual adjustments by the authors of the present report, assuring a complete match between the available dataset of the RIS and the NUTS-2 shapefile provided by Eurostat. Moreover, data availability at regional level is only provided for the Summary Innovation Index and some of the 32 basic indicators described above (European Commission, 2023). As the 12 dimensions are not provided, the present report is only going to show the outcome for the Summary Innovation Index.

Once the adaptation was completed, the same maps were developed through the Geoda software as the ones provided above for the European Innovation Scoreboard.

Therefore, the figures 3.3 to 3.5 present the distribution of the Regional Innovation Scoreboard with three different figures. The first (Fig. 3.3) shows the RIS's distribution in 2016 using the group subdivision suggested by the original report. Fig. 3.4 provides a picture for 2023 using the same subdivisions, while Fig. 3.5 customizes breaks based on 2023 values[2]. Finally, the bar charts (Figures 3.6 to 3.9) below provide a focus on the regional development of the indicator with regards to the four analysed case studies in the considered period.



[2] Hence recalculating the new EU average for the indicator and the related new 70%, 100% and 125% thresholds.

Figure 3.3. Regional Innovation Index 2016. Source: Own elaboration from European Commission (2024) through the Geoda software

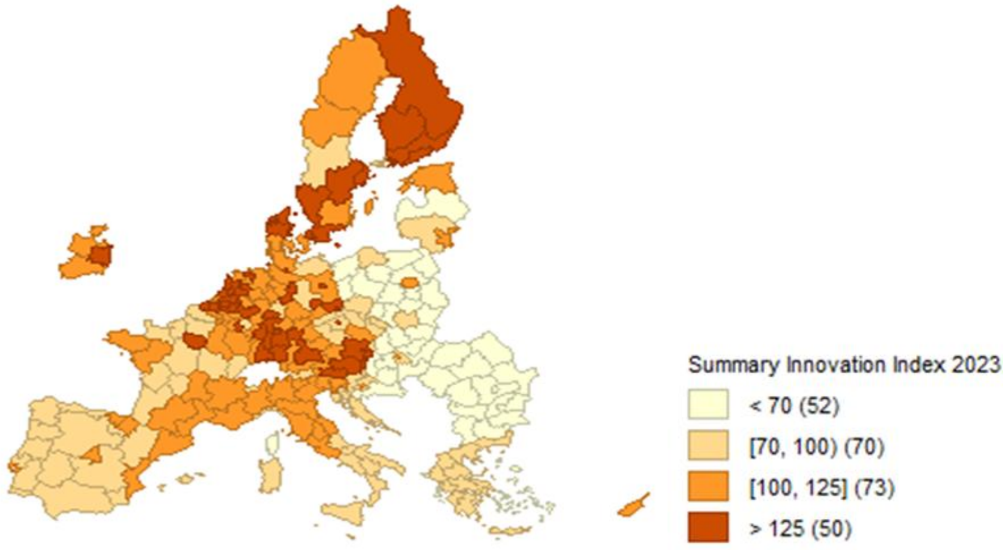


Figure 3.4.Regional Summary Innovation Index for 2023 (2016 thresholds). Source: Own elaboration from European Commission (2024) through the Geoda software

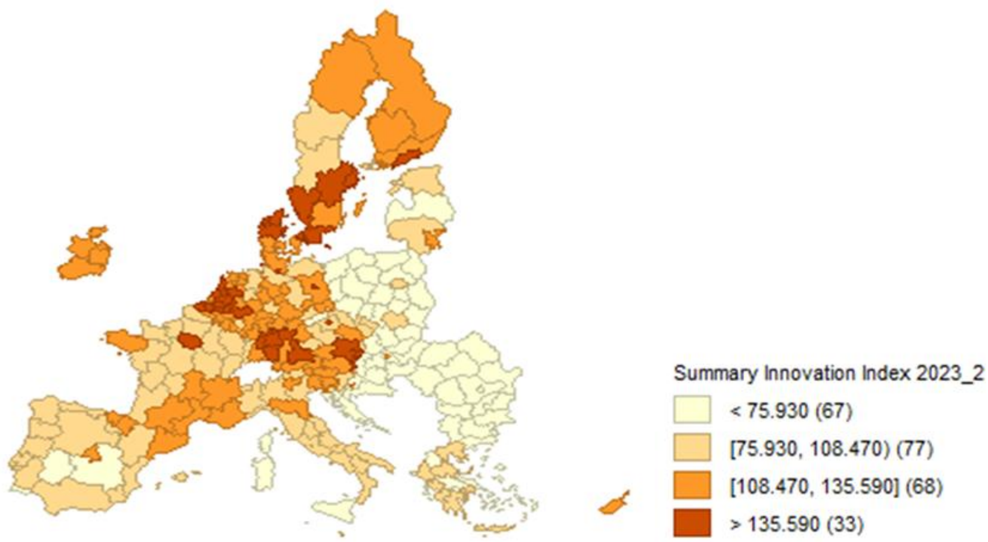


Figure 3.5. Regional Summary Innovation Index for 2023 (new customised thresholds)[3]. Source: Own elaboration from European Commission (2024) through the Geoda software

The maps show the Regional Innovation Scoreboard has increased quite homogeneously at regional level, implying the increase shown above is not due to few regions (e.g. where the capital or main cities of the countries are located) that might lead the trend by increasing national averages, but it is

[3] Fig. 3.5 shows how the RIS has changed between 2016 and 2023, while Fig. xx shows how countries proportionally perform in 2023 compared to the average EU performance in 2023.

indeed a broad change influencing territories in similar ways. While some regions and clusters (e.g. in France) have exceptionally reduced their innovation scores, most of the continent has either conserved their position in the groups subdivision (especially in Northern Europe) or improved it (especially in the South and East). The four case studies considered in the present report have all been subject to an improvement that moved their regions either from emerging to moderate innovators (Greece and Southern Italy) or from moderate to strong innovators (Northern Italy). A focus on these four countries is provided below in Figures 3.6 to 3.9.

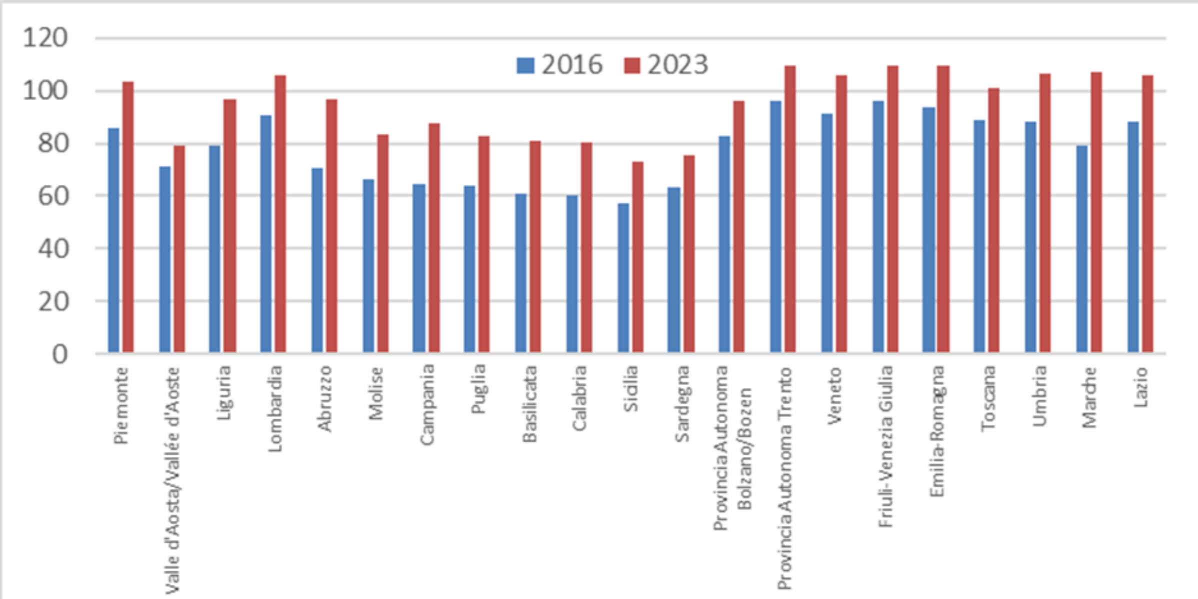


Figure 3.6. Regional Summary Innovation Index (Italy 2016/2023). Source: Own elaboration from European Commission (2024) through the Geoda software

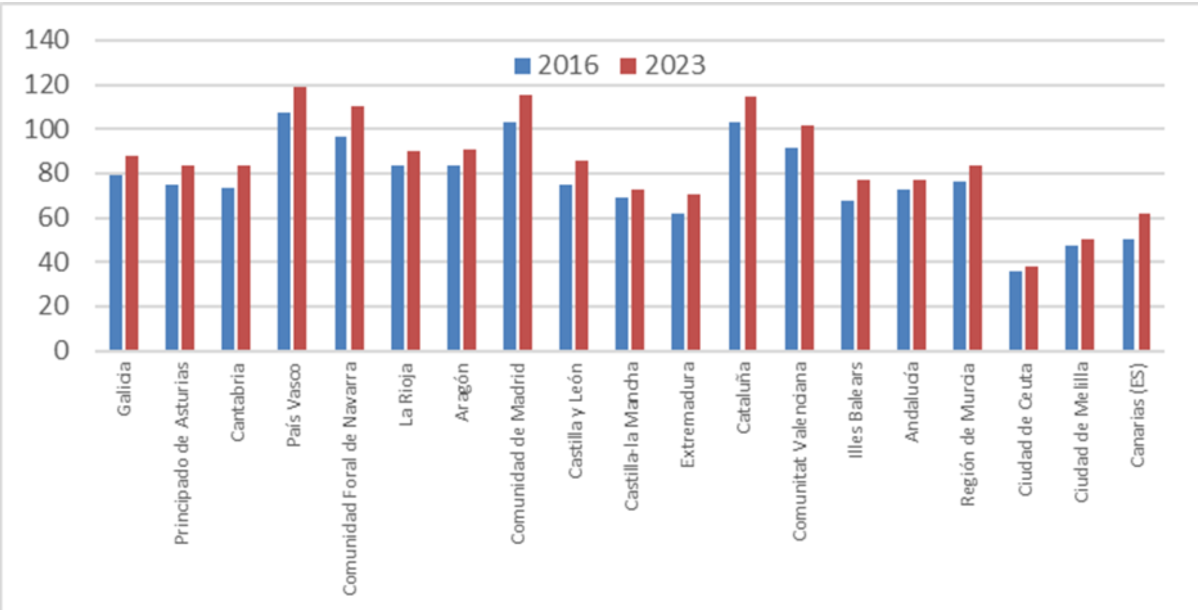


Figure 3.7. Regional Summary Innovation Index (Spain 2016/2023). Source: Own elaboration from European Commission (2024) through the Geoda software

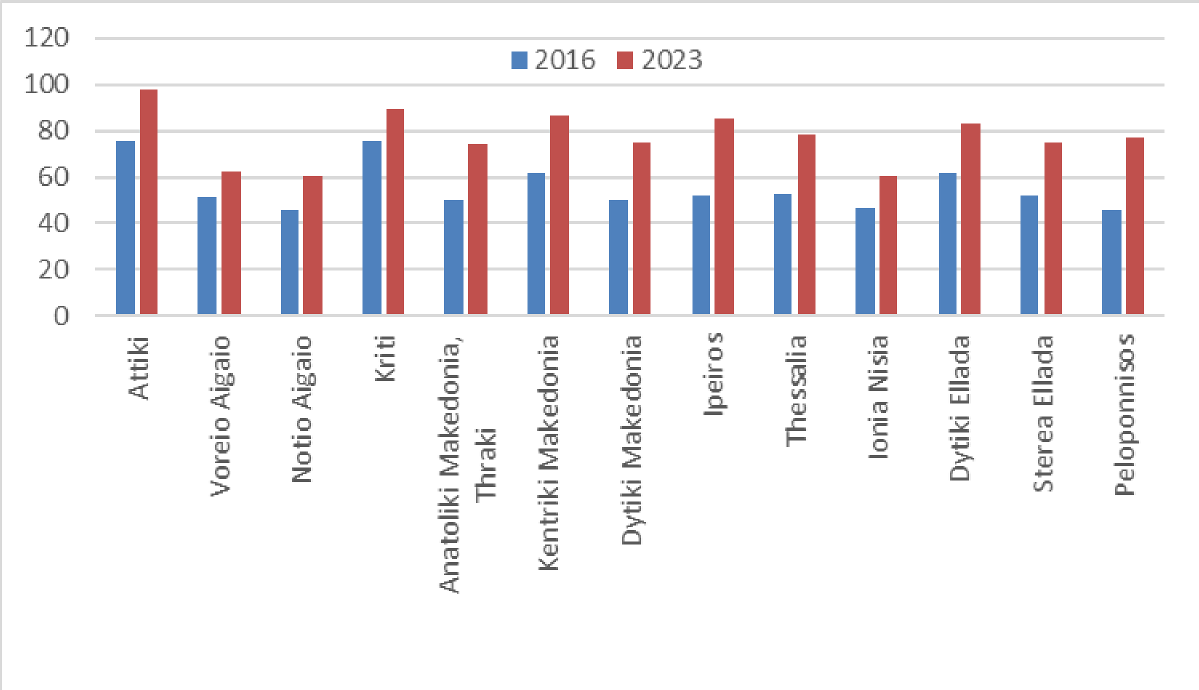


Figure 3.8. Regional Summary Innovation Index (Greece 2016/2023). Source: Own elaboration from European Commission (2024) through the Geoda software

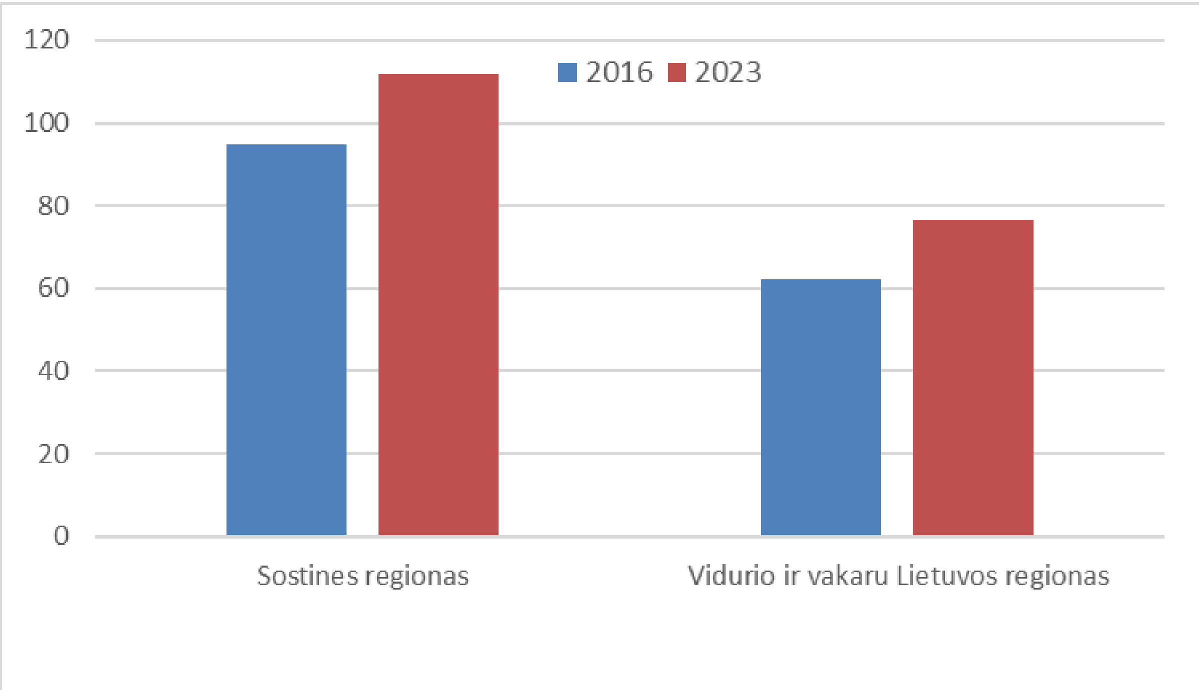


Figure 3.9. Regional Summary Innovation Index (Lithuania 2016/2023). Source: Own elaboration from European Commission (2024) through the Geoda software

The bar charts further show how the improvement has been proportionally very similar at regional level for all the four countries, and particularly for the least developed areas (Southern Italy and

Greece) that started off with lower values. The outcome may show that improvements are generally not driven much at regional level, but more likely at national or macroregional (east/west/north/south) level, with regions in the same country or area responding similarly.

3.3 Eco-Innovation Index

3.3.1 Introduction

An eco-innovation is an innovation that has a positive impact on the environment and increases resilience to climate change. These innovations are considered essential in achieving the aims of the European Green Deal and the transition to a circular economy. Moreover, eco-innovation for companies could lead to reduced costs, new capacities to capture growth opportunities, and enhanced reputation (EEA, 2025; EC, 2025).

In this context it is important to monitor the evolution of eco-innovation in Europe. To achieve so, the European Commission (EC) has developed the Eco-Innovation Index (EII), a composite indicator based on five different thematic areas (Al-Ajlani et al., 2022):

1. **Eco-innovation inputs**, in which are included financial and human capital investments.
2. **Eco-innovation activities**, in which is defined the extent to which companies are active in eco-innovation.
3. **Eco-innovation outputs**, in which are measured the outputs in terms of patents and academic publications.
4. **Resource efficiency outcomes**, in which the efficiency of resources and GHG emissions is addressed for each MS.
5. **Socio-economic outcomes**, in which the aim is to measure the positive impact on the societal and economic area of eco-innovation.

For each of these dimensions, the performance of every Member State (MS) is assessed using a range of specific indicators (EEA, 2025). Indeed, the EII is considered a much relevant tool for monitoring the progress made by each country towards a more sustainable and innovative Europe since 2010 and helps identify where further efforts are needed by the MSs to achieve the EU goals for a green and competitive economy (EC, 2024; EC, 2025).

3.3.2 Indicators

The overall environmental performance of the MSs is measured through the summary EII, which is constructed by taking an unweighted average of all the 12 indicators included in the methodological framework. The EII performance of each MS is measured in comparison with the EU27 average. In the 2024 Report, the EII uses 2014 as the reference year and the EU score for 2014 is set at 100. Comparisons are based on how far the performance deviates from the EU27 level in 2014. In particular, scores above 100 indicate that a MS (or the EU27) is performing better than EU in 2014, while scores below 100 indicate underperformance compared to EU in 2014. (EC, 2024).

In the next table 3.3 a summary of the twelve indicators, divided by each thematic area, along with their definition is provided:

Thematic Area	Indicator	Definition
Eco-Innovation Inputs	**1.1. Government environmental and energy R&D appropriations and outlays**	Indicates the relative priority that governments give to investing in R&D in the areas of energy, renewables, and environment.
	1.2. Total R&D personnel and researchers	Indicates the knowledge and research capabilities of a country.
Eco-Innovation Activities	**2.1. Number of ISO 14001 certificates.**	It is a proxy indicator for the level of environmental awareness and management capabilities of businesses.
Eco-Innovation Outputs	**3.1. Eco-innovation related patents**	It considers patent data indicating new inventions in the filed of eco-innovation, using the latest OECD framework of measuring eco-innovation related patents.
	3.2. Eco-innovation related academic publications	It measures the quantity of academic publications in the field of eco-innovation.
Resource efficiency outcomes	**4.1. Material productivity**	Illustrates the GDP generated by domestic material consumption

Thematic Area	Indicator	Definition
	4.2. Water productivity (GDP/total freshwater abstraction)	Illustrates the GDP generated by domestic water consumption.
	4.3. Energy productivity	It is an indicator that derives from the division of the GDP by the gross available energy for a given calendar year, and it measures the productivity of energy consumption. It gives also a picture of the decoupling degree of energy use from growth in GDP.
	4.4. GHG productivity	Illustrates the GDP generated by GHG emissions.
Socio-economic outcomes	**5.1. Exports of environmental goods and service sector**	Export of goods and services in the field of environmental protection and resource management activities.
	5.2. Employment in environmental protection and resource management activities	Employment in the field of environmental protection and resource management activities.
	5.3. Value added in environmental protection and resource management activities	Value added in the field of environmental protection and resource management activities.

Table 3.3: EII indicators. Source: authors' elaboration from EC (2024).

3.3.3 Measures and Classification

For what concerns the EII, the EC classifies MSs based on a homogeneous distribution into three different performance groups equally sized (EC, 2024):

1. **Eco-innovation leaders**
2. **Average eco-innovation performers**
3. **Eco-innovation catching up**

Each group includes nine MSs, determined by their ranking in the EII score distribution (EC, 2024).

3.3.4 Analysis and Discussion

The following maps display, through a color gradient, the values of the EII for all MSs in 2014 (Figure 3.10a) and in 2024 (Figure 3.10b). The gradient is based on the classification introduced in the previous paragraph, dividing MSs into "Eco-innovation leaders", "Average eco-innovation performers", and "Eco-innovation catching up". The homogeneous distribution facilitates a visual comparison between countries over time.

At a glance, the overall structure of the three groups has not changed dramatically between the two years, suggesting a broad continuity in eco-innovation performance across the EU. However, there have been a few notable shifts. Lithuania, for example, moved up from the “catching up” group to join the “average performers,” while the Netherlands advanced into the top tier, becoming one of the “eco-innovation leaders.” In contrast, Romania slipped from the “average” group down to “catching up,” and Spain moved from the top tier to the middle group, marking a relative decline (EC, 2024).

These changes reflect both steady patterns and emerging trends, as some MSs build momentum in their eco-innovation strategies while others face challenges in keeping pace. Overall, the maps offer a snapshot of how efforts toward sustainability and innovation have evolved across Europe over the past decade.

