“[…] *Dammi*
un’intelligenza assetata di verità,
un braccio forte per difenderla,
un cuore coraggioso per testimoniarla”
La preghiera del Cavaliere

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Essays on the Economics of Innovation in the Italian Agricultural sector

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Table of Contents

Preface

This thesis investigates agricultural public-private partnerships for innovation, established through national public subsidies, with the aim of understanding whether the agricultural sector is evolving from a supplier-based system toward a science-based one. In economic terms, this transition corresponds to the emergence of what is commonly defined as bioeconomy. However, Europe has not yet assumed