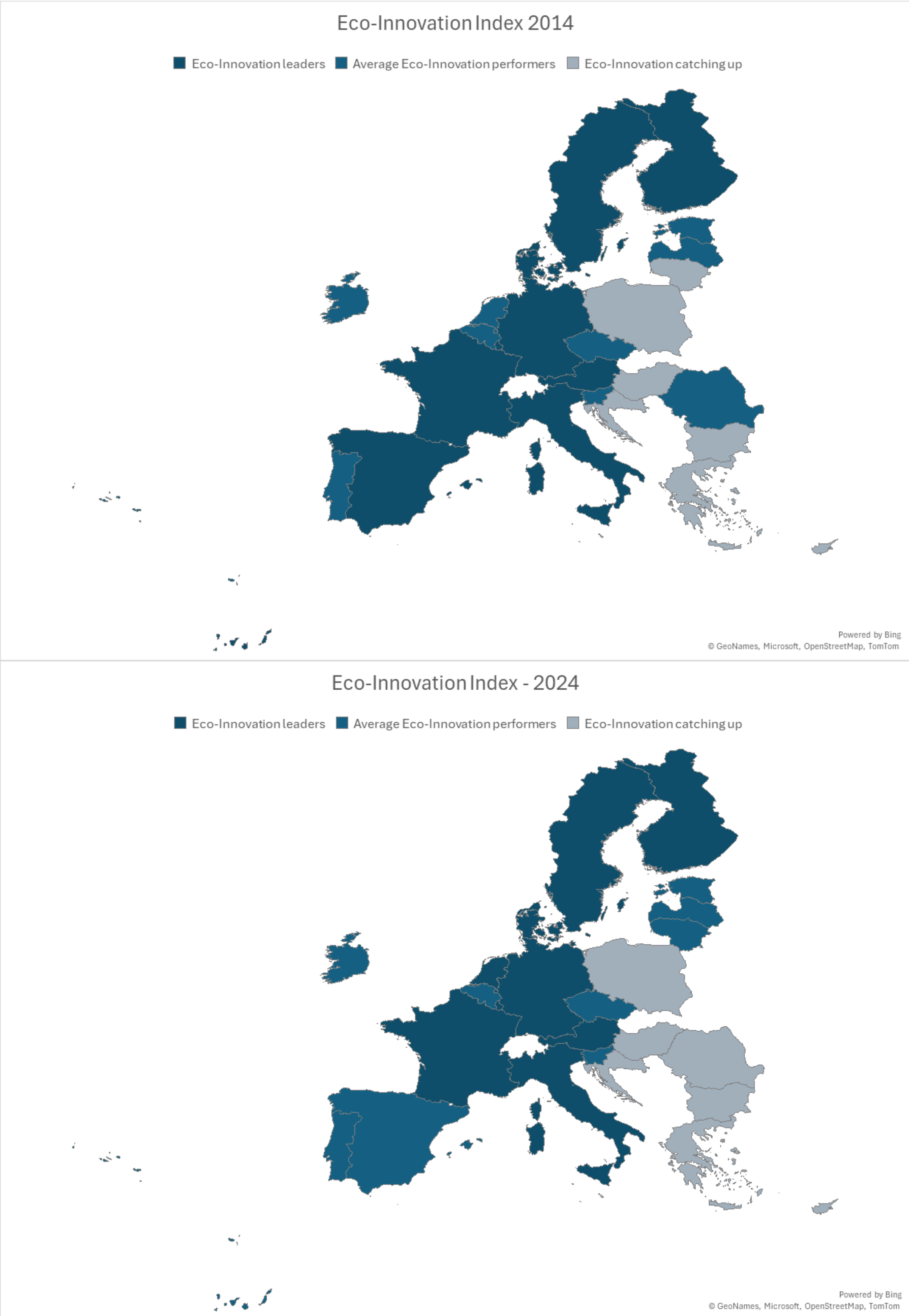


Figure 3.10. EII scores (a) 2014; (b) 2024. Source: own elaboration from EC (2024) data

In the following sections, each of the five thematic areas is analyzed. A comparison of 2014 and 2024 scores is provided for each Member State, along with a dedicated time series analysis for the four case studies: Greece, Italy, Lithuania, and Spain.

3.3.4.1 Eco-innovation inputs

The first thematic area concerns eco-innovation inputs. It focuses on financial and human capital investments in eco-innovative activities and is measured through two indicators: "Government environmental and energy R&D appropriations and outlays" and "Total R&D personnel and researchers."

Figure 3.11. Eco-innovation inputs in EU - 2014 vs 2024. Source: own elaboration from EC (2024) data.

Fig. 3.12 presents a histogram illustrating the scores for the eco-innovation input area in 2014 and 2024 for each MS, relative to the EU average. In 2014, only a small group of countries scored above the EU average, with Finland emerging as the top performer, followed by Denmark and Germany. Some countries, such as Slovenia and the Netherlands, have significantly improved their performance since 2014, surpassing the EU average. Overall, most countries have increased their scores, with the exception of Denmark, Luxembourg, Hungary, Estonia, Poland, and Romania, which experienced a decrease. In 2024 the top performer is Finland, followed by Germany and France. On average, the EU has seen an increase of 22.3 points compared to 2014 (EC, 2024).

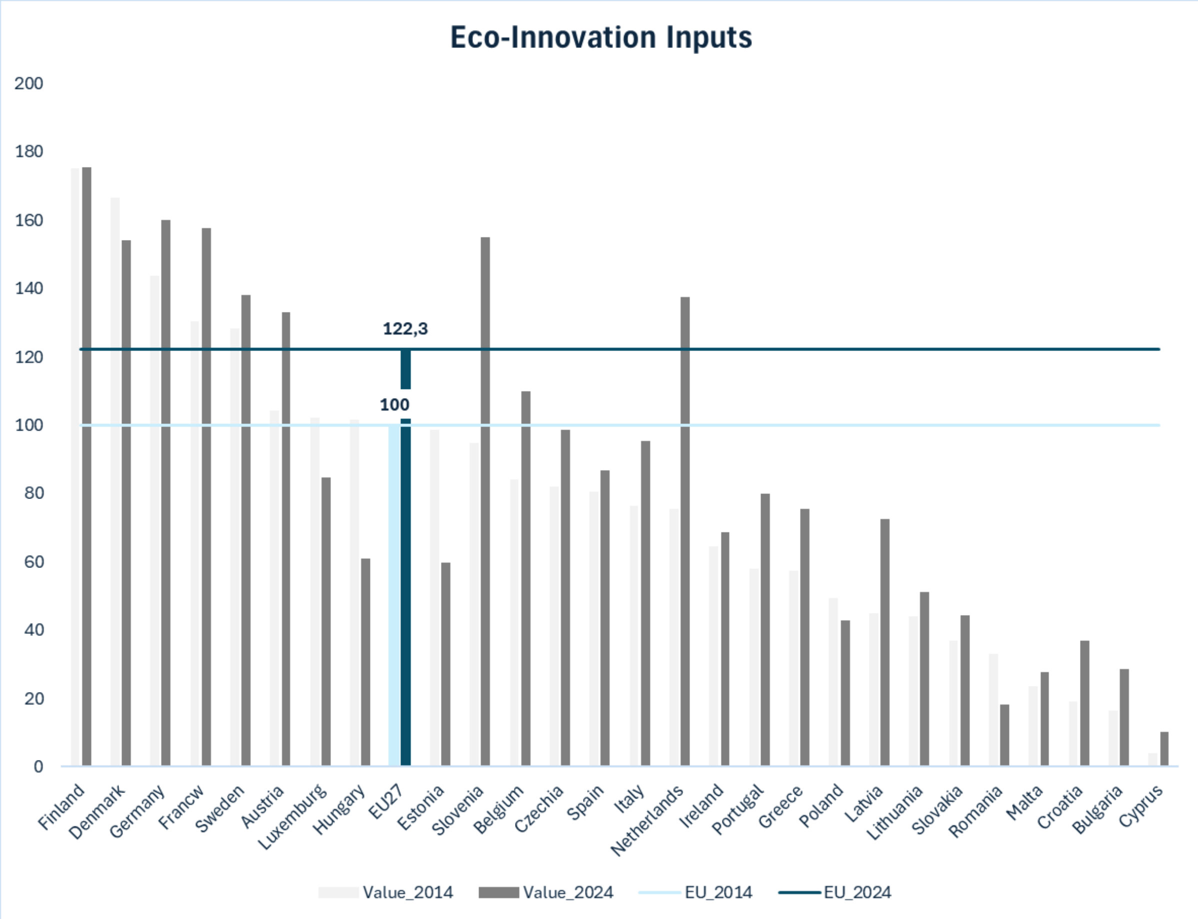


Figure 3.12. Eco-innovation inputs: scores 2014 vs 2024. Source: own elaboration from EC (2024) data.

For the purpose of this analysis, we consider the time series evolution of eco-innovation input scores for selected MS case studies: Greece, Italy, Lithuania, and Spain. Fig. 3.13 illustrates the trends for each of these countries, alongside the EU average, over the period from 2014 to 2024.

As shown in the graph, the average EU score has gradually increased over the years, rising from the baseline value of 100 to 122.3 in 2024. With the exception of Greece, all countries consistently fall below the EU average throughout the observed period. Greece experienced several peaks in 2018, 2020, 2021, and 2022, during which its score exceeded the EU average. However, it is now on a downward trend. Italy saw a sharp increase until 2021, after which its score began to decline, albeit at a slower pace than Greece. Among the four countries, Italy holds the highest score in 2024. Lithuania is the weakest performer in this domain, with scores well below the EU average and, by 2024, nearly returning to its 2016 level. Spain is the only country among the four showing a steady upward trend since 2018, although it remains below the EU average. In 2024, it surpasses Greece (Diestre, 2022; Iadecola, 2022; Orfanidou & Kondylidou, 2022; Spudyte, 2022).

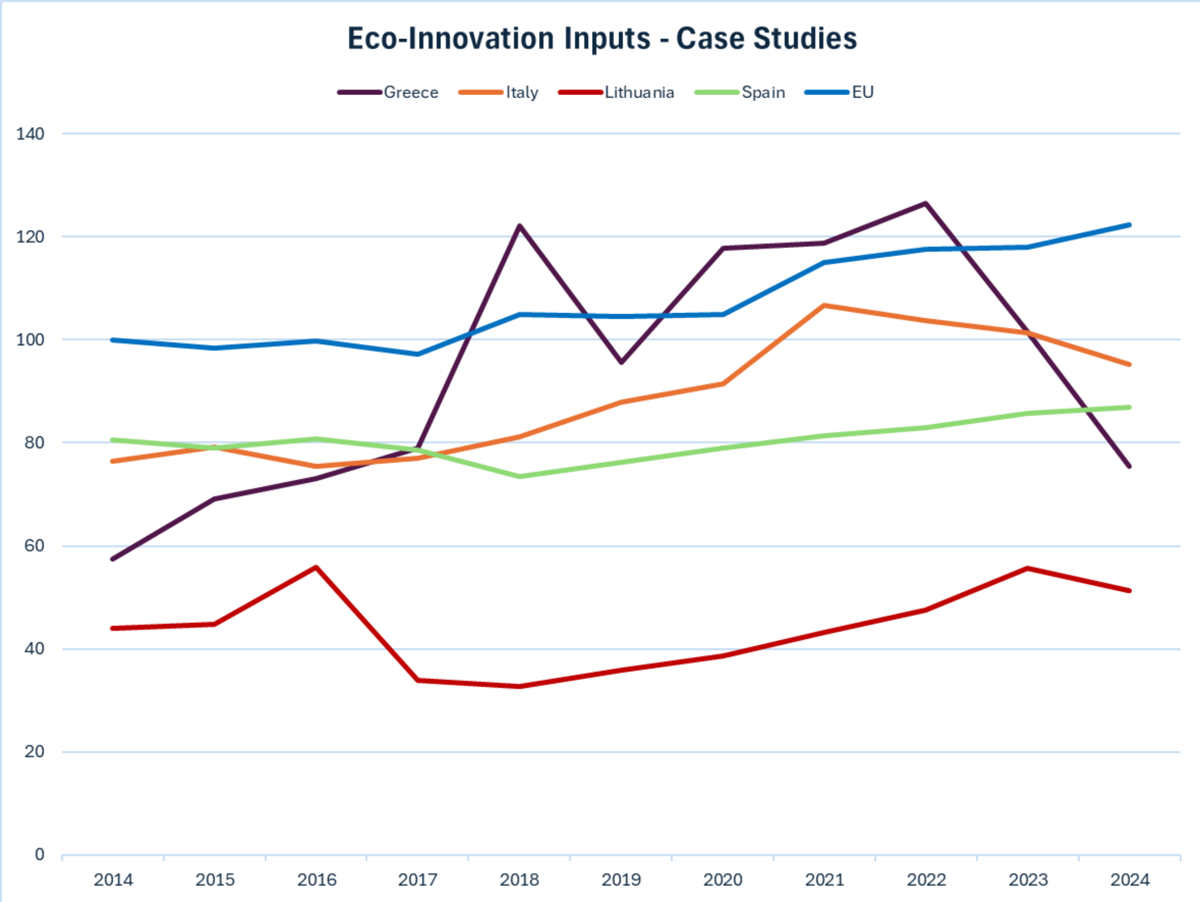


Figure 3.13. Eco-innovation inputs evolution: case studies. Source: own elaboration from EC (2024) data.

3.3.4.2 Eco-innovation activities

The second thematic area concerns eco-innovation activities. It focuses on the extent to which companies in a given country are active in eco-innovation and is measured only through one indicator: "Number of ISO 14001 certificates."

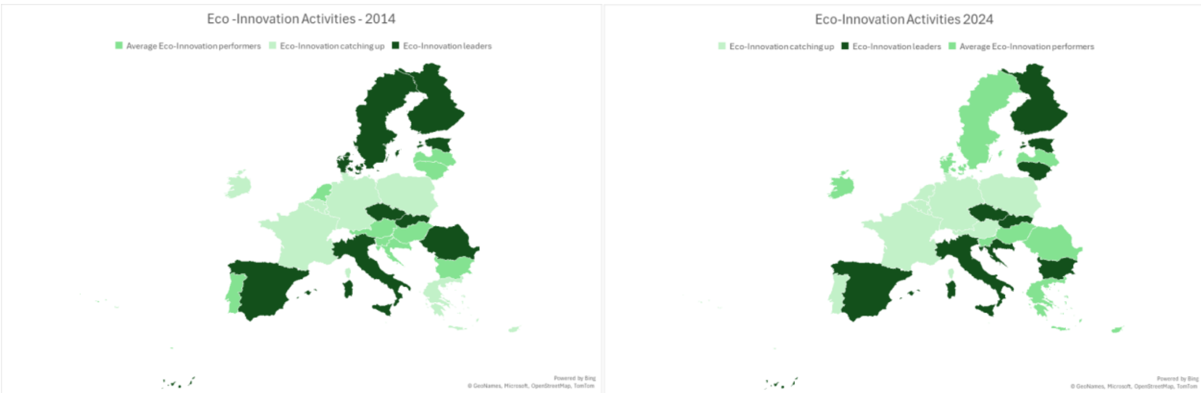


Figure 3.14. Eco-innovation activities in EU - 2014 vs 2024. Source: own elaboration from EC (2024) data.

Fig. 3.15 presents a histogram showing the eco-innovation activity scores for each MS in 2014 and 2024, relative to the EU average. In 2014, ten countries scored above the EU average, with Romania, Spain, and Sweden ranking as the top performers. Interestingly, these countries were among those that experienced a decline in their scores by 2024, in contrast to the vast majority of other MS, which improved their performance. By 2024, fifteen countries exceeded the EU average, with Czechia leading, followed by Estonia and Bulgaria. Overall, the EU average score increased by 8 points compared to 2014 (EC, 2024).

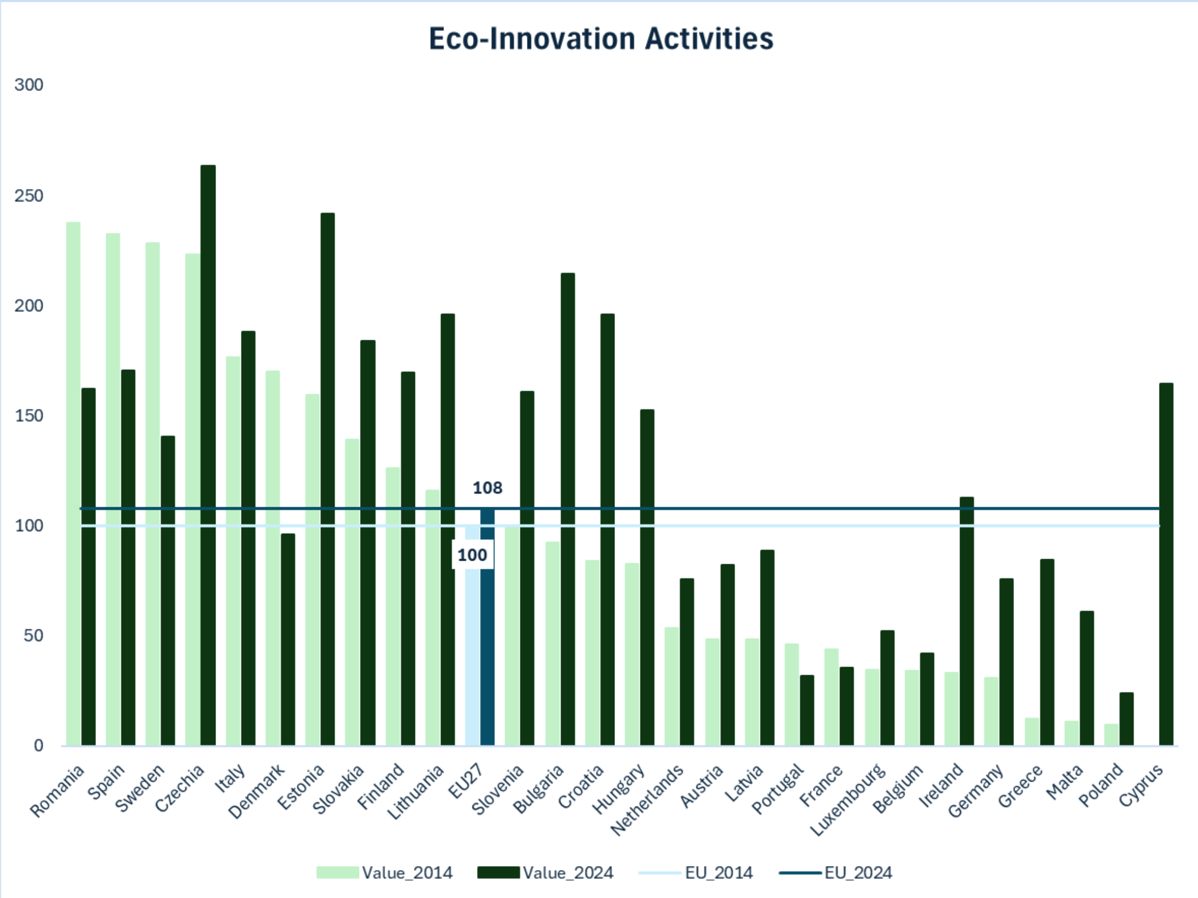


Figure 3.15. Eco-innovation activities: scores 2014 vs 2024. Source: own elaboration from EC (2024) data.

For the specific case studies, as illustrated in Figure 3.16, the EU average score reached its lowest point in 2020, after which it gradually began to rise again, reaching 108 in 2024. With the exception of Greece, all countries consistently remained above the EU average throughout the observed period, exhibiting a trend opposite to that discussed in the previous section. Greece has shown a steady upward trajectory since 2014, progressively narrowing the gap with the EU average. Italy peaked in 2018 with a score of 250—nearly 150 points above the EU average—but experienced a sharp decline in 2019, followed by a gradual recovery. Among the four countries, Lithuania recorded the highest score in 2024. Spain, on the other hand, experienced a marked decline over time and, although it is currently on an upward trend, its score remains well below the level observed in 2014 (Diestre, 2022; Iadecola, 2022; Orfanidou & Kondylidou, 2022; Spudyte, 2022).

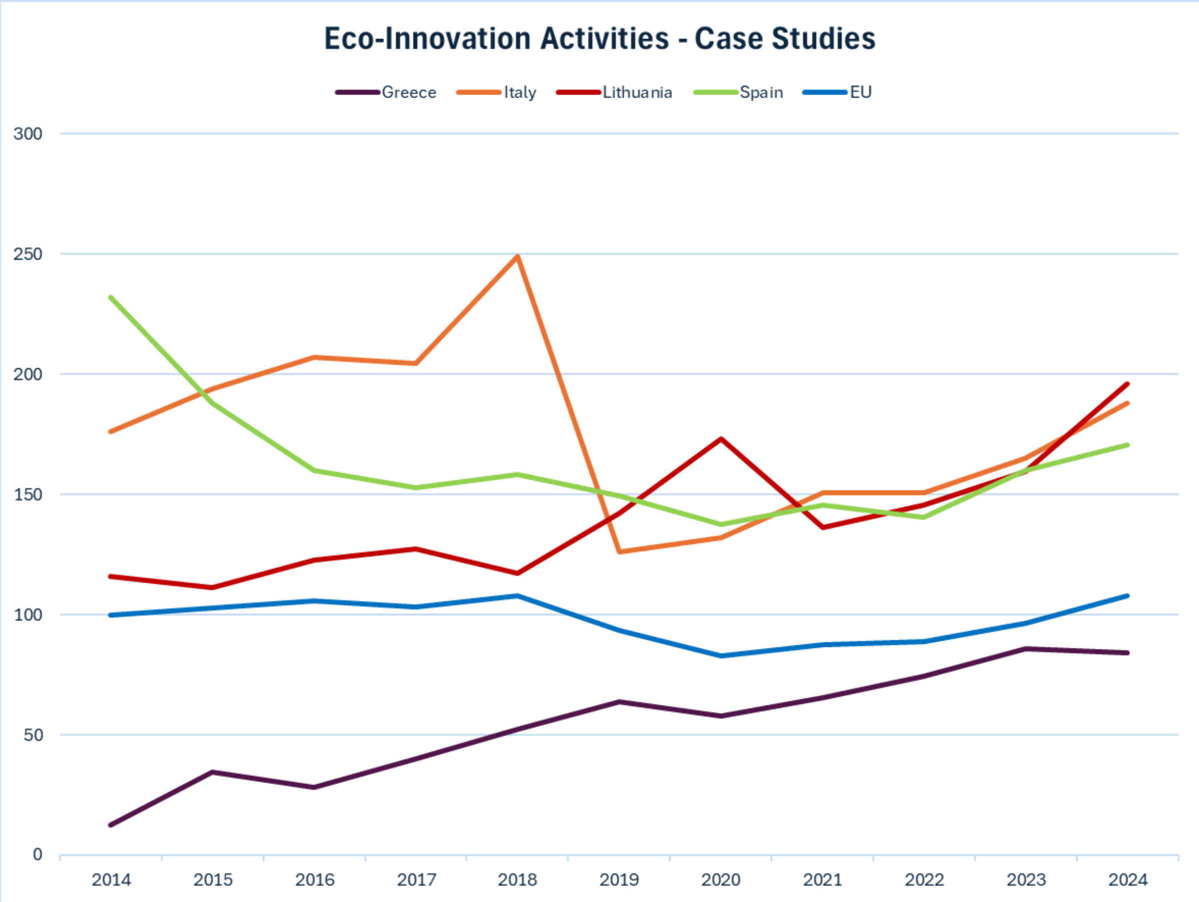


Figure 3.16. Eco-innovation activities evolution: case studies. Source: own elaboration from EC (2024) data.

3.3.4.3 Eco-innovation outputs

The third thematic area concerns eco-innovation outputs. It focuses on the number of patents and academic literature associated with eco-innovation, and is measured through the unweighted mean of two indicators: "Eco-innovation related patents" and "Eco-innovation related academic publications".

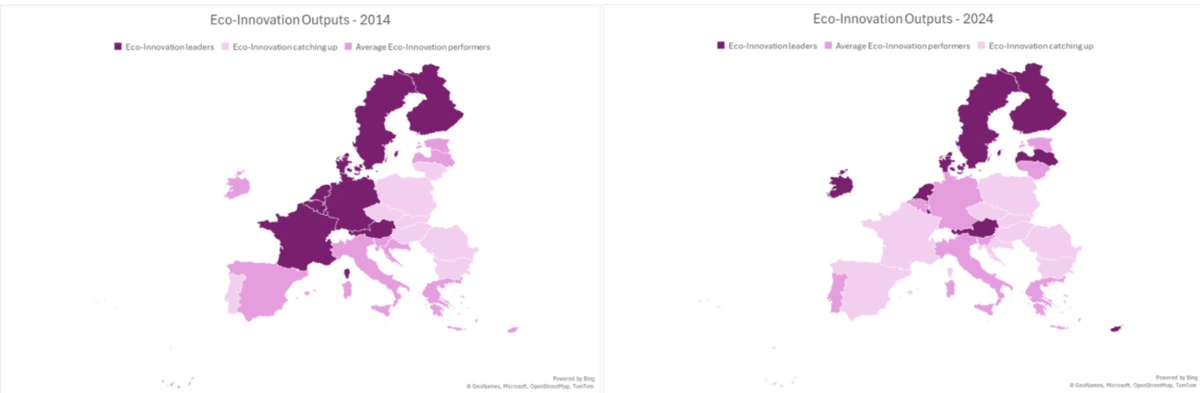


Figure 3.17. Eco-innovation outputs in EU - 2014 vs 2024. Source: own elaboration from EC (2024) data.

As shown in Fig.3.18, on average, the EU remained stable, with almost no change in its overall score between 2014 and 2024. With the exception of Luxembourg, Germany, and France, all other Member States recorded higher scores in 2024—likely driven by a growing interest in environmental issues and related applications.

Denmark emerged as the top performer in 2024, followed by Sweden and Finland, underscoring the leading role of Northern European countries. In contrast, Eastern European countries lag behind, with Bulgaria, Hungary, and Romania showing the lowest scores.

Several countries significantly closed the gap with the EU average by 2024. Notably, Belgium, Ireland, Slovenia, Greece, Estonia, Cyprus, and Latvia—all of which were below the EU average in 2014—surpassed the EU average by 2024 (EC, 2024).

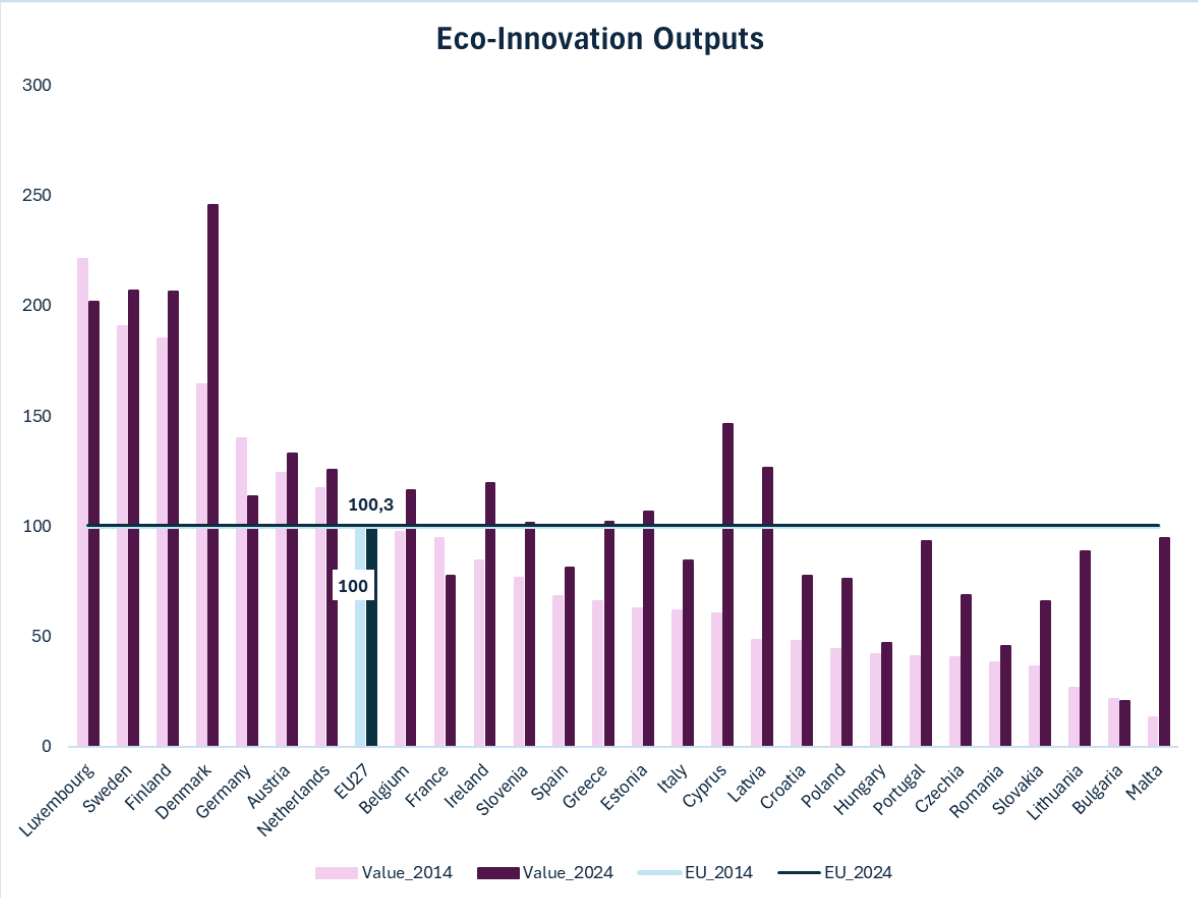


Figure 3.18. Eco-innovation outputs: scores 2014 vs 2024. Source: own elaboration from EC (2024) data.

Regarding the case studies (Fig. 3.19), all four countries consistently recorded scores below the EU average throughout the period analysed. Only Greece managed to close this gap between 2023 and 2024, due both to its own upward trend and to a decline in the EU average, which, after several years of growth, began to show lower scores starting in 2022.

Spain and Italy have followed a very similar trajectory, with both countries showing an increase in scores up to 2018, followed by a more stable trend. However, in 2024, their paths diverge: Spain shows a renewed upward trend, while Italy experiences a decline compared to its 2023 score. Lithuania, on the other hand, recorded a sharp and continuous increase throughout the period considered, with a slight slowdown between 2022 and 2023. Nevertheless, by 2024, it had returned to nearly the same level as in 2022. As previously mentioned, Greece stands out as the best-performing country among the four in 2024. Although its historical trend is marked by fluctuations, since 2022 it has shown a steady upward trajectory (Diestre, 2022; Iadecola, 2022; Orfanidou & Kondylidou, 2022; Spudyte, 2022).

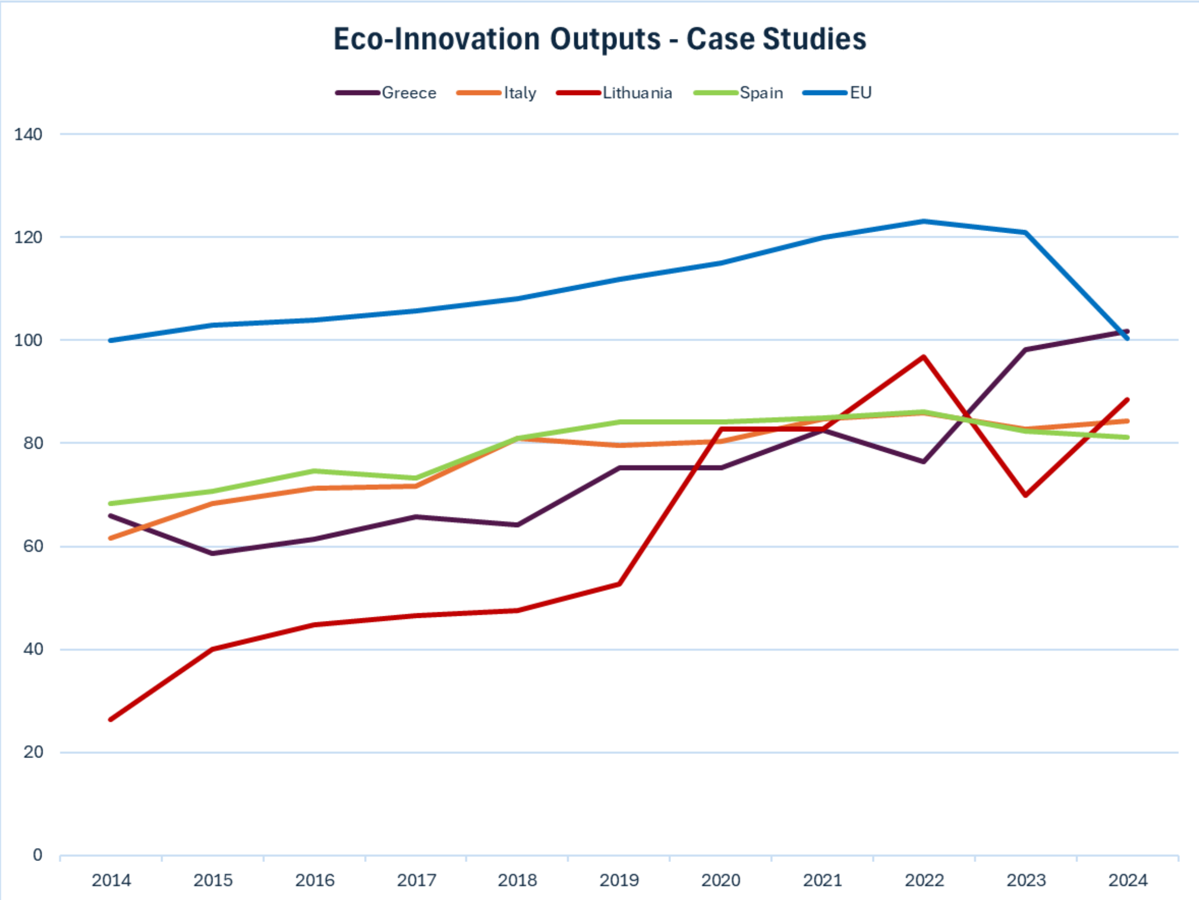


Figure 3.19. Eco-innovation outputs evolution: case studies. Source: own elaboration from EC (2024) data.

3.3.4.4 Resource efficiency outcomes

The fourth thematic area regards Resource Efficiency Outcomes, which measures the efficiency of the resources and the GHG emissions intensity. It is the area that comprehends the most indicators, which are the following: “Material productivity”; “Water productivity (GDP/total fresh water abstraction)”; “Energy productivity”; and “GHG productivity”.

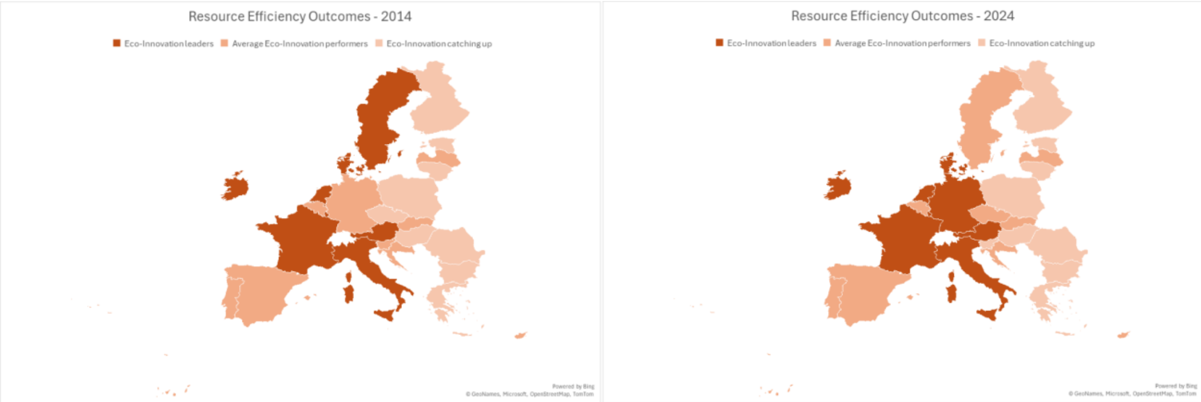


Figure 3.20. Resource efficiency outcomes in EU - 2014 vs 2024. Source: own elaboration from EC (2024) data.

As illustrated in Fig.3.21, the EU average score for Resource Efficiency Outcomes has increased significantly—by nearly 62 points—since 2014. Interestingly, the group of countries that were above the EU average in 2014 remains largely unchanged in 2024, suggesting a certain persistence in performance levels over time. The top performers in 2024 are Luxembourg and Ireland, followed closely by Italy and Austria. At the other end of the spectrum, several Eastern European countries—namely Romania, Bulgaria, Estonia, and Poland—continue to lag behind, recording the lowest scores (EC, 2024).

A total of 12 EU member states consistently outperformed the average in both 2014 and 2024, indicating stable leadership in advancing resource efficiency. Importantly, all EU countries improved their scores over the decade, highlighting a positive overall trend. Among them, Ireland stands out for having achieved the most significant progress, suggesting effective national strategies or favorable conditions for advancing resource efficiency (EC, 2024).

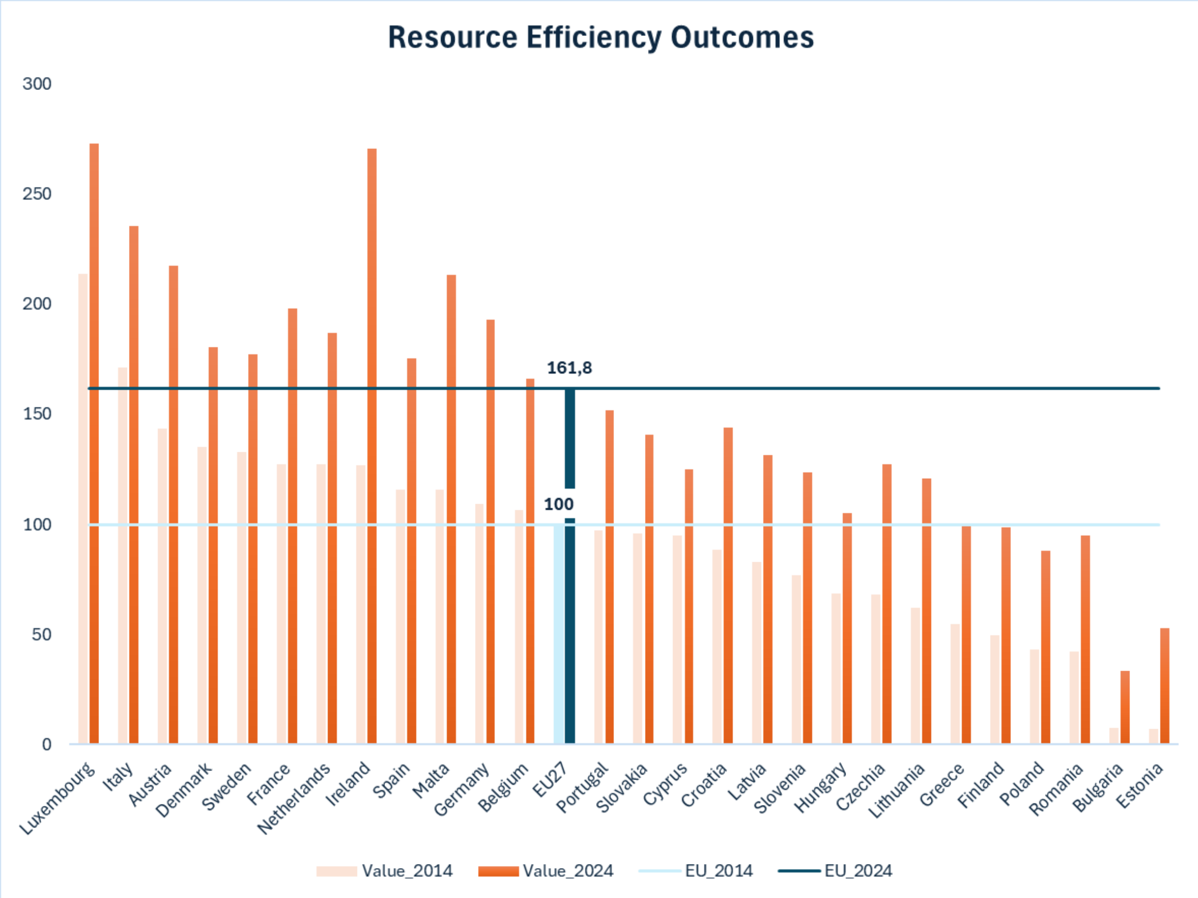


Figure 3.21. Resource efficiency outcomes: scores 2014 vs 2024. Source: own elaboration from EC (2024) data.

Looking at the specific case studies shown in Fig. 3.22, both Italy and Spain consistently score above the EU average across all observed years, whereas Greece and Lithuania remain below the average throughout the period. What stands out in this area, compared to other dimensions previously analyzed, is the similar upward trend observed across all countries. Every country shows continuous improvement over time, suggesting a general convergence in performance (Diestre, 2022; Iadecola, 2022; Orfanidou & Kondylidou, 2022; Spudyte, 2022).

The only exception is Lithuania, which registered a slight decline in 2024 compared to 2023, indicating a small setback in its performance. This contrasts with the otherwise steady progress seen in the other countries and highlights the importance of closely monitoring national-level developments to sustain long-term gains (Spudyte, 2022).

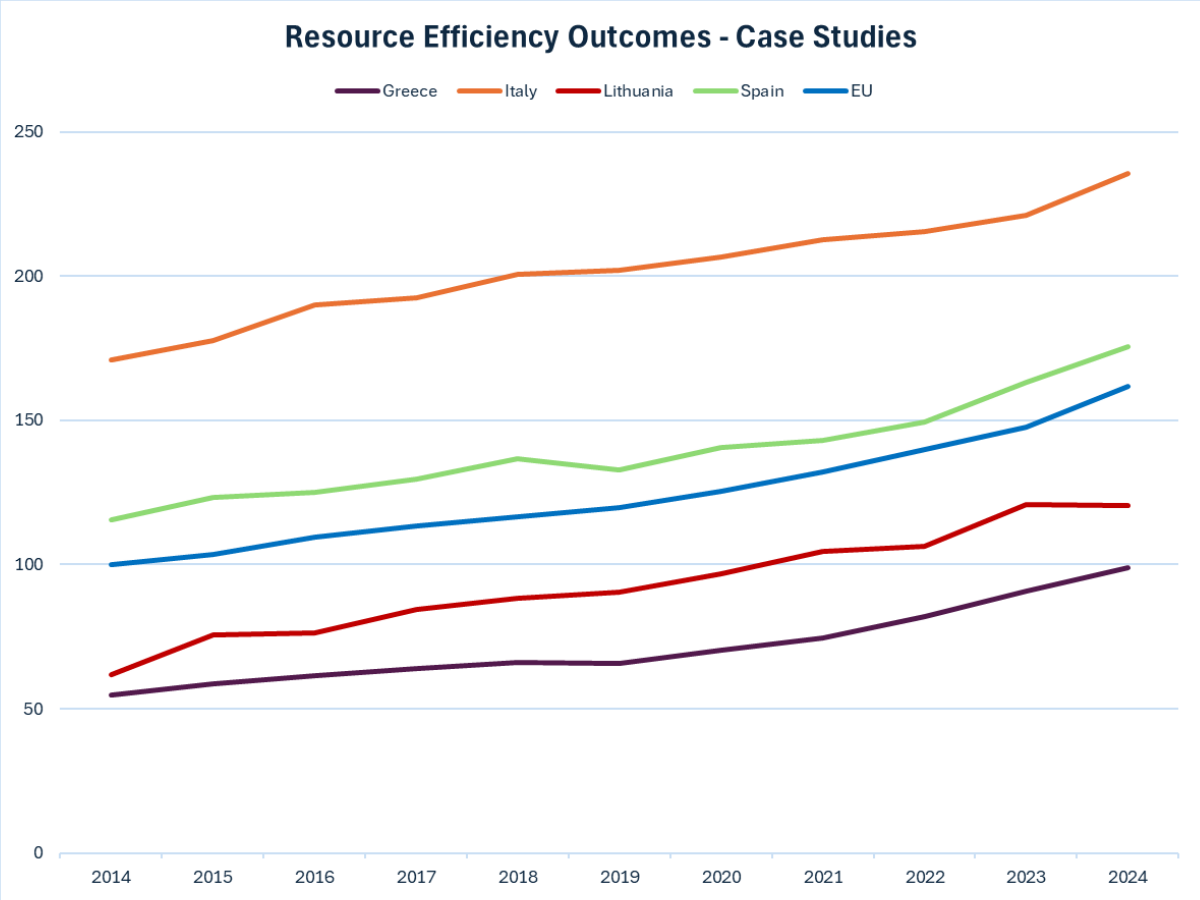


Figure 3.22. Resource efficiency outcomes evolution: case studies. Source: own elaboration from EC (2024) data.

3.3.4.5 Socio-economic outcomes

The fifth and last thematic area concerns socio-economic outcomes, and it gives us information about the positive societal and economic outcomes of eco-innovation. It is measured through the unweighted mean of three different dimensions: "Exports of environmental goods and service sector", "Employment in environmental protection and resource management activities", and "Value added in environmental protection and resource management activities".

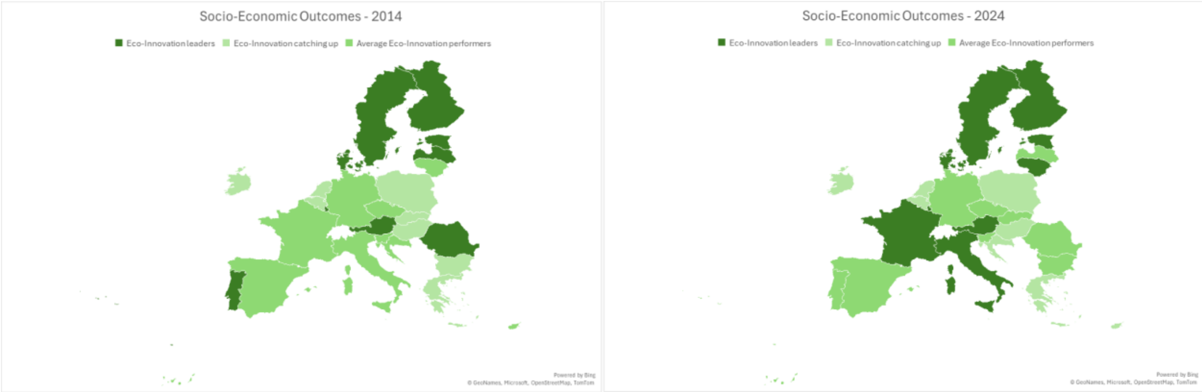


Figure 3.23. Socio-economic outcomes in EU - 2014 vs 2024. Source: own elaboration from EC (2024) data.

Fig. 3.24 presents the evolution of performance scores related to the socio-economic outcomes of eco-innovation across all EU countries between 2014 and 2024. The leading countries have remained consistent over the decade, with Finland, Austria, and Estonia occupying the top three positions in both years. On the other hand, the lowest performers are Malta, Ireland, and Hungary.

What is particularly striking is the diversity of trends across member states. While some countries—such as Lithuania, France, and Italy—have made significant progress, others have seen a decline. Romania, for example, recorded a noticeable drop in its performance score over the period. Minor setbacks were also observed in countries like Finland, Cyprus, Hungary, and Croatia, suggesting that progress in eco-innovation socio-economic impacts is neither linear nor uniform (EC, 2024).

Despite these mixed trajectories, the overall EU average improved by 15 points, indicating a general, albeit uneven, positive shift across the Union.

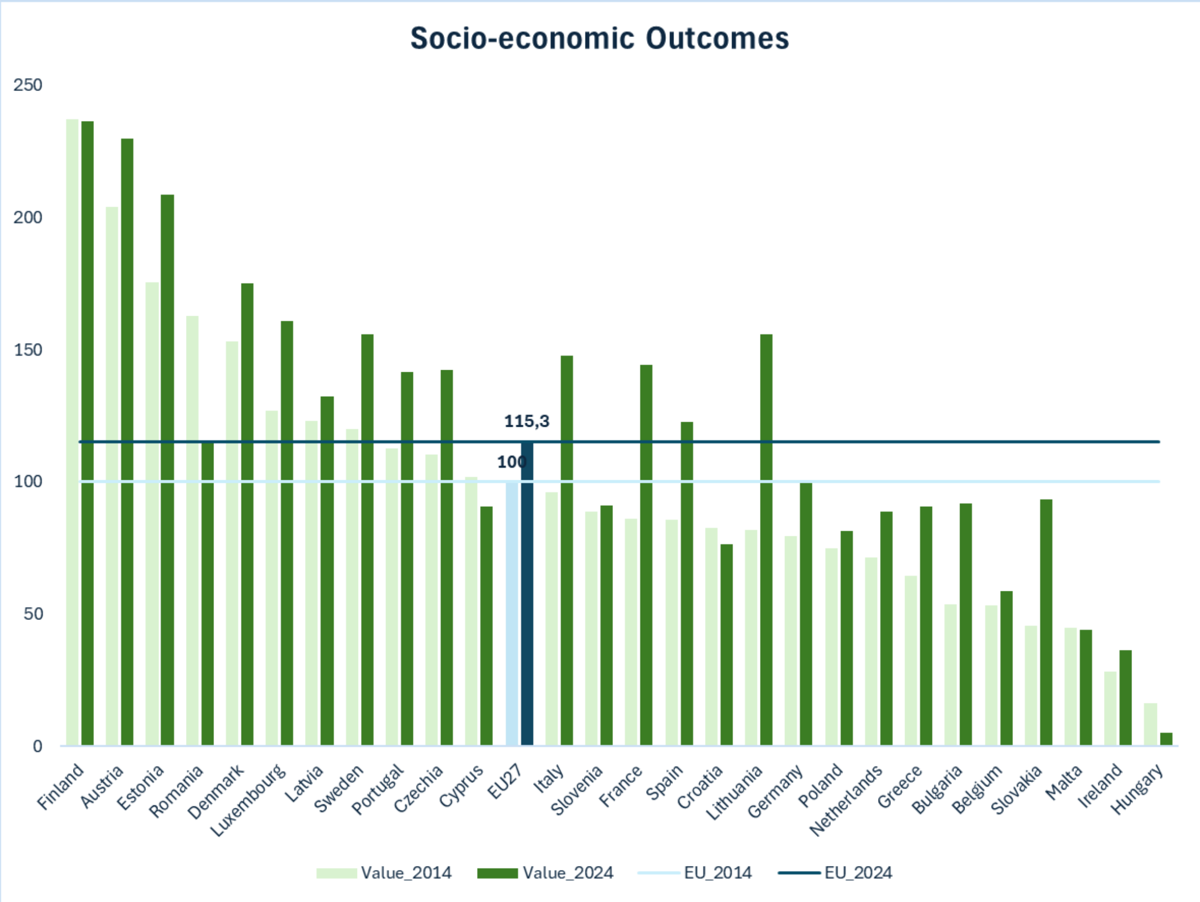


Figure 3.24. Socio-economic outcomes: scores 2014 vs 2024. Source: own elaboration from EC (2024) data.

The analysis of the case studies in Figure 3.25 reveals that, up until 2023, only Spain consistently performed above the EU average in terms of socio-economic outcomes linked to eco-innovation. However, recent improvements in Italy and Lithuania enabled both countries to reach—and eventually surpass—the EU average by 2024. Notably, all countries under review, including Greece—which remained below the EU average throughout the entire period from 2014 to 2024—have demonstrated a positive upward trend (Diestre, 2022; Iadecola, 2022; Orfanidou & Kondylidou, 2022; Spudyte, 2022).

Lithuania showed only modest gains up to 2023, followed by a significant leap in performance between 2023 and 2024. A similar breakthrough occurred for Italy, though it came earlier, in 2022. Spain, while already a top performer, recorded the most sustained and marked upward trend over the entire period, reinforcing its leadership in this area (Diestre, 2022; Spudyte, 2022).

This collective progress points to growing momentum across the case study countries, although at different paces and starting points.

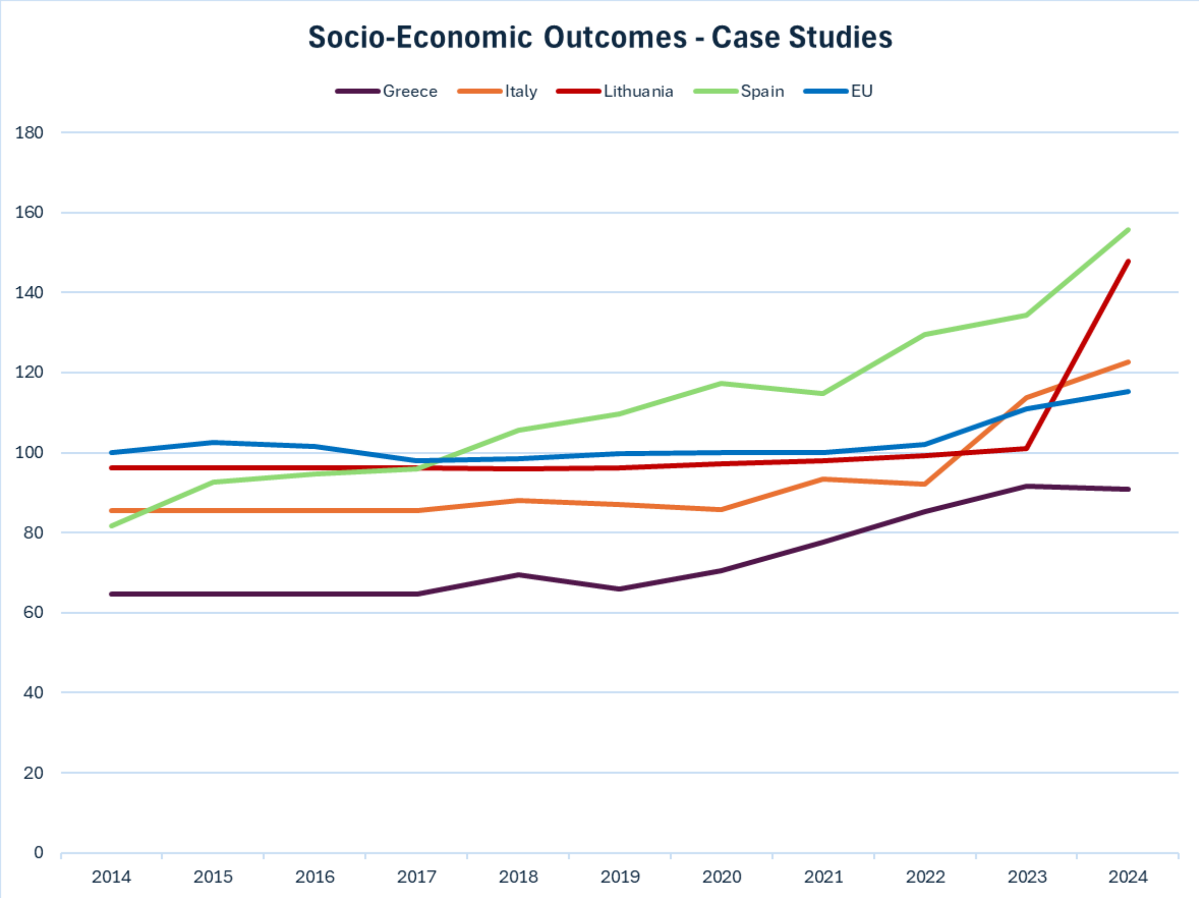


Figure 3.25. Socio-economic outcomes evolution: case studies. Source: own elaboration from EC (2024) data.

3.4 Conclusions

The present report has attempted to provide a thorough overview of the European Innovation Scoreboard and Eco-Innovation Index, particularly useful for the aims of the SOSFood project, which also aims to identify the influence and related relevance of innovation in the Food&Beverage production chain. The provided figures and comments can be used as a map of the past, present and development of innovation in the EU, with a further focus on eco-innovation and the cases of Italy, Spain, Greece and Lithuania. They can be of inspiration and provide useful suggestions for all the further steps of the analysis concerning the next phases of the Project.

4. Innovation metrics in the agri-food sector: the case of Italy, Spain, Greece and Lithuania

This section outlines key aspects related to innovation within the case studies considered in the project (i.e. Spain, Italy. Lithuania and Greece). The data employed are sourced from Moody's ORBIS database, which contains economic and financial information on over 400 million companies across the globe. The dataset provides standardized and comparable firm-level data, primarily based on financial statements. Access to ORBIS is subscription-based and not publicly available; for the purposes of this study, access was provided by Università Cattolica del Sacro Cuore, under the condition that the data be used strictly in aggregated form.

The analysis specifically utilizes ORBIS Intellectual Property (ORBIS IP), a dedicated module that combines economic information with data on firms' innovation activities. Innovation is proxied by patent publications, i.e., official documents disclosed by national or international patent offices following the submission of a patent application by a company. It is important to note that a patent publication does not necessarily imply that the patent has been granted; rather, it includes all published applications, regardless of their final outcome. As such, the number of patent publications serves as a widely used, though imperfect, proxy for firms' innovation output.

The analysis focuses on firms operating in the agri-food sector, identified according to the following NACE Rev. 2 codes:

- 01 – Crop and animal production, hunting and related service activities
- 03 – Fishing and aquaculture
- 10 – Manufacture of food products
- 11 – Manufacture of beverages

Despite the broad firm coverage of ORBIS, the dataset exhibits significant missing data for several key innovation-related variables particularly those not derived directly from firms' balance sheets. This limitation poses challenges in the identification and analysis of the main drivers of innovation, as variables such as R&D expenditures or technological investment are either unreported or sparsely populated across firms.

Consequently, the following analysis is restricted to available data aggregated at the country level. Among the countries included in the dataset, Spain stands out for its relatively higher data availability. A dedicated box is therefore provided to illustrate selected innovation-related indicators for Spanish firms in more detail.

4.1 Number of patents in the agri-food sector

When examining innovation activity across the four case study countries, significant differences emerge. Italy and Spain exhibit markedly higher levels of innovation compared to Greece and Lithuania. This outcome is largely expected, as the economic scale of Italy and Spain far exceeds that of the other two countries. Specifically, based on Eurostat (2025) data, the average GDP at current prices over the period 2015–2024 amounted to EUR 1,852,860 million for Italy and EUR 1,267,436 million for Spain, both well above the EU-27 average GDP of EUR 538,799 million. By contrast, Greece and Lithuania reported significantly lower average GDPs of EUR 191,573 million and EUR 54,033 million, respectively.

In addition to macroeconomic size, firm density also plays a crucial role in shaping innovation potential. A larger number of active firms increases the probability of innovation at the sectoral level, as it broadens the base from which patent applications and technological advancements can emerge. In this regard, Italy and Spain also demonstrate a higher number of firms operating in the agri-food sector, which contributes to their comparatively greater volume of innovation outputs (Orbis, 2025).

Figure 4.1 presents the GDP at current prices (in million euros) for the years 2016–2024, based on Eurostat data for Italy, Spain, Greece and Lithuania. Figure 4.2 illustrates the total number of agri-food sector firms, as defined by the relevant NACE Rev. 2 codes, in the four countries in the year 2024, using data extracted from the ORBIS database.

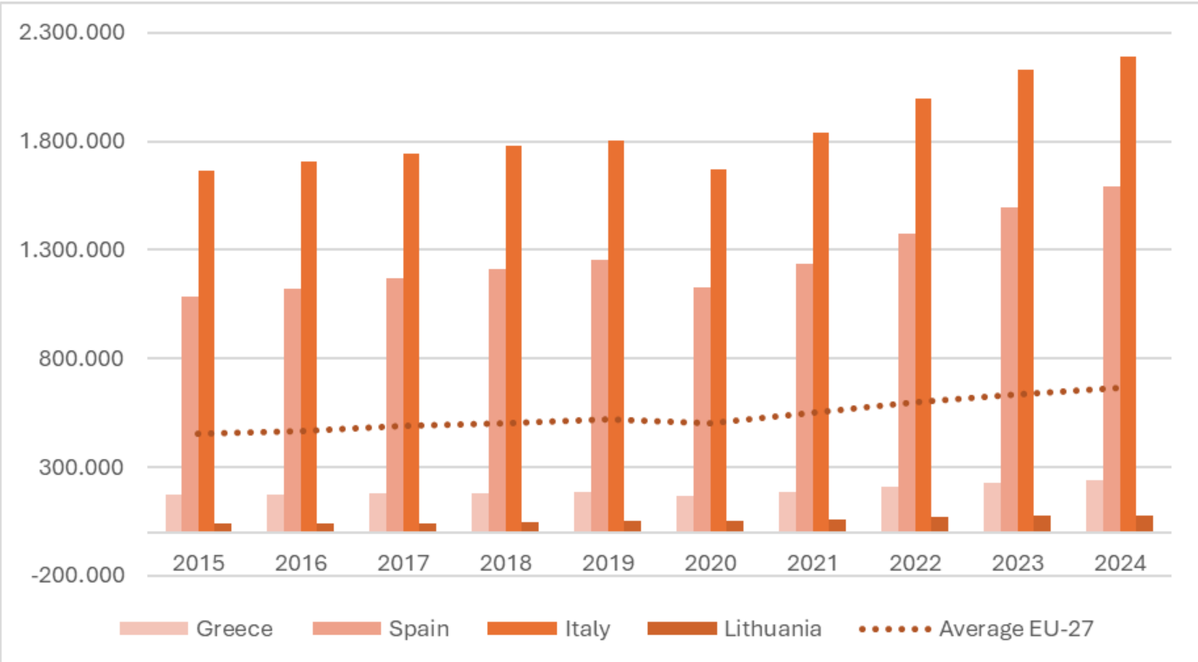


Figure 4.1. GDP at current prices in million of euros for Italy, Spain, Greece, Lithuania with the EU-27 average GDP as a reference. Source: authors' elaborations on Eurostat (2025).

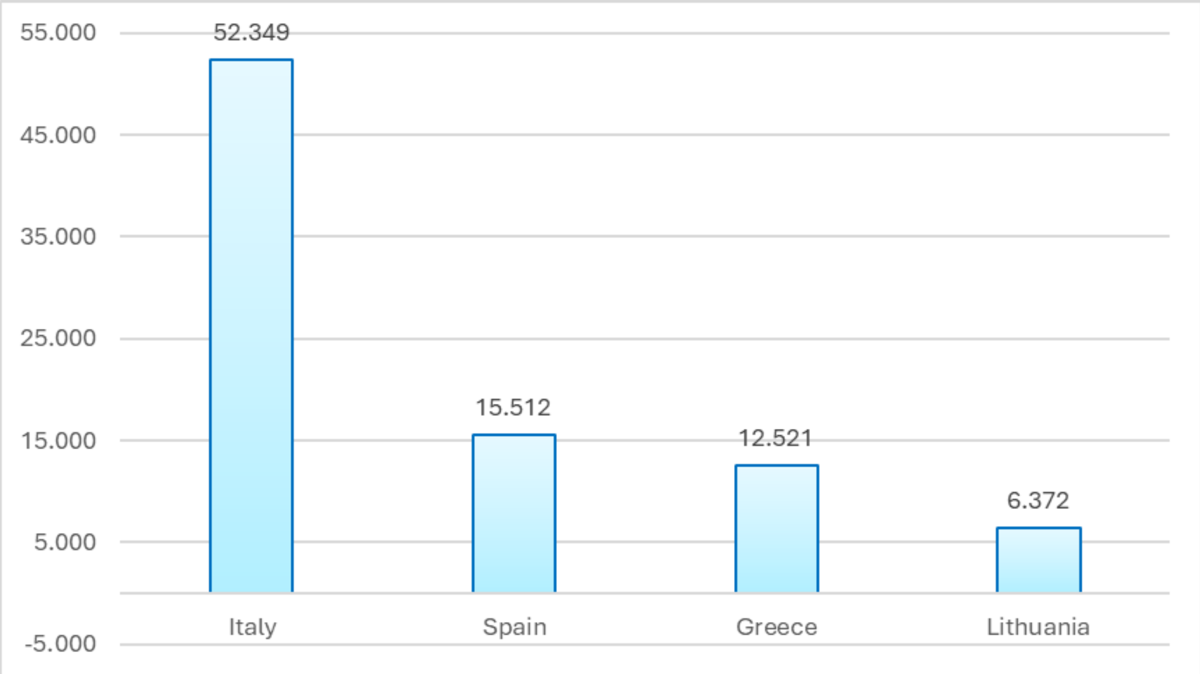


Figure 4.2. Total number of Agri-food firms in Italy, Spain, Greece and Lithuania (year 2024). Source: authors' elaborations on Orbis (2025).

As previously noted, innovation activity in this analysis is measured through the number of patent applications submitted by firms operating in the agri-food sector. It is important to highlight that the share of firms actually engaging in patenting activity represents only a small fraction of the total number of firms available in the ORBIS database.

On average, over the period 2016–2022, the number of agri-food firms with at least one recorded patent application amounted to:

- 120 firms in Italy
- 48 firms in Spain
- 3 firms in Greece
- 2 firms in Lithuania

These figures correspond to approximately 0.21% of agri-food firms in Italy and 0.30% in Spain, while the percentage is even lower for Greece and Lithuania. These data clearly indicate that patenting firms represent a very small minority within the agri-food sector, reinforcing the notion that innovation, as captured through formal intellectual property protection, is highly concentrated.

Table 4.1 reports the total number of patent applications submitted by agri-food firms in each country between 2016 and 2022. Italy shows the highest volume of patent activity, with figures remaining relatively stable from 1,145 patents in 2016 to 1,009 in 2019, followed by a slight decline in the post-2020 period, reaching 959 patents in 2022. Overall, Italy recorded 7,130 patent applications during the reference period, corresponding to an annual average of 965 patents.

Spain also demonstrates a relatively high level of innovation activity within the sample, following a pattern broadly similar to that of Italy. Patent applications increased from 377 in 2016 to a peak of 385 in 2019, followed by a modest decline, with 360 applications in 2020 and 254 in 2022. Over the full period, Spain submitted 2,512 patent applications, yielding an annual average of 328 patents (Figure 4.3).

In stark contrast, Greece and Lithuania exhibit significantly lower levels of patenting activity in the agri-food sector. Greek firms filed a total of 38 patent applications over the period, averaging approximately 7 per year, while Lithuanian firms submitted 29 applications, with an annual average of just over 6 patents.

Country	2016	2017	2018	2019	2020	2021	2022
Italy	1145	1111	1014	1009	980	912	959
Spain	377	409	415	385	360	312	254
Greece	7	6	3	16	3	3	-
Lithuania	1	2	3	6	11	5	1

Table 4.1: Total number of patent applications submitted by agri-food firms in each country between 2016 and 2022. Source: authors' elaboration on Orbis (2025).

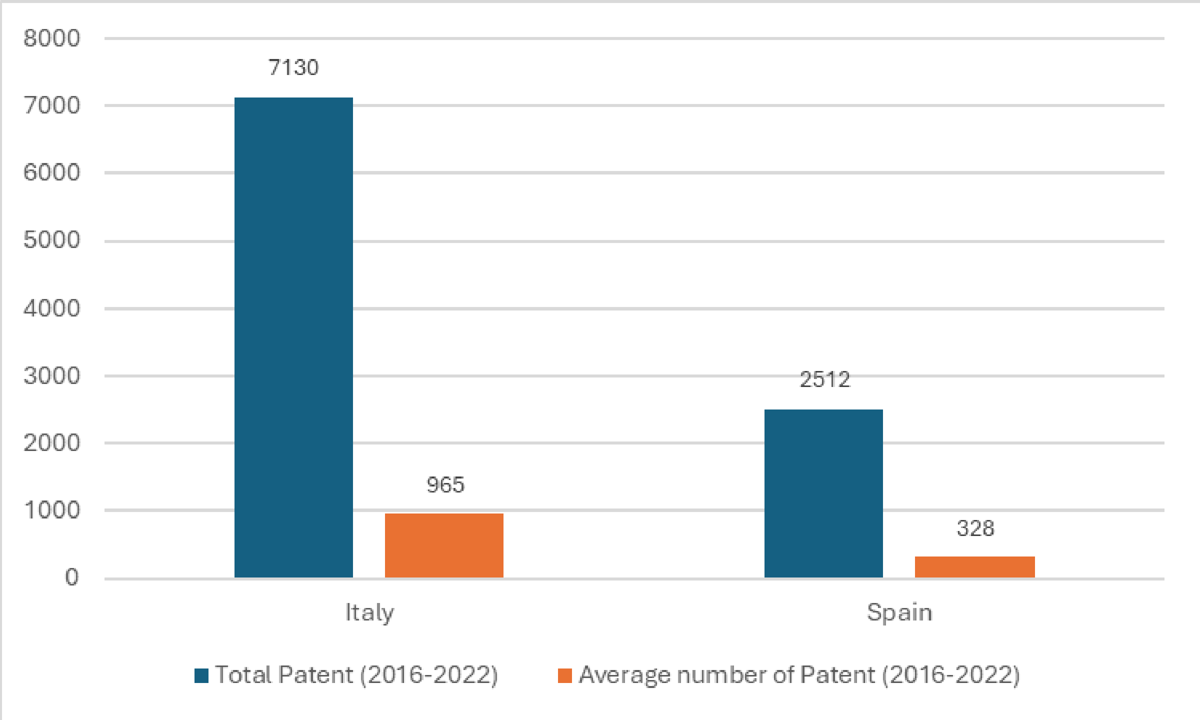


Figure 4.3. Total patent and average patent per year during the period 2016-2022 for Italy and Spain. Source: authors' elaborations on Orbis (2025).

The extremely limited share of patenting firms underscores the highly concentrated nature of innovation efforts, typically restricted to a small group of large or resource-rich companies. The data also highlight the structural challenges faced by the broader agri-food sector in adopting and investing in innovation-related activities.

Moreover, these figures underscore the existence of a substantial gap in innovation output between the larger economies of Italy and Spain and the smaller ones of Greece and Lithuania, both in absolute and relative terms.

4.2 Farm size

In terms of firm size, measured by the number of employees, a substantial difference emerges between firms that engage in patenting activity and those that do not. The number of employees is used here as a proxy for the economic structure and organizational capacity of firms. Across all countries in the sample, patenting firms are significantly larger than non-patenting ones.

This disparity is particularly pronounced in Spain and Italy, where the average number of employees in patenting firms reaches 605 and 465, respectively, compared to only 51 and 21 employees among non-patenting firms. These figures clearly indicate that large firms (defined as those with more than 250 employees) are the most active in innovation. This outcome is consistent with the literature, as larger firms typically benefit from greater financial and human capital resources, easier access to credit, and a more robust capacity to absorb the risks associated with innovation activities.

In Greece and Lithuania, the pattern is similar, albeit less marked. Patenting firms in these countries also exhibit a higher average number of employees compared to their non-innovating counterparts, but their size generally falls within the medium-sized category (defined as firms with 50 to 250 employees). Non-patenting firms across all four countries are overwhelmingly concentrated in the small-size category (fewer than 50 employees). This substantial difference in firm size reinforces the notion that larger firms are more likely to engage in innovation, possibly due to greater availability of financial, human, and technological resources required to support research and development, as well as the capacity to bear the risks associated with innovation processes.

These findings suggest that firm size is a key determinant of innovation propensity, with larger organizational scale being strongly associated with the likelihood of engaging in patenting activity.

This may reflect greater access to external financing, possibly used to support R&D activities, technological investments, or other capital-intensive innovation processes. Taken together, these findings suggest that innovating firms not only exhibit stronger financial performance but also operate with distinct cost structures and financing strategies, consistent with the demands and risks associated with innovation.

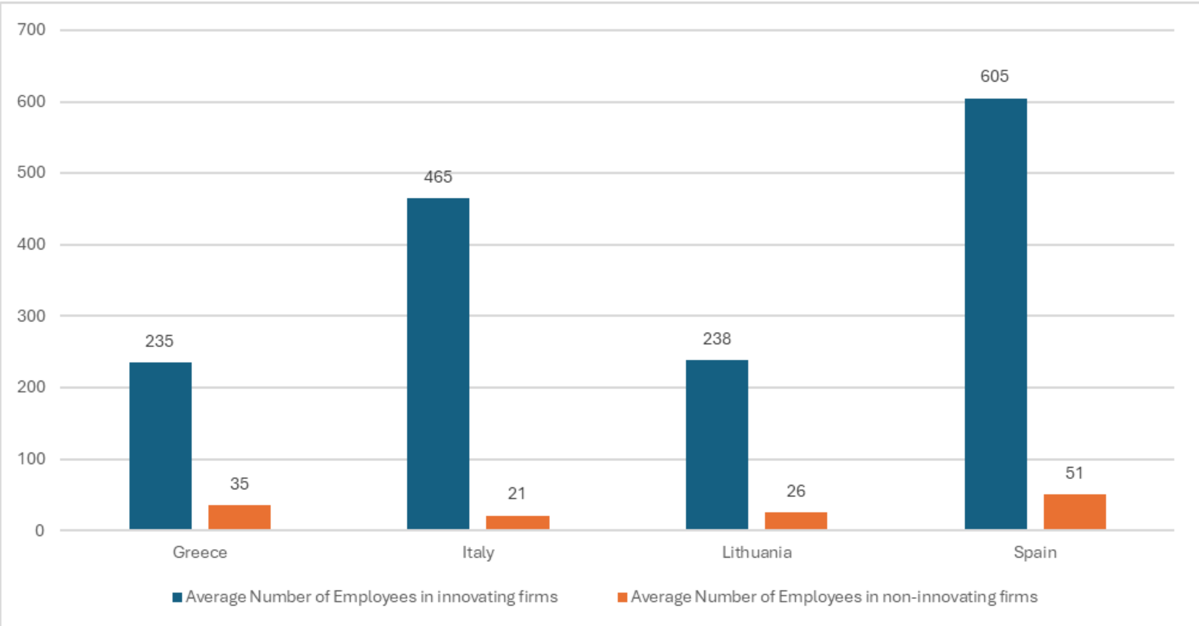


Figure 4.4. Average number of employees for innovating and non-innovating firms by countries (Italy, Spain, Greece and Lithuania). Source: authors' elaborations on Orbis (2025).

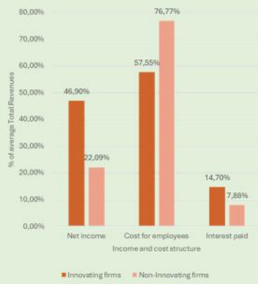
Focus on Spain

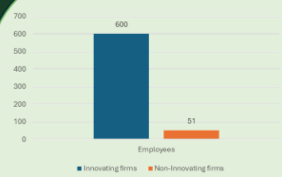
Number of patents in the agri-food sector

Spain exhibits a declining trend in patent activity in the agri-food sector over the observed period. In 2016, Spanish firms submitted 377 patent applications, with a slight increase in the following two years: 409 in 2017 and 415 in 2018. However, starting in 2019, a downward trajectory becomes evident: the number of patent applications decreased to 385 in 2019, followed by a steady decline in subsequent years: 360 in 2020, 312 in 2021, 254 in 2022, and 195 in 2023.
This trend may reflect a variety of underlying factors, including economic uncertainty, reduced R&D investment, or structural limitations within the sector. Further analysis would be required to disentangle the relative importance of these drivers.

Income and Cost Structure

A comparative analysis of the economic structure of innovating and non-innovating firms reveals marked differences in key financial indicators. Spanish innovating firms, identified as those with at least one patent application, report significantly higher net profits, averaging 47% of total revenues, compared to 22% for non-innovating firms. This suggests that firms engaging in innovation activities tend to achieve greater profitability, potentially as a result of increased competitiveness, product differentiation, or access to high-value markets. Regarding labor costs, personnel expenses account for 57% of total revenues in innovating firms, while this share rises to 77% among non-innovating firms. This may indicate a more efficient use of human resources or higher labor productivity among firms engaged in innovation.
On the other hand, innovating firms allocate a larger share of their revenues to interest payments, with an average of 15%, compared to 7.9% in non-innovating firms.



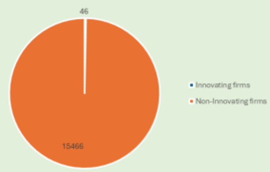


Employees

In terms of workforce size, innovating firms in Spain are significantly larger than their non-innovating counterparts. On average, firms engaged in patenting activities employ approximately 600 workers, classifying them as large enterprises (i.e., firms with more than 250 employees according to the EU definition). By contrast, non-innovating firms have an average of 51 employees, placing them within the small to medium-sized enterprise (SME) category.

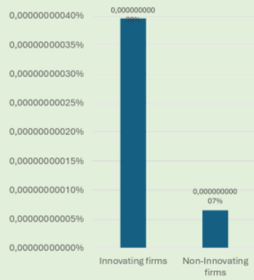
Total Firms: Innovating vs Non-Innovating firms

In the Spanish agri-food sector, the vast majority of firms do not engage in patenting activities. According to ORBIS IP data for 2023, the total number of firms operating in the sector amounts to 15,512, of which only 46 firms have filed at least one patent application. This implies that non-innovating firms account for nearly the entire population, while innovating firms represent only 0.3% of the total.



R&D Expenditure

Although research and development (R&D) expenditure represents only a marginal share of total revenues for firms in the agri-food sector, innovating firms consistently report higher absolute levels of R&D spending compared to non-innovating firms. Specifically, the average R&D expenditure for innovating firms amounts to approximately €1,411 million, whereas for non-innovating firms it is significantly lower, at around €159 million.
This finding suggests that even if R&D intensity, measured as a percentage of revenues, is low across the sector, firms engaged in patenting allocate considerably more resources to R&D in absolute terms, which likely contributes to their innovation capacity. It also reflects the structural gap between larger, innovation-driven firms and the broader population of smaller, resource-constrained enterprises.



5. The impact of R&D investment on patents creation in the agri-food sector

5.1 Introduction

Following the outcome of the systematic literature review and descriptive analysis, the present section aims at developing a more empirical assessment with regards to innovation practices in the European Union. The systematic literature review has provided some interesting insights into what fosters innovation in the agrifood sector and has already shown some detailed differences between the two main steps of the production chain and related agents (farms and firms). The descriptive analysis has provided an overview of what parameters can be adopted to represent and therefore predict innovation on a territorial basis. Aggregating the outcome of the two sections allows for the development of a good theoretical basis for the implementation of a quantitative model providing a more detailed picture of how innovation fostering works in the EU and what factors might require more attention and are worth of more resource's investment.

Entering the details of what this section is mainly interested in, the systematic literature review suggested that investment on technological innovation is one of the main drivers of economic growth (Solow, 1957). The descriptive analysis better described what indicators are most reasonably driving innovation, in terms not only of investment, but also of framework activities, human resources and impacts. However, the different steps of the chain might be responding differently to drivers and barriers. While both agriculture and food manufacturing can benefit from innovation, the literature shows drivers and barriers can differ consistently. More specifically, farms might be more reliant on public incentives and related investments, policy instruments and cooperation with public institutions, while firms might be more facilitated in accessing private sources of funding (Borrello et al., 2016; Gambelli et al., 2021; Paolotti et al., 2023; Viaggi & Cuming, 2012; García-Cortijo et al., 2019). On the opposite, firms appear to be much more market-driven, also benefiting from public funding and collaboration with the public authority, but also from the creation of new higher quality production to satisfy increasingly demanding consumers, the digitalisation process and connections with research institutions (Petridis et al., 2020; Zarbà et al., 2022; López-Becerra et al., 2016; Crisp et al., 2021; De Martino and Magnotti, 2018; Val and Harris, 2018).

Following these considerations, the present section will try to answer the following research hypotheses:

H1: Expenditure for research and development is a significant driver of innovation fostering in the EU agrifood sector.

H2: The effect of expenditure for research and development, as well as other relevant factors, provides different results when assessing agriculture (farms) and food manufacturing (firms).

5.2 Methodology

The present work will be based on an econometric model assessing the quantitative effect of domestic expenditure on research and development on patent creation in the agri-food sector. It is here assumed that patent generation in a specific sector is a good representative of innovation propensity in that sector. The data have been collected through two main institutional databases, them being Regpat and Eurostat. More specifically, Regpat is going to be used for the identification and collection of the model's variable(s) of interest, while Eurostat is the main source for the data collection of controls.

Regpat (OECD, 2024) is a collection of publicly available databases which provides virtually all patent applications developed by OECD countries between 1970 and the present day. As it is not originally aimed at researchers, the preparation of the dataset which has been then subject to the analysis has required merging and thorough cleaning of several databases among those made available by the institution. For the main interest of the study, the elaborated dataset provides information on the kind of patent (e.g. agricultural, food manufacturing etc.), the location (based on the address of the applicant), and the year of the application.

The full dataset has then been limited for the specific interests of this Project. In particular:

The countries of interest have been limited to European Union member states. The observations are regional territories. Following the international Nomenclature of Territorial Units for Statistics (Nuts), the analysis is going to use territorial observations at Nuts2 level (Eurostat, 2025).

The patents of interest have been limited to agrifood related patents. This has been done by cross-checking the code of the available patents with the codes provided by the International Patent Classification (IPC) provided by the World Intellectual Property Organisation (WIPO) (IPC, 2025) Only patents in the following four categories have been considered:

- A01: Agriculture, forestry, animal husbandry, hunting, trapping, fishing
- A21: Baking, equipment for making or processing doughs, doughs for baking
- A22: Butchering, meat treatment, processing poultry or fish
- A23: Foods, foodstuffs or non-alcoholic beverages, preparation, treatment or preservation thereof

The first category of patents, whose codes start with A01, is represented by strict collection of raw biomasses. For the sake of simplicity, they will be from now on identified as "agricultural" patents. The three following categories, from A21 to A23, refer to the subsequent steps of the food production chain, and will be here identified from now on as "food" or "food manufacturing" patents. The model presented in this paper will attempt to quantify and isolate the effect of domestic expenditure on R&D on the generation of all these patents put together (total agri-food patents) and on each step of the production chain (hence on "agricultural" and "food manufacturing" patents taken separately).

Therefore, the variable of interest for the model is the number of applications for agrifood patents generated at Nuts2 regional level in the European Union. This is represented in more detail by three specific variables, that are:

- The total number of applications for agrifood patents generated at regional Nuts2 level in the EU
- The number of applications for strictly "agricultural" patents, hence representative of raw biomasses collection at Nuts2 regional level in the EU (following the A01 category in the International Patents Classification)
- The number of applications for "food manufacturing" patents, hence representative of the next step of the food production chain, at Nuts2 regional level in the EU (following the A21-A23 categories in the International Patents Classification)

As mentioned above, our main explanatory variable subject to the analysis is the amount of domestic expenditure on R&D (GERD). These data have been collected through the Eurostat publicly available dataset at Nuts2 regional level (Eurostat, 2025) to assess its impact on the generation of applications for patents in the agrifood sector. As the territory subject to the analysis is the European Union, it is calculated in Euros. As of this specific piece of work, the study is going to consider also the shape of the curve of the effect of domestic expenditure on R&D as investments on research and development increase. In practice, the model will include the natural logarithm of GERD and the squared natural logarithm of GERD, to detect how the effect of GERD marginally changes with its increase. This will open an avenue towards better understanding the optimal size of investments for R&D with regards to the agricultural sector.

The effect of domestic expenditure on research and development is quantified against a series of controlling variables that are either directly referred to research and development or that have been identified as relevant by the literature. They are as follows:

*Gross Value Added for the agricultural secto*r: it is the per-capita total value added produced by agriculture in the region of interest, for each year, divided by per capita GDP. It is therefore the percentage of gross value added referred to the agricultural sector. It is assumed that a productive and profitable agricultural sector might be correlated to a more pronounced innovation predisposition. As the size of companies can significantly influence financial and funding availability for research (Dicecca et al., 2016), it is here assumed the same to be true for the overall size of the sector in the economy of interest at a macro level.

Tertiary education: It is the percentage of people between the ages of 24 and 65 (working age) with at least a university degree. University education is presumably an important prerequisite for workers to be involved in the implementation of research and development strategies. This follows the choice of the European Commission (2024) to identify tertiary education as one of the proper indicators of innovation.

Employees in research and development: the number of employees directly involved in research and development practices can be easily and reasonably associated with higher innovation. It is here expressed as the per-capita number of R&D employees over the total population (in terms of thousands of people). This follows the choice of the European Commission (2024) to identify the number of employees in R&D as one of the proper indicators of innovation.

Population density: on the one hand, there is a good basis to suggest that communities where people are more easily connected and work symbiotically can foster relatively complex practices more easily than contexts where they are more disconnected from each other. More specifically, population density has been identified as a good promoter of success in some sustainable management related practices such as waste sorting rates (Romano et al., 2022). On the other hand, agricultural territories are generally characterised by a low population density. A low population density might therefore be a symptom of agricultural land's presence, and therefore agricultural patents more likely to be generated. Population density is here calculated as thousands of people per square kilometre.

The model is then enriched with factorial variables aimed at further checking its robustness taking into account different categories the observations might fit in. These are:

Population size: Observations have been distributed into five quintiles based on their population size. Therefore, each group has exactly the same number of observations. This checks whether the model is overall stable independently of the kind of region analysed in terms of population (e.g. very crowded regions inclusive of the main cities, peripheral less inhabited regions etc.). The model will also be able to identify whether the size of the population is particularly significant (or not significant) for some specific groups.

GDP size: Observations have been distributed into five quantiles based on their GDP. Therefore, each group has exactly the same number of observations. This checks whether the model is overall stable independently of the size of the region's economy (e.g. very crowded regions inclusive of the main cities, peripheral less inhabited regions etc.). The model will also be able to identify whether the size of the economy is particularly significant (or not significant) for some specific groups.

Year: Finally, the structure of the model checks for its overall validity independently of the year subject to the analysis. The model repeats the analysis for each year (from 2005 to 2020), enabling the authors to understand whether specific years and related events can make consistent differences in determining the outcome (e.g. the global financial crisis in 2008, the covid pandemic in 2020 etc.).

The model is then made robust against errors' heteroskedasticity. To put it more simply, the model basically corrects a potential heterogenic distribution of errors throughout the regression curve, that might compromise the validity of results if not accounted for. In case errors are homogenously distributed, the inclusion of this correction does not have any effect on the outcome.

Finally, fixed effects are established as part of the model. Fixed effects essentially identify patterns in the regression curve that might imply the presence of unobserved variables that might be correlated to explanatory variables (controls) through a relatively homogenous pattern. The model indirectly assesses their relevance without estimating them directly and adjusts the model accordingly as if they were accounted for, based on the identified patterns and assumed correlation with explanatories (Wooldridge, 2010).

As the response variable is represented by the absolute number of patents (hence whole numbers), the chosen model here is a Poisson regression curve. It is a linear regression model which is particularly indicated when the aim is to assess how many times an event occurs in a fixed period of time. It is therefore particularly indicated when the model is applied on a data panel where the response variable is expressed in whole numbers, like in this case (Cameron and Trivedi, 1998).

In this case, the study elaborated a model on a data panel involving sixteen years, the solar year being the fixed period of time in which the event (patent applications) occurs. While data on patents is available starting 1970, several controls are only available for more recent periods of time. Given the actuality of the interest of this study and data availability, the data panel has been developed to include data for the period 2005-2020, for a total of sixteen years. As will be better explained in the limitations section, data are not accessible for all Nuts2 regions in the European Union for all years. In particular, as most data for French regions is not available for years after 2013, France has not been considered in the present analysis. Therefore, only 1632 observations out of a total of 3392 have been subject to the computation of the model at this stage. The adopted software is Stata.

The variables of the model and related main descriptive statistics are included in table 5.1 below:

Variable	Measure	Source	Abbreviation	Obs.	Mean	St. Dev.	25th percentile	75th percentile
Agrofood patents	N.	OECD (2024)	AGFP	3392	25.96	68.71	0	21
Agricultural patents	N.	OECD (2024)	AGP	3392	13.79	49.25	0	10
Food patents	N.	OECD (2024)	FP	3392	12.17	35.32	0	10
Gross Domestic Expenditure for Research and Development	Euros	Eurostat (2025)	GERD	2293	8.02e+08	1.37e+09	7.53e+07	9.26e+08

Variable	Measure	Source	Abbreviation	Obs.	Mean	St. Dev.	25th percentile	75th percentile
Natural logarithm of Gross domestic Expenditure for Research and Development	Euros	Eurostat (2025)	ln_GERD	2293	19.3302	1.7457	18.1371	20.6469
Natural logarithm of the square of Gross Domestic Expenditure for Research and Development	Euros	Eurostat (2025)	ln_GERD2	2293	376.7018	66.3902	328.954	426.294
Agricultural Gross Added Value	%	Eurostat (2025)	GVA	2501	0.2476	0.2476	0.0068	0.0334
Tertiary education rate	%	Eurostat (2025)	EDUC	3188	26	9.4165	18.7	31.7
Employees in R&D	Per capita (1000 people)	Eurostat (2025)	EmpR&D	2237	4.5079	3.7502	1.7855	6.0484
Population density	N. (thousands) of people per sq. km.	Eurostat (2025)	PD	3040	0.3458	0.8667	0.0707	0.2412
Population size	Factor (5 quintiles)	Eurostat (2025)	qPS	2292	2.9077	1.3972	2	4

Variable	Measure	Source	Abbreviation	Obs.	Mean	St. Dev.	25th percentile	75th percentile
GDP size	Factor (5 quintiles)	Eurostat (2025)	qGDP	3312	2.9574	1.4721	2	4
Year	Factor (16 values)	Eurostat (2025)	qYear	3392	2012.5	4.6105	2008.5	2016.5

Table 5.1: Descriptive statistics for the variables included in the model. Source: own elaboration from OECD (2024) and Eurostat (2025).

Based on the above description and listed variables, the model can be presented with the following equation (1):

$$(1)\quad AGFP_{i,t}\ /AGP_{i,t}\ /FP_{i,t} = \alpha + \beta_1 ln\_GERD_{i,t} + \beta_2 ln\_GERD2 + \beta_3 GVA_{i,t} + \beta_4 EDUC_{i,t} + \beta_5 EmpR\&D_{i,t} + \beta_6 PD_{i,t} + \beta_7 qPS_{i,t} + \beta_8 qGDP_{i,t} + \beta_9 iYEAR_{i,t} + e_{i,t}$$

5.3 Results

As specified above, the model has been run three times, once for each response variable subject of interest (total agri-food patents, agricultural patents only, food manufacturing patents only). Results are shown in the table below:

Variables	1. Total Patents	2. Agricultural Patents	3. Food Patents
ln_GERD	6.478*** (2.513)	7.978** (3.337)	4.133 (2.597)
ln_GERD2	-0.165** (0.0649)	-0.211** (0.0841)	-0.0982 (0.0678)
GVA	-6.087	-2.764	-8.954***

Variables	1. Total Patents	2. Agricultural Patents	3. Food Patents
	(3.835)	(5.537)	(3.434)
empR&D	0.110** (0.0542)	0.201*** (0.0751)	0.00122 (0.0406)
EDUC	0.0291* (0.0167)	0.0285 (0.0260)	0.0217 (0.0147)
PD	-0.945 (0.642)	-3.134* (1.619)	0.0969 (0.477)
qPS	Yes	Yes	Yes
qGDP	Yes	Yes	Yes
qYEAR	Yes	Yes	Yes
Observations	1,632	1,584	1,559
Number of ID	159	155	151
Robust standard errors in parentheses			
*** p<0.01, ** p<0.05, * p<0.1			

Table 5.2: Results of the poisson regression analysis (self-developed with Stata)

Results show expenditure on R&D is an interesting driver of agrifood patents creation at Nuts2 regional level. The natural logarithm of domestic investment on research and development appears to have a positive and highly significant correlation with the number of patents, which appear to be also encouraged by the number of employees involved in the research and development sector and the rate of people with tertiary education (university degree) at working age. This is reasonable and easy to explain, as also suggested in the methodological section. It is quite straightforward to expect those regions with the most specialised human capital and knowledge to better perform in innovation related practices, and therefore patents creation. Interestingly, the squared natural logarithm of domestic expenditure on R&D is negatively correlated to patents creation. This does not imply a negative correlation between domestic expenditure and patents creation (a positive correlation is shown by the non-squared values), but only a marginal decrease of the effect of domestic expenditure. What the model essentially shows is a consistent positive correlation between domestic expenditure and patents creation when the size of the investment is relatively low. After a certain threshold, expenditure on R&D within a specified territory decrease their impact in favouring the creation of new patents. Assuming patents are a good proxy for research and development, it suggests domestic funding might be the tool to foster it when the region of interest is lacking a strong and consistent R&D apparatus.

When looking at the specific shape and features of the model for agricultural and food patents taken separately, we see the outcome of the model shows relevant differences. Beyond some differences in the rate of significance of the model's explanatories and controls, agricultural patents appear to follow the main model's outcome. Following the same logic, the effect of domestic expenditure appears to be proportionally more consistent when it is comparatively low, and to decrease when it rises over a certain point. Interestingly, tertiary education's incidence is not significant in this case, while population density is negatively (and significantly) correlated to agricultural patents creation.

Finally, when looking at only food manufacturing related patents, the outcome is clearly very different from the overall outcome of the model. Here, despite the direction of the correlation is the same, domestic expenditure does not appear to be significant in determining patents creation. The same is true for almost all the controls inserted in the model, with the only exception of the proportional gross value added by the agricultural sector in the economy of the region of interest, which is assessed as negatively correlated with food patents generation.

To conclude this section, the model shows domestic expenditure on research and development is significantly and positively impacting patents creation in the agrifood sector. This impact, however, appears to be mainly driven by strictly agricultural patents, while the next steps of the production chain (food manufacturing) are not significantly influenced by it. Therefore, with regards to the proposed research hypotheses, we can conclude that, according to the proposed methodological framework and model:

H1: R&D expenditure is confirmed to positively influence agrifood patents creation.

H2: This influence significantly changes when we look either at raw resources production (agriculture and related farms) or its manufacturing (food preparation and related firms).

5.4 Discussion

The model's outcome tends to confirm the suggested hypotheses and the theoretical framework they are based on. Overall, it therefore confirms from an empirical perspective what the literature and the structure of the main innovation indicators adopted at EU level suggested.

First, it empirically confirms that domestic expenditure on R&D can enhance innovation practices in the agrifood sector, as already suggested by Alarcón and Arias (2019), Paoloni et al. (2023), Viaggi & Cuming (2012) and García-Cortijo et al. (2019). It also shows the marginal effect of domestic expenditure on R&D over patents creation is more consistent at low values of R&D and tends to decrease at higher values. In other words, R&D has a declining marginal contribution to innovation activities in the agrifood sector. Following Alarcón and Arias (2019), Riandita (2022) and Paoloni et al. (2023), this might indirectly corroborate the idea that investments are particularly useful for those territories where there is not a structured research and development apparatus, which might be related to a proportional stronger presence of SMEs instead of big farms and corporations. An alternative interpretation might be related to the specific use of patents as a proxy for innovation in the present piece of work. Although there was not a specific reference from the analysed literature to suggest it, it might be argued that a region does not need to generate too many patents in order to have a satisfying volume of inventions. There might reasonably be a threshold over which the market might be unable to efficiently cope with too many new tools in short periods of time. After such threshold is reached, it is possible that innovation practices drift towards different forms that cannot be detected by assessing the number of patents locally generated (like, for instance, internal organisation improvements and higher training for internal personnel). However, as long as the specific interest of a R&D related financial effort aims at the creation of new inventions within the agrifood sector's companies, the paper shows a more evident outcome is to be reasonably expected when the same injection is applied to territorial contexts where R&D domestic investment is currently low.

Second, it shows such effect is different according to the specific step of the production chain subject to the analysis, where agricultural enterprises respond much more significantly than food manufacturing to R&D investment injections. In both cases, the model identifies a positive effect associated to a decreasing marginal effect, but statistical significance is high only for agricultural patents and not for food manufacturing related ones. This well aligns with the literature's suggestion that farms might be more in need of a strong connection and related support from R&D investors (Viaggi & Cuming, 2012; García-Cortijo et al., 2019) while firms might be comparatively benefiting more from other sources of funding. Even in this case, the recorded effect might be limited to patents generation, other than innovation as a whole. It might be that agricultural enterprises (mainly farms) are more inclined to other forms of innovation that are not as easily quantifiable and might be subject to further analyses. However, this outcome appears to be aligned with previous literature suggestions. Kuhmonen and Siltajoa (2022) already noticed a general difficulty for farmers to adapt to shocks and changes in the sector, mainly due to the structure of the farming entrepreneurial system, where the presence of many small agents reduces the power of individual enterprises to make an actual difference in a relatively stable and not very flexible market. It is therefore reasonable that in an entrepreneurial context where innovation is not easily implied in the system, external injections inclusive of public/academic institutions might be comparatively more important to move from a relatively static system to a further step in the expected innovation path.

Considering the implications of the other explanatories (controls) inserted in the model, the choices of the European Innovation Scoreboard to adopt the number of R&D personnel and tertiary education as useful indicators for the development of the scoreboard are aligned to the model's empirical results. Both indicators are statistically significant in fostering agrifood patents creation in the EU. R&D personnel are particularly significant when it comes to agricultural patents. To the contrary, population density appears to be negatively correlated to their generation. This is reasonably related to the nature of the agricultural sector, which is mainly located in rural areas where population density is expected to be low. A high population density is almost by definition associated to non-rural areas, where innovation might be more easily fostered in other sectors, but where agriculture (and therefore farms generating patents) is weak. This is not necessarily the case for food manufactures, that might well be potentially closer to retailers in more populated areas.

5.5 Limitations

As all pieces of research, this study is subject to limitations. The most important limit in the development of the model at this stage was the reduced availability of data for the territorial units of analysis (Nuts2), with regards to domestic expenditure on research and development and other controls, that consistently reduced the number of observations compared to the whole EU. In particular, data for France are almost entirely lacking since after 2013, while data for Germany were only available once for every two years. The authors are working on the completion of the dataset expecting to propose a new readapted version of the model that would take into account all (or almost all) the territories in the EU.

Finally, the study shows domestic expenditure tends to be fostering innovation, although the marginal effect decreases over a certain threshold. Once the full data is available for the EU, it would be ideal to also identify such threshold to provide a more detailed picture of how much expenditure actually provides the highest productivity in terms of patents applications and consequent generation.

5.6 Conclusion

Reaching the conclusions of this section, the statistical model has presented an initial picture of what empirically fosters innovation, here represented by patents generation, in the European Union's agricultural sector. It has done so by assessing the effect of some of the indicators that have been identified by the literature or institutional indicators to be relevant in influencing innovation in the EU. The model confirms the main suggestions provided by the literature, providing at the same time new insights for future research and policy implementation options.

With regards to the first research hypothesis, the model confirms the general effect of domestic expenditure on research and development is positively and significantly influencing agrifood patents generation. However, it also suggests that its marginal effect decreases with a more consolidated innovative apparatus sustained by R&D funding. To the authors' knowledge, this is the first empirical model explicitly providing such outcome. While it might be of interest for future research to delve into this aspect for a more profound understanding of all the potential implications, it is of potential interest for policy making on innovation practices in the agricultural and food sector. Indeed, it suggests the marginal impact of R&D investment is higher in those territories that do not yet possess a developed patents generation (and therefore potentially innovation) framework. As suggested in the discussion, this might also be due to a higher incidence of other sources of funding in more developed R&D agrifood ecosystems, suggesting territories might gradually become more and more independent from R&D funding once they have reached a certain level of R&D structure, or drift to innovation practices that are more subtle and not represented by patents generation after the number of inventions injection in the market is enough for the market to cope with. It is suggested here that the specific implications and a more advanced quantitative assessment involving also other sources of funding and innovation proxies can be of great interest for the sector, as well as for academic purposes. However, standing by the model's outcome, it is recommendable that at least as long as the focus of interest is the generation of new tools and practices that can be registered under the form of patents, a good investment strategy should expect a higher yield in those regional contexts where R&D financial effort is currently lower. While a more complete data coverage and related advanced modelling might provide better insights on the drivers of innovation on a territorial basis, the present work shows that innovation returns in terms of recorded and legally recognised inventions (patents) is enhanced when aimed investments are located in regional contexts where previously invested resources are low, and should therefore be particularly incentivised in those contexts.

When it comes to the second research hypothesis, the model confirms that domestic expenditure on research and development provides different impacts on agriculture and food manufacturing related patents generation. Following the implications from the literature and considerations provided in the discussion session, the comparatively higher presence of small and medium farms than food manufacturers might once again imply a higher need of R&D investment support because of their structural financial constraints that might work as a barrier in the implementation of R&D practices. While this might be better assessed with a micro-level empirical assessment, it implies that policy incentives have a more pronounced effect on farms than firms, that might even in this case gain comparatively more benefits from other sources of funding. This conclusion is somewhat aligned to the overall outcome of the model referring to the agrifood sector as a whole. It appears indeed that investments on R&D provide a statistically more significant effect in those economic areas where the tendency to the development of new tools and inventions in the agrifood sector is lower. While it appears to be the case on a territorial basis with regards to the sector as a whole, it also appears to be true for the considered steps of the production chain, where the least structured with these regards appear to benefit the most from aimed resources injections. While even in this case more complete analyses are recommended, the present work suggests that a policy aimed at innovation in terms of creative and original dedicated inventions in the agrifood sector should pay particular attention to biomass generation and extraction related activities.

Starting from the proposed model and related outcome, future research might provide further insights on the effect of domestic expenditure on R&D in agrifood related innovation in the EU. As a suggestion for the future, as the descriptive analysis showed innovation propensity tends to cluster in macro areas in Europe, a step forward might be considering the effect of spatial spillovers among regions, assuming data availability for all the involved territories.

To conclude, this section has provided some novel insights over the effect of R&D funding and other socioeconomic figures in fostering innovation, here represented by patents generation, in the agrifood system. While still not fully representative of all territories and potential explanatory factors that might be involved in influencing innovation in the EU, it can provide interesting and novel insights into new research potential on the specific topic, as well as a good overview of policy making options to incentivise and consolidate innovation practices in the EU agrifood system.

6. Conclusions and Policy Implications

This report has examined the critical role of innovation—and in particular, eco-innovation—in enabling a transition toward a more sustainable, resilient, and inclusive agri-food system within the European Union. Evidence confirms that innovation is not only a driver of economic growth, but also a strategic instrument to address major societal challenges, including climate change, resource scarcity, and inequality. Innovation in agriculture and food production is not a luxury—it is a necessity for ensuring food security, improving environmental outcomes, and maintaining competitiveness in a globalized economy.

The literature review highlighted both enabling factors and persistent barriers to innovation in the agri-food sector. Key drivers include strong policy frameworks, digital and technological advancements, consumer demand for sustainable products, and increasing public and private investment in R&D. However, barriers such as limited access to funding, institutional inertia, low innovation capacity among small and medium-sized enterprises (SMEs), and fragmented knowledge systems continue to hinder progress. These findings suggest the need for comprehensive policy packages that not only incentivize innovation but also remove systemic obstacles—particularly for lagging regions and vulnerable actors in the food value chain.

The analysis of EU innovation indices (EIS, RIS, and EII) revealed significant disparities in innovation performance across member states and regions. This geographic heterogeneity calls for stronger implementation of place-based innovation strategies, supported by the EU's cohesion policy and tailored to local needs and capacities. Tools such as the Eco-Innovation Index are particularly useful in assessing environmental progress and should be integrated more systematically into regional development planning and investment prioritization.

Quantitative results show a strong link between domestic investment and regional innovation output, as measured by patent activity. This demonstrates that well-targeted domestic funding—especially when directed toward sustainable technologies—can yield measurable returns in terms of innovation capacity. Firm-level analysis further shows that innovation uptake is influenced by firm size, sectoral dynamics, and integration into broader knowledge and support networks.

Eco-innovation, in particular, offers a dual benefit: enhancing economic performance while reducing environmental impacts. Policymakers should recognize eco-innovation as a distinct and high-priority domain requiring dedicated support, including incentives for green technologies, reforms to facilitate regulatory alignment, and enhanced monitoring systems to track environmental outcomes. Embedding environmental goals directly into innovation policies represents a strategic opportunity to align growth with sustainability objectives.

In addition, EU institutions and national governments should foster transnational cooperation and knowledge sharing, particularly through frameworks such as Horizon Europe, the European Innovation Partnership for Agricultural Productivity and Sustainability (EIP-AGRI), and the Common Agricultural Policy (CAP). These platforms can help spread best practices, support technology transfer, and close the innovation gap between leading and lagging regions.

To further enhance policy effectiveness, it is recommended that innovation support mechanisms incorporate monitoring and evaluation systems that go beyond output indicators. A stronger focus on outcome-based metrics—such as reductions in greenhouse gas emissions, improvements in soil health, or increases in farmer resilience—would ensure that innovation is not only occurring but also delivering on sustainability goals. Aligning EU-wide indicators with regional and national strategies will improve accountability and help guide more adaptive, data-driven policymaking.

Lastly, this report integrates innovation into the broader framework of sustainable food systems transformation. Innovation policy cannot be detached from broader agricultural, environmental, and social policies. Only through an integrated, systemic approach, where innovation is aligned with the EU Green Deal, the Farm to Fork Strategy, and the Sustainable Development Goals, can successfully build a resilient, fair, and environmentally sustainable agri-food future.

References

Al-Ajlani, H., Cvijanović, V., Es-Sadki, N., & Müller, V. (2022). EU Eco-Innovation Index 2022: Policy brief. Ecorys; UNU-MERIT, Maastricht University. https://doi.org/10.13140/RG.2.2.11440.43522

Alarcón, S., & Arias, P. (2019). The public funding of innovation in agri-food businesses. Spanish Journal of Agricultural Research, 16(4), e0111. https://doi.org/10.5424/sjar/2018164-12657

Barth, H., Ulvenblad, P.-O., & Ulvenblad, P. (2017). Towards a conceptual framework of sustainable business model innovation in the agri-food sector: A systematic literature review. Sustainability, 9(9), 1620. https://doi.org/10.3390/su9091620

Bentivoglio, D., Giampietri, E., & Finco, A. (2016). The new EU innovation policy for farms and SMEs' competitiveness and sustainability: The case of cluster agrifood marche in Italy. Quality-Access To Success, 17(1), pp. 57-63. ISSN 1582-2559.

Bjerke, L., & Johansson, S. (2022). Innovation in agriculture: An analysis of Swedish agricultural and non-agricultural firms. Food Policy, 109, 102269. https://doi.org/10.1016/j.foodpol.2022.102269

Borrello, M., Lombardi, A., Pascucci, S., & Cembalo, L. (2016). The seven challenges for transitioning into a bio-based circular economy in the agri-food sector. Recent Patents on Food, Nutrition & Agriculture, 8(1), 39–47. https://doi.org/10.2174/2212798408011603041439939

Bossle, M. B., Dutra de Barcellos, M., Vieira, L.M., & Sauvée, L. (2016). The drivers for adoption of eco-innovation. Journal of Cleaner Production, 113, 861–872. https://doi.org/10.1016/j.jclepro.2015.11.033

Cameron, A. C., & Trivedi, P. K. (1998). Regression Analysis of Count Data. Cambridge University Press. https://doi.org/10.1017/CBO9780511814365

Carrillo-Hermosilla, J., Del Rio, P., & Könnölä, T. (2009). Eco-innovation: When sustainability and competitiveness shake hands. Palgrave Macmillan. https://doi.org/10.1057/9780230244856

Crisp, C., Grosso, C., Checchinato, F., Finotto, V., & others. (2021). Configuration challenges for the "Made in Italy" agrifood industry. International Journal of Industrial Engineering and Management, 12(3), 151–162. https://doi.org/10.24867/IJIEM-2021-3-284

De Martino, M., & Magnotti, F. (2018). The innovation capacity of small food firms in Italy. European Journal of Innovation Management, 21(3), 362–383. https://doi.org/10.1108/EJIM-04-2017-0041

Dicecca, R., Pascucci, S., & Contò, F. (2016). Understanding reconfiguration pathways of agri-food value chains for smallholder farmers. British Food Journal, 118(8), 1857–1882. https://doi.org/10.1108/BFJ-05-2016-0194

Diestre, P. (2022). Eco-Innovation Country Profile 2022: Spain. Ecorys.

Dumay, J., & Cai, L. (2014). A review and critique of content analysis as a methodology for inquiring into IC disclosure. Journal of Intellectual Capital, 15, 264–290. https://doi.org/10.1108/JIC-01-2014-0010

European Commission. (2023) Directorate-General for Research and Innovation, Hollanders, H. and Es-Sadki, N., Regional Innovation Scoreboard 2023, Publications Office of the European Union, 2023, https://data.europa.eu/doi/10.2777/70412

European Commission. (2024) Directorate-General for Research and Innovation, European Innovation Scoreboard 2024, Publications Office of the European Union, 2024, https://data.europa.eu/doi/10.2777/779689

European Commission. (2024-2). EU Eco-Innovation Index 2024. Publications Office of the European Union. https://doi.org/10.2777/4878812

European Environment Agency. (2025). Eco-innovation index (8th EAP). European Environment Agency. Retrieved July 8, 2025, from https://www.eea.europa.eu/en/analysis/indicators/eco-innovation-index-8th-eap?activeAccordion=ecdb3bcf-bbe9-4978-b5cf-0b136399d9f8

Eurostat, 2025. Statistics | Eurostat [WWW Document]. URL https://ec.europa.eu/eurostat/databrowser/explore/all/all_themes (accessed 9.6.25).

Finger, R. (2023). Digital innovations for sustainable and resilient agricultural systems. European Review of Agricultural Economics, 50(4), 1277–1309. https://doi.org/10.1093/erae/jbad021

Gambelli, D., Solfanelli, F., Orsini, S., & Zanoli, R. (2021). Measuring the economic performance of small ruminant farms using balanced scorecard and importance-performance analysis: A European case study. Sustainability, 13(6), 3321. https://doi.org/10.3390/su13063321

García-Cortijo, M. C., Castillo-Valero, J. S., & Carrasco, I. (2019). Innovation in rural Spain. What drives innovation in the rural-peripheral areas of Southern Europe? Journal of Rural Studies, 71, 114–124. https://doi.org/10.1016/j.jrurstud.2019.02.027

Germundsson, L. B., Frankelius, P., & Norrman, C. (2021). The role of innovation intermediary organisations in forming value-creating meetings: The agri-food firm perspective. International Food and Agribusiness Management Review, 24(6), 993–1004. https://doi.org/10.22434/IFAMR2020.0167

Iadecola, F. (2022). Eco-Innovation Country Profile 2022: Italy. Ecorys.

IPC, 2025. International Patent Classification (IPC) [WWW Document]. classification-ipc. URL https://www.wipo.int/web/classification-ipc (accessed 9.6.25).

Jack, C., Anderson, D., & Connolly, N. (2014). Innovation and skills: Implications for the agri-food sector. Education + Training, 56(4), 271–286. https://doi.org/10.1108/ET-11-2012-0122

Kühne, B., Lefebvre, V., Vermeire, B., & Gellynck, X. (2010). Measuring innovation capacity in the agrifood sector: From single companies to value chains. Journal on Chain and Network Science, 10(3), 145–157. https://doi.org/10.3920/JCNS2010.x185

Lamprinopoulou, C., Renwick, A., Klerkx, L., Hermans, F., & Roep, D. (2014). Application of an integrated systemic framework for analysing agricultural innovation systems and informing innovation policies: Comparing the Dutch and Scottish agrifood sectors. Agricultural Systems, 129, 40–54. https://doi.org/10.1016/j.agsy.2014.05.001

Latino, M. E., Corallo, A., Menegoli, M., & Nuzzo, B. (2023). Agriculture 4.0 as enabler of sustainable agri-food: A proposed taxonomy. IEEE Transactions on Engineering Management, 70(10), 3678–3696. https://doi.org/10.1109/TEM.2021.3101548

López-Becerra, E. I., Arcas-Lario, N., & Alcon, F. (2016). The websites adoption in the Spanish agrifood firms. Spanish Journal of Agricultural Research, 14(4), e0107. https://doi.org/10.5424/sjar/2016144-10113

Marchiol, L. (2019). Nanofertilisers. An outlook of crop nutrition in the fourth agricultural revolution. Italian Journal of Agronomy, 14(3), 183–190. https://doi.org/10.4081/ija.2019.1367

Massaro, M., Dumay, J., & Garlatti, A. (2015). Public sector knowledge management: A structured literature review. Journal of Knowledge Management, 19, 530–558. https://doi.org/10.1108/JKM-11-2014-0466

Musostova, D., Geraskin, Y., & Tokaeva, B. (2023). Current state of innovation infrastructure in the world. BIO Web of Conferences. https://doi.org/10.1051/bioconf/20237609007

OECD, 2024. The OECD REGPAT Database [WWW Document], 2024. . OECD. URL https://www.oecd.org/en/publications/the-oecd-regpat-database_241437144144.html (accessed 6.9.25).

Orbis, 2025. Orbis Database, https://www.moodys.com/web/en/us/capabilities/company-reference-data/orbis.html, Last access July 2025.

Orfanidou, T., & Kondylidou, M. (2022). Eco-Innovation Country Profile 2022: Greece. LDK SED.

Paoloni, M., Tutino, M., Paoloni, N., & Santolamazza, V. (2023). Financing innovation in agri-food industries: An analysis of the Italian micro, small and medium enterprises. British Food Journal, 125(13), 183–204. https://doi.org/10.1108/BFJ-04-2022-0342

Paolotti, L., Corridoni, F., Rocchi, L., & Boggia, A. (2023). Evaluating environmental sustainability of pasta production through the method LCA. Environmental and Climate Technologies, 27(1), 593–605. https://doi.org/10.2478/rtuect-2023-0044

Parra-López, C., Reina-Usuga, L., Carmona-Torres, C., Sayadi, S., & Klerkx, L. (2021). Digital transformation of the agrifood system: Quantifying the conditioning factors to inform policy planning in the olive sector. Land Use Policy, 108, 105537. https://doi.org/10.1016/j.landusepol.2021.105537

Petridis, N. E., Digkas, G., & Anastasakis, L. (2020). Factors affecting innovation and imitation of ICT in the agrifood sector. Annals of Operations Research, 294(1–2), 501–514. https://doi.org/10.1007/s10479-018-2834-y

Reinhardt, T. (2023). The farm to fork strategy and the digital transformation of the agrifood sector—An assessment from the perspective of innovation systems. Applied Economic Perspectives and Policy, 45(2), 819–838. https://doi.org/10.1002/aepp.13246

Riandita, A. (2022). To collaborate and innovate for sustainability: Food retailers and their external partners. Technological Forecasting and Social Change, 180, 121681. https://doi.org/10.1016/j.techfore.2022.121681

Romano, G., Lombardi, G.V., Rapposelli, A., Gastaldi, M., 2022. The factors affecting Italian provinces' separate waste collection rates: An empirical investigation. Waste Management.

https://doi.org/10.1016/j.wasman.2021.12.037

Ryan, M., Hennessy, T., Buckley, C., Dillon, E. J., Donnellan, T., Hanrahan, K., & others. (2016). Developing farm-level sustainability indicators for Ireland using the Teagasc national farm survey. Irish Journal of Agricultural and Food Research, 55(2), 112–125. https://doi.org/10.1515/ijafr-2016-0011

Schumpeter, J. A. (1934). The theory of economic development: An inquiry into profits, capital, credit, interest, and the business cycle (R. Opie, Trans.). Harvard University Press.

Singh, M., Marchis, A., & Capri, E. (2014). Greening, new frontiers for research and employment in the agro-food sector. Science of The Total Environment, 472, 437–443. https://doi.org/10.1016/j.scitotenv.2013.11.078

Solow, R. M. (1957). Technical change and the aggregate production function. The Review of Economics and Statistics, 39(3), 312–320. https://doi.org/10.2307/1926047

Spudyte, I. (2022). Eco-Innovation Country Profile 2022: Lithuania. Ecorys.

Viaggi, D., & Cuming, D. (2012). Innovation in multiple networks and networks of networks: The case of the fruit sector in Emilia-Romagna. International Journal on Food System Dynamics, 3(3), 258-263. https://doi.org/10.18461/ijfsd.v3i3.336

Wooldridge, J. M. (2010). Econometric Analysis of Cross Section and Panel Data (2nd ed.). MIT Press. https://mitpress.mit.edu/9780262232586

Yue, L., Yu, L., & Ho Char Fei, T. (2025). The innovation beat: Global rhythms and pulse points. International Journal of Academic Research in Economics and Management Sciences, 14(1). https://doi.org/10.6007/ijarems/v14-i1/24500

Zarbà, C., Chinnici, G., Pecorino, B., Pappalardo, G., & D'Amico, M. (2022). Recent scenarios in Italy on fresh-cut products in the COVID-19 context. AIMS Agriculture and Food, 7(2), 403–425. https://doi.org/10.3934/agrfood.2022026

Annex 1

The present Annex shows the main maps and graphs for the eleven dimensions of the European Innovation Scoreboard that have not been presented in the text of the report. For each dimension, three figures are presented. One figure for the dimension's scores distribution in 2017 (the first available year), using the value of 100 as the average value for the EU and distributing countries among four categories as for the Summary Innovation Index and Environmental Sustainability dimension presented above. One figure then shows the dimension's score distribution in 2024, with a readaptation of the thresholds and categories distribution based on the new average value in 2024. Finally, a bar chart is presented that shows the dimension of interest for the four case studies of the project and their evolution in time, year by year, between 2017 and 2024.

1. Framework Conditions

Human Resources

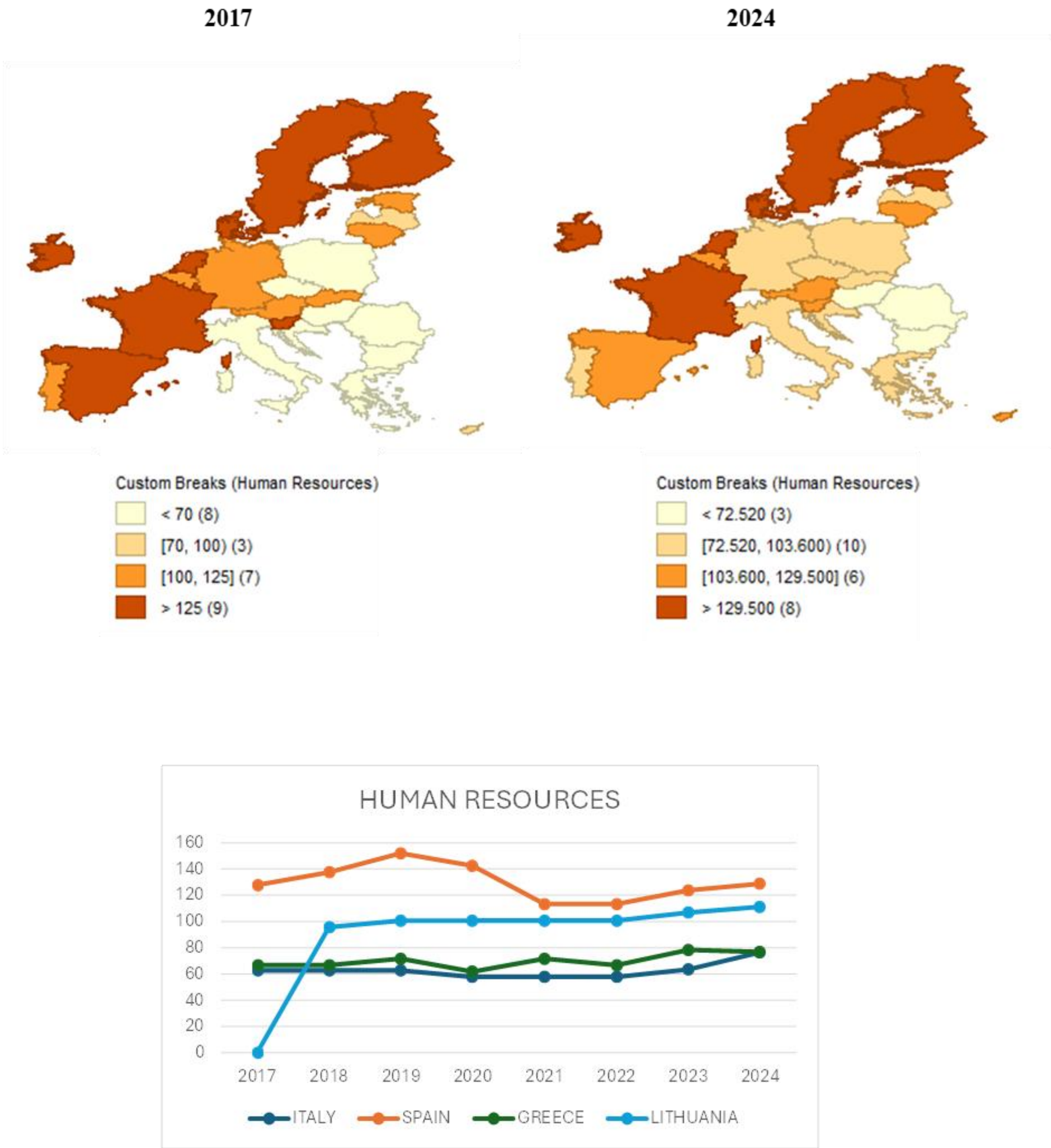


Figure Ann.1 a) Human Resources 2017. b) Human Resources 2024 (2024 thresholds). c) Human Resources line chart (2017-2024). Source: Own elaboration from European Commission (2023) through the Geoda software.

Attractive Research Systems

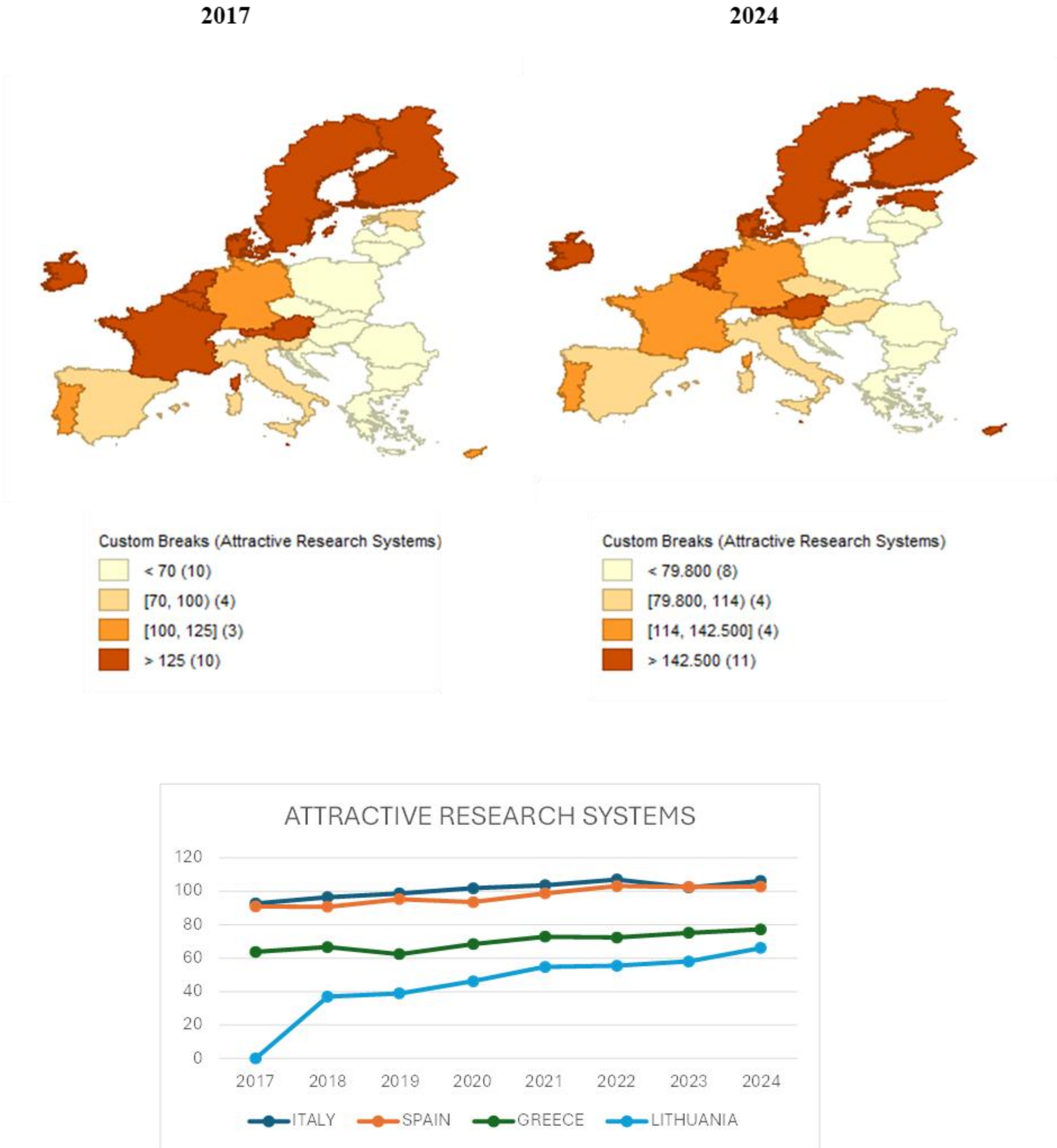


Figure Ann.2 a) Attractive Research Systems 2017. b) Attractive Research Systems 2024 (2024 thresholds). c) Attractive Research Systems line chart (2017-2024). Source: Own elaboration from European Commission (2023) through the Geoda software.

Digitalisation

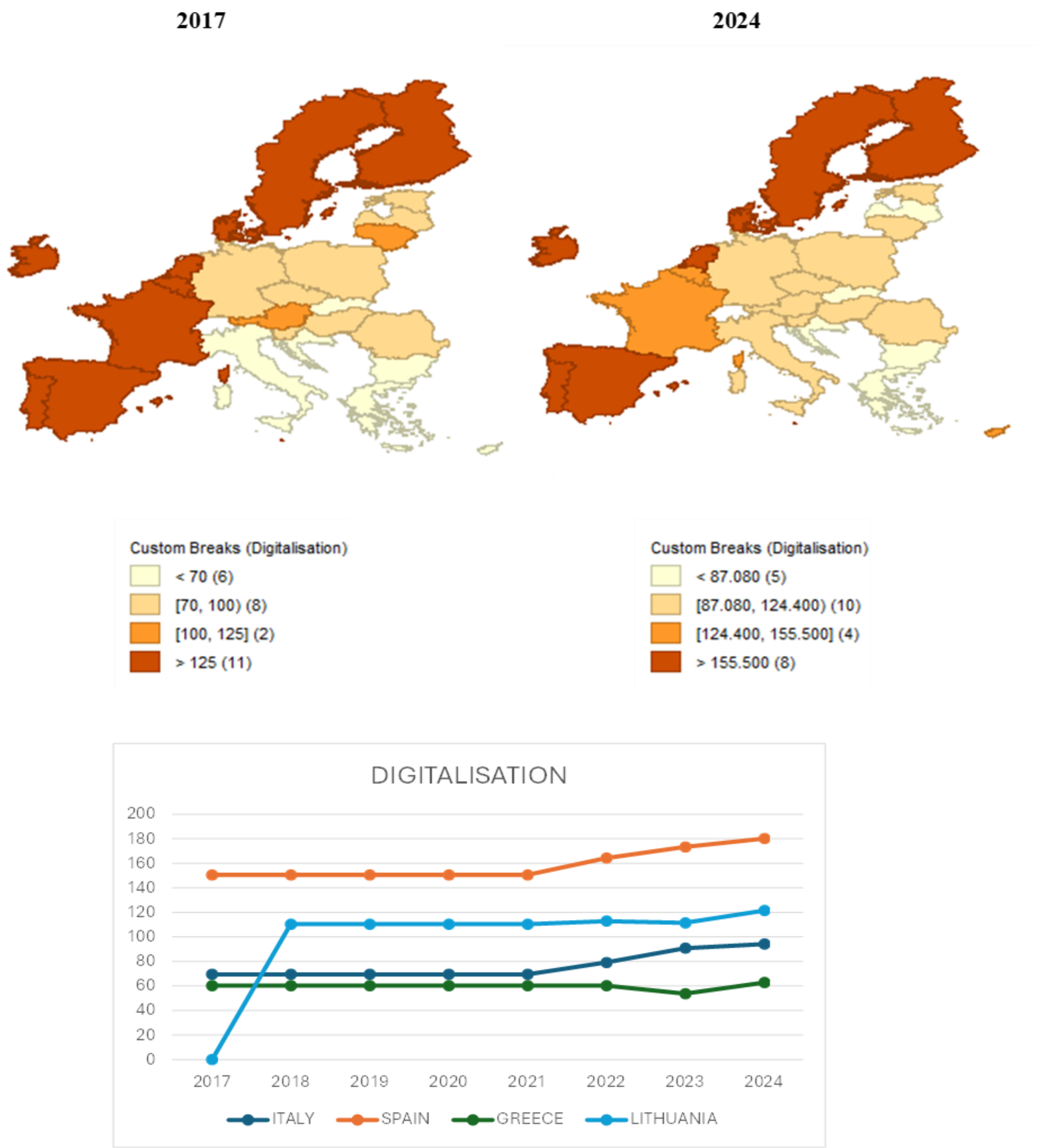
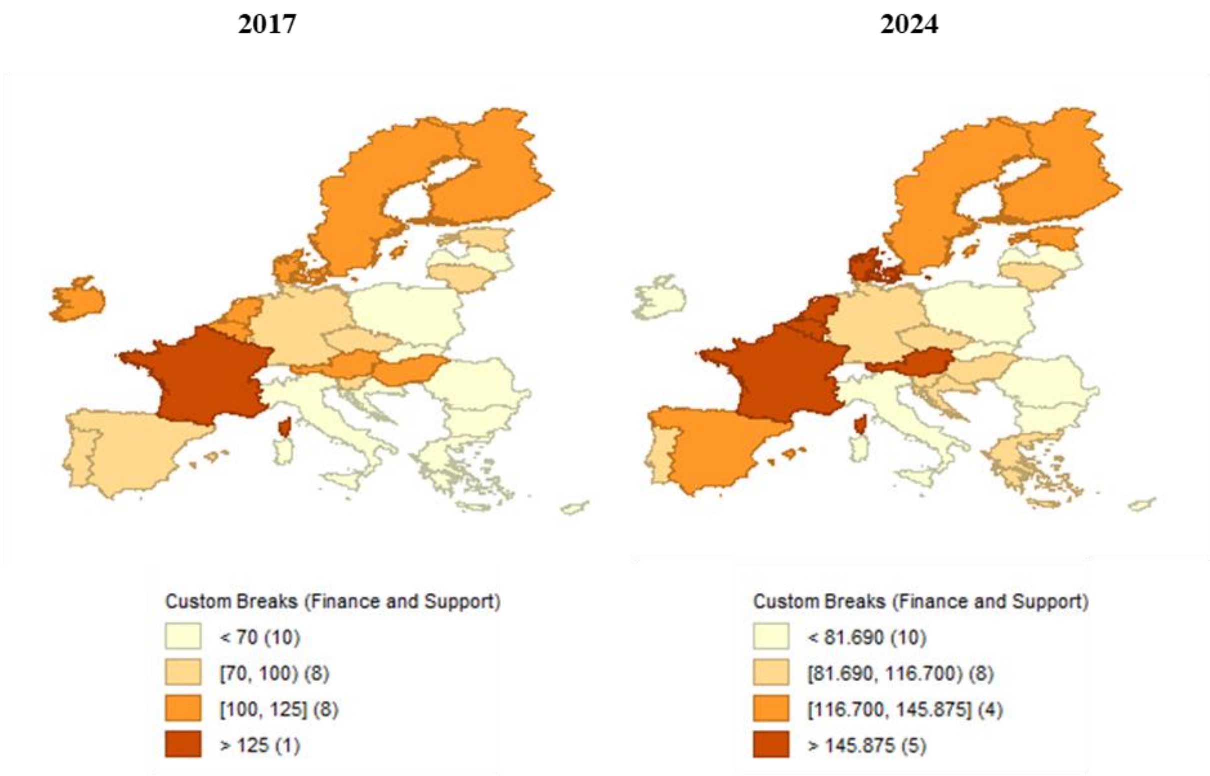


Figure Ann.3 a) Digitalisation 2017. b) Digitalisation 2024 (2024 thresholds). c) Digitalisation line chart (2017-2024). Source: Own elaboration from European Commission (2023) through the Geoda software.

Finance and Support



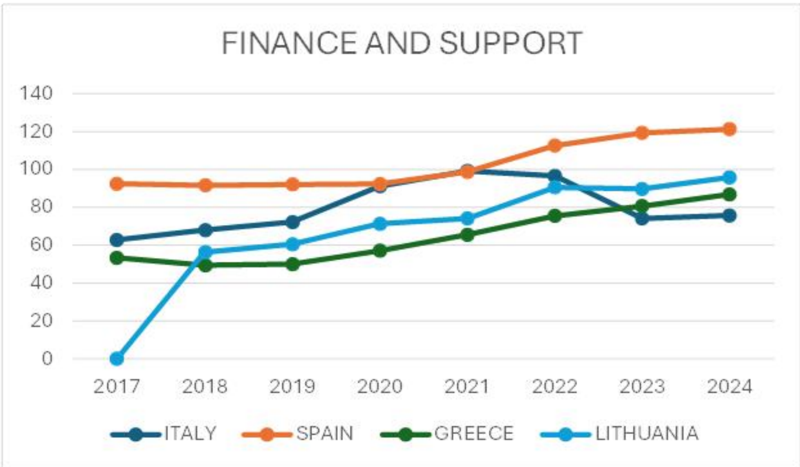


Figure Ann.4 a) Finance and Support 2017. b) Finance and Support 2024 (2024 thresholds). c) Finance and Support (2017-2024). Source: Own elaboration from European Commission (2023) through the Geoda software.

2. Investment

Firm Investment

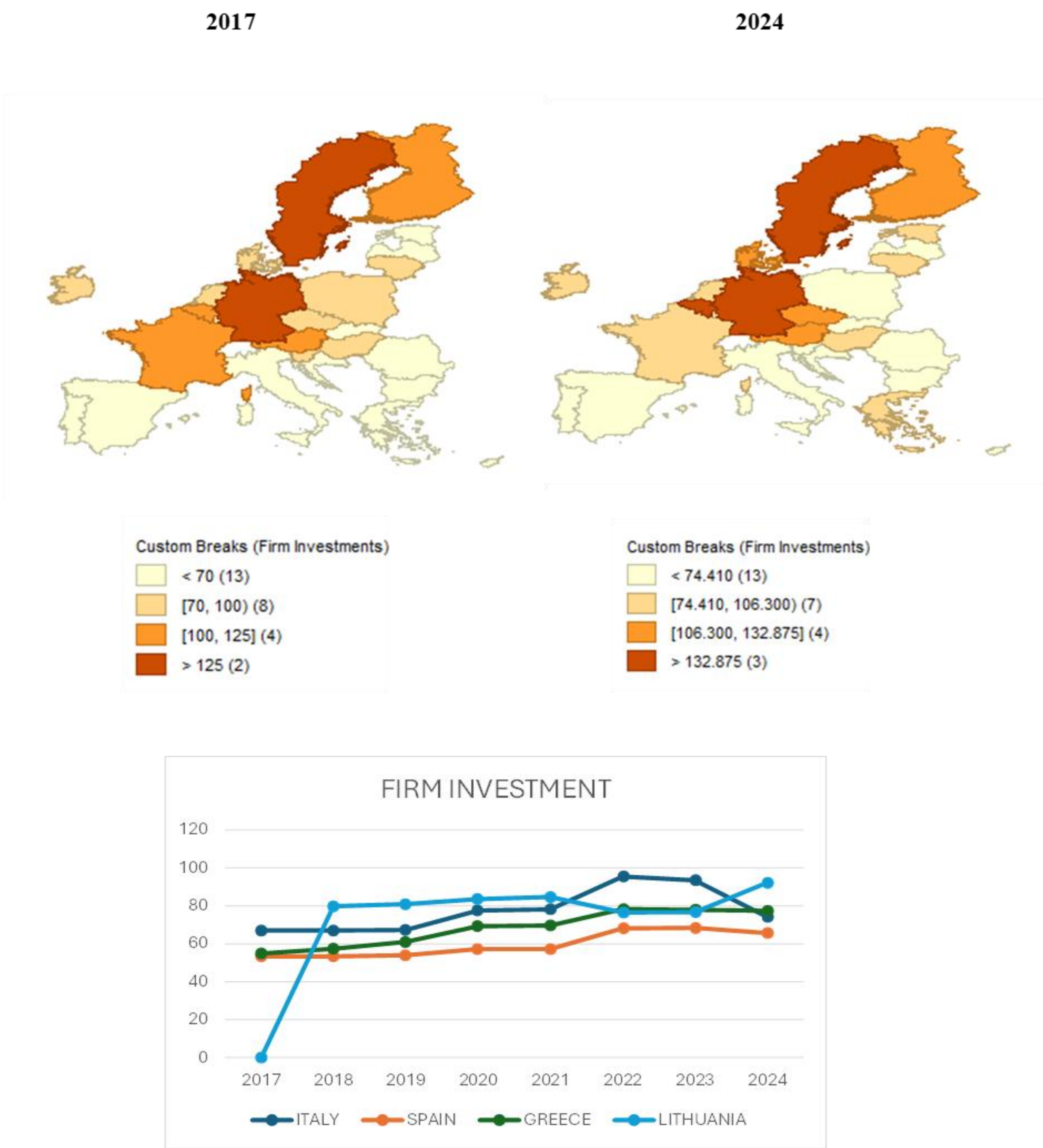
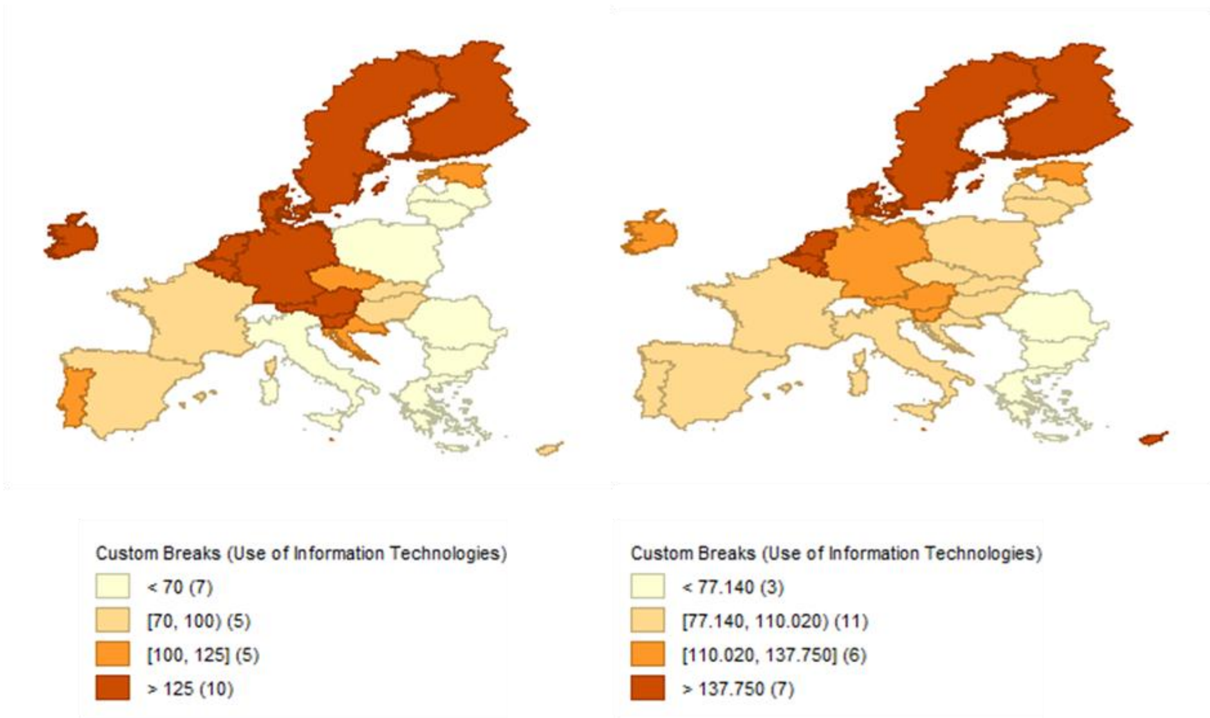


Figure Ann.5 a) Firm Investment 2017. b) Firm Investment 2024 (2024 thresholds). c) Firm Investment (2017-2024). Source: Own elaboration from European Commission (2023) through the Geoda software.

Use of Information Technologies

2017 **2024**



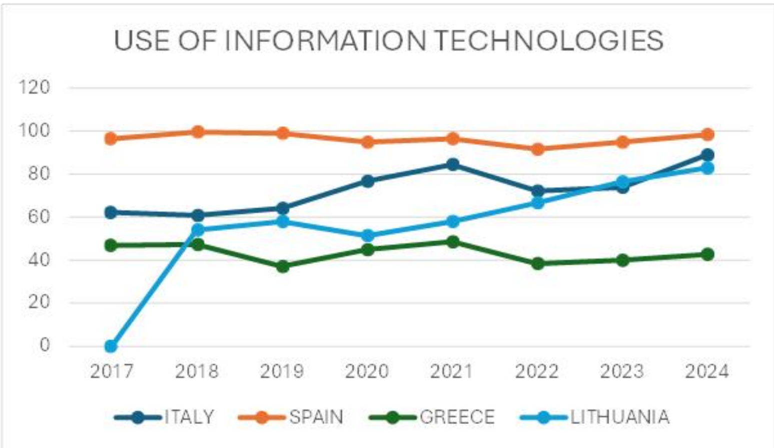


Figure Ann.6 a) Use of Information Technologies 2017. b) Use of Information Technologies 2024 (2024 thresholds). c) Use of Information Technologies (2017-2024). Source: Own elaboration from European Commission (2023) through the Geoda software.

3. Innovation Activities

Innovators

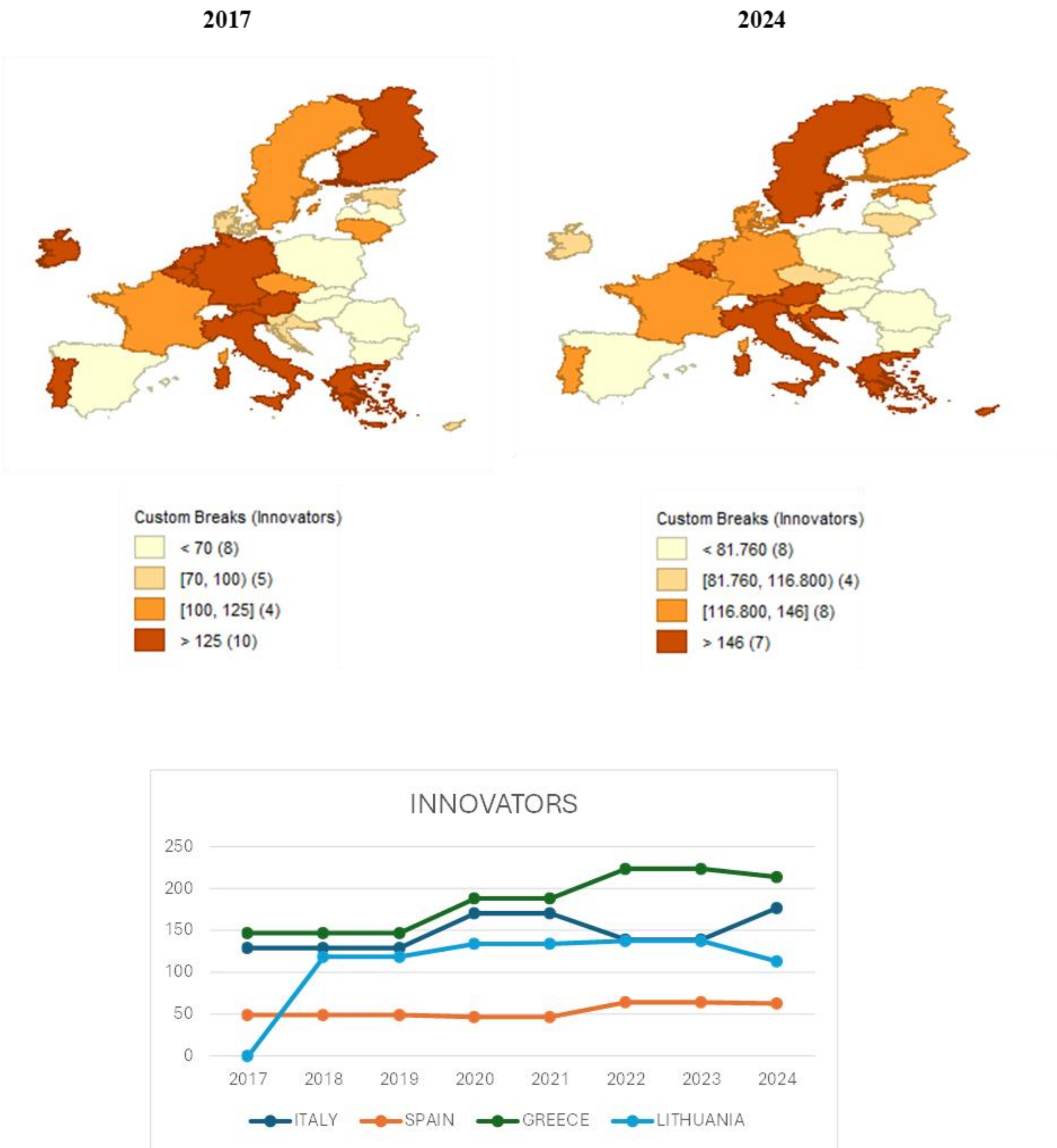
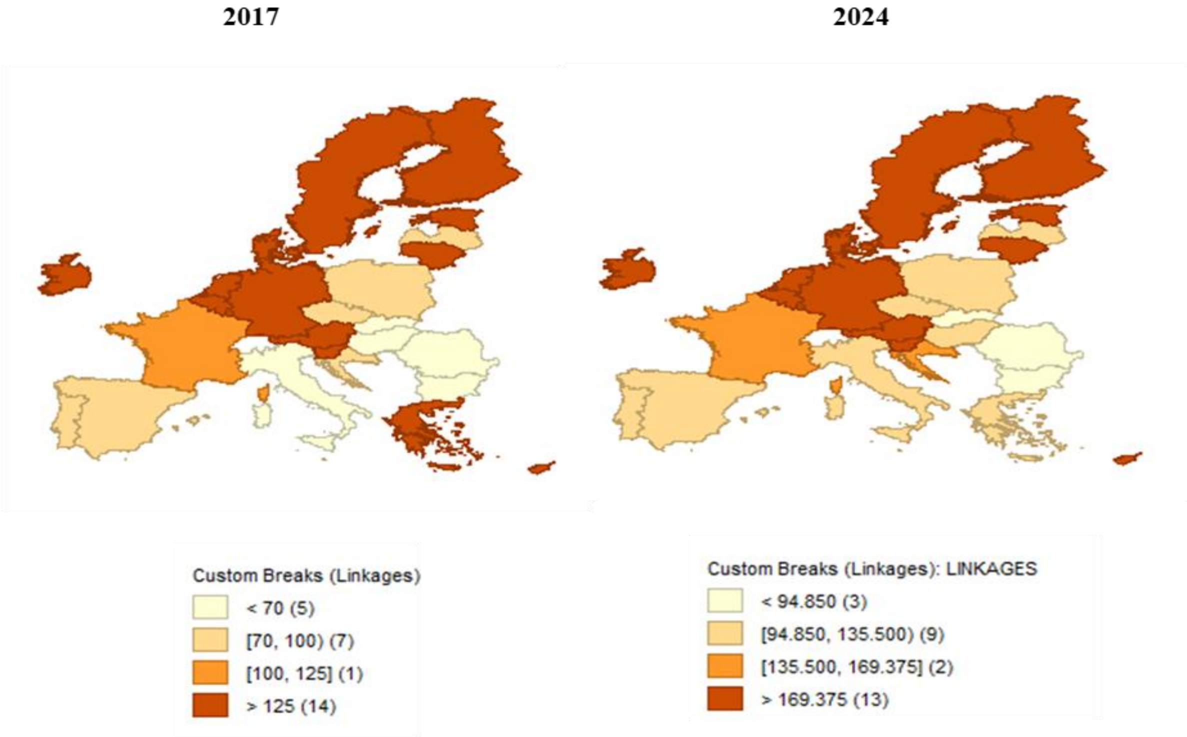


Figure Ann.7 a) Innovators 2017. b) Innovators 2024 (2024 thresholds). c) Innovators (2017-2024). Source: Own elaboration from European Commission (2023) through the Geoda software.

Linkages



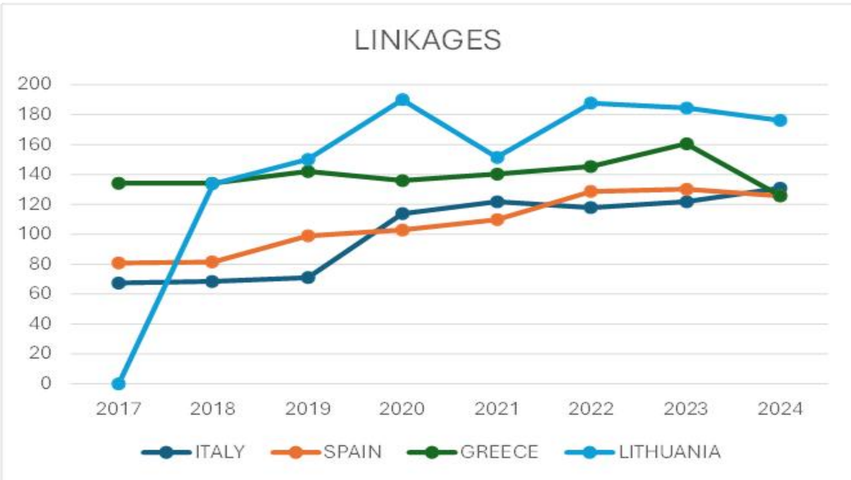


Figure Ann.8 a) Linkages 2017. b) Linkages 2024 (2024 thresholds). c) Linkages (2017-2024). Source: Own elaboration from European Commission (2023) through the Geoda software.

Intellectuals' Assets

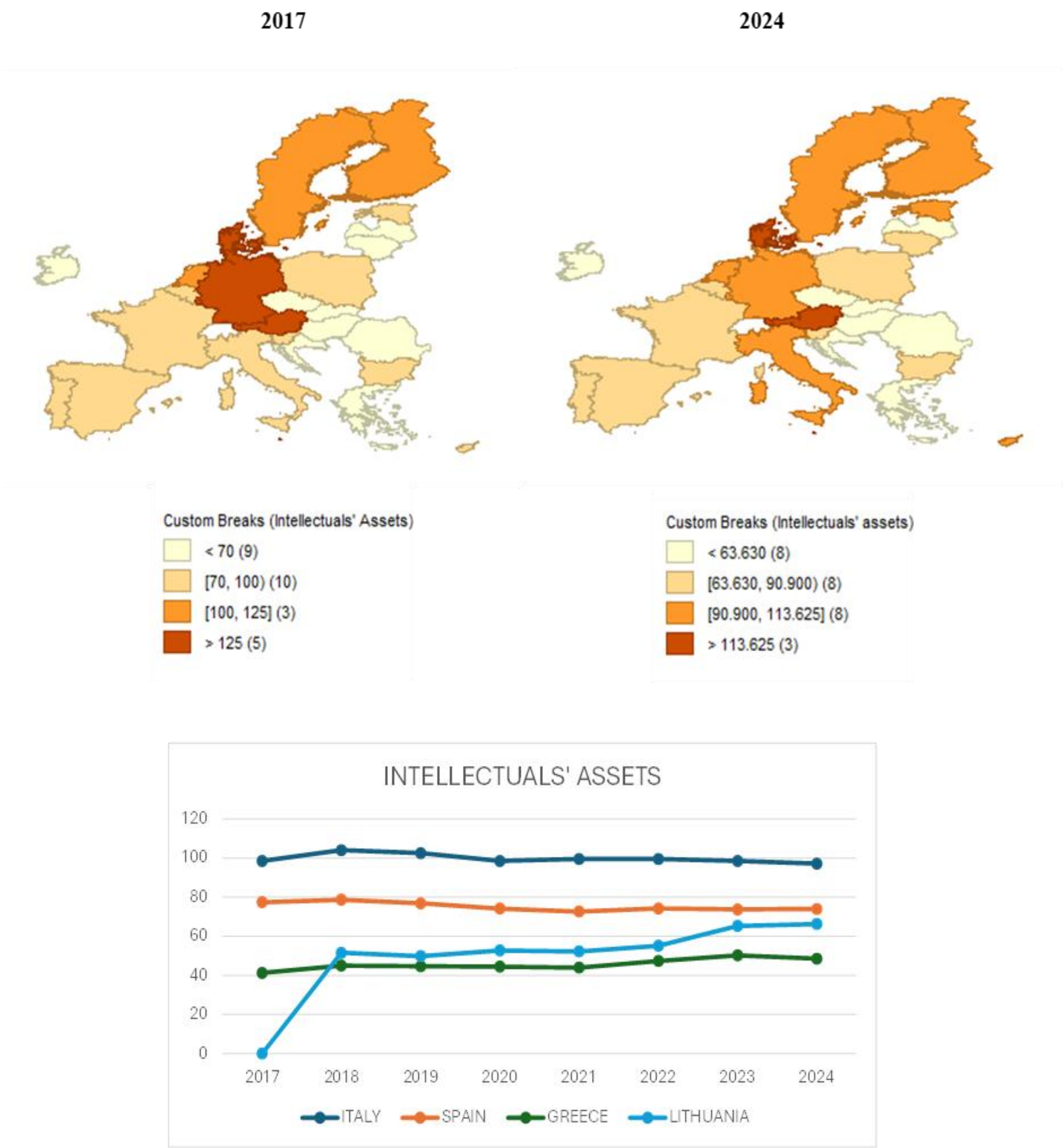


Figure Ann.9 a) Intellectuals' assets 2017. b) Intellectuals' assets 2024 (2024 thresholds). c) Intellectuals' assets (2017-2024). Source: Own elaboration from European Commission (2023) through the Geoda software.

4. Impacts

Employment Impacts

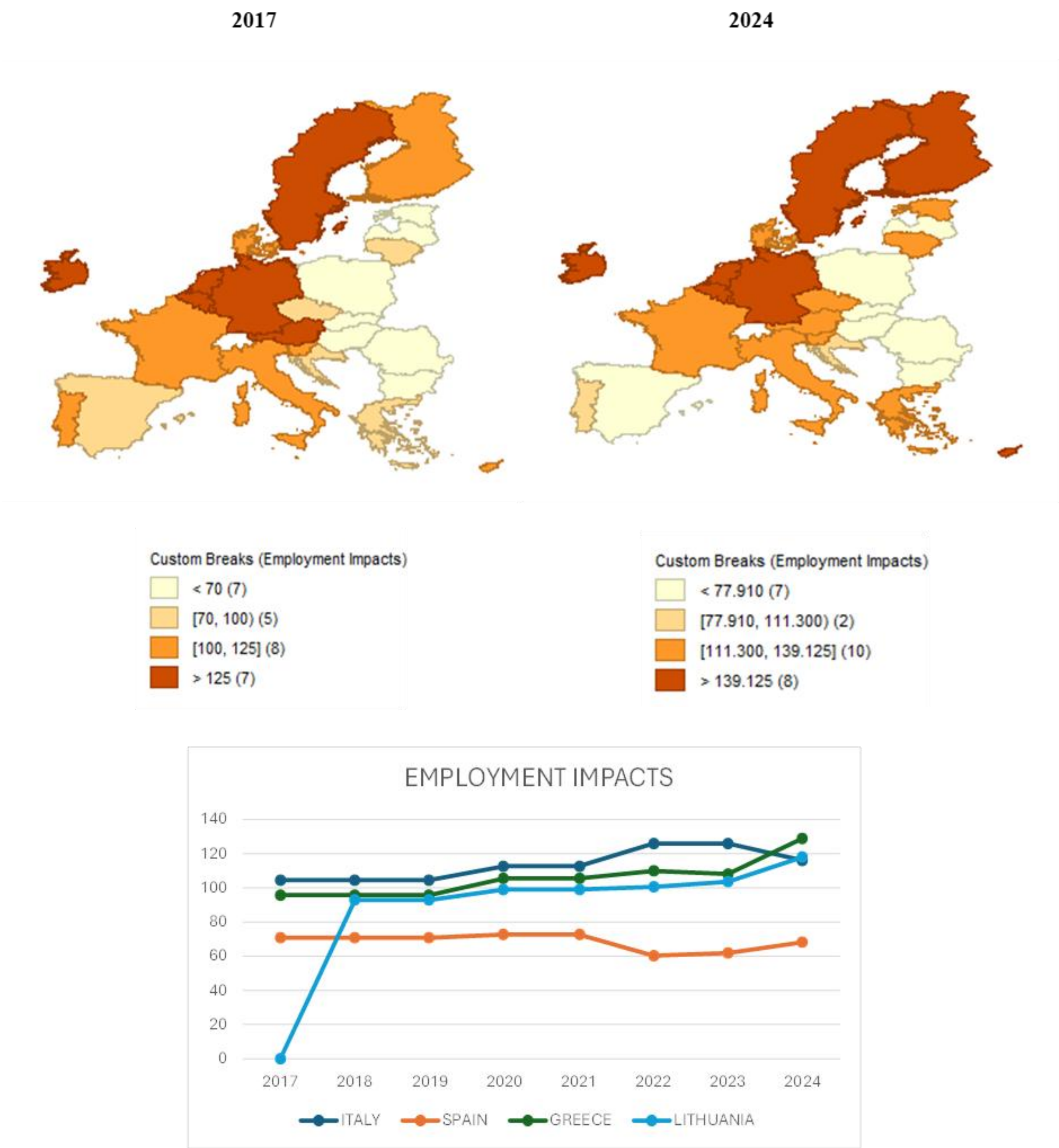


Figure Ann.10 a) Employment Impacts 2017. b) Employment Impacts 2024 (2024 thresholds). c) Employment Impacts (2017-2024). Source: Own elaboration from European Commission (2023) through the Geoda software.

Sales Impacts

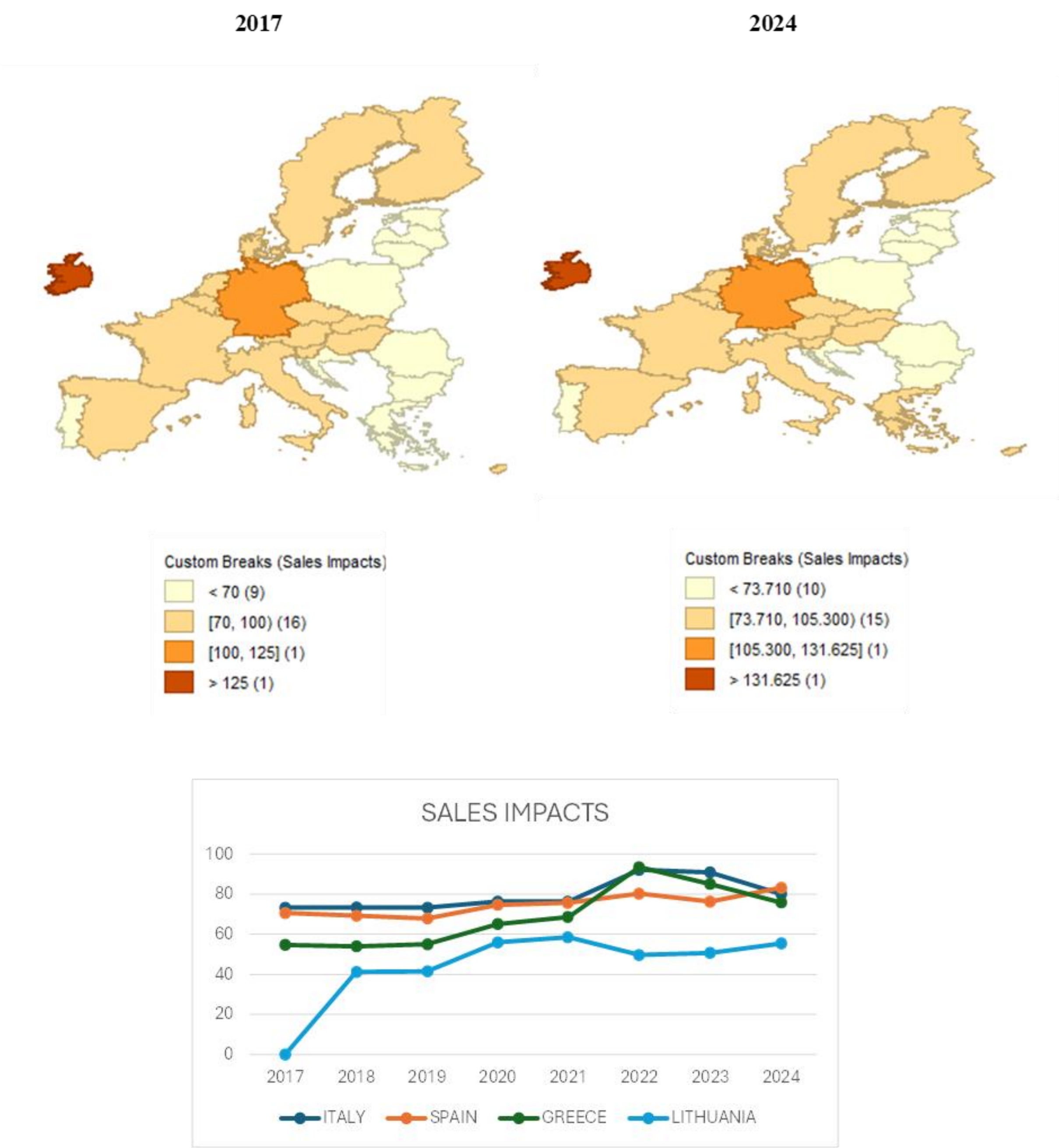


Figure Ann.11 a) Sales Impacts 2017. b) Sales Impacts 2024 (2024 thresholds). c) Sales Impacts (2017-2024). Source: Own elaboration from European Commission (2023) through the Geoda software.

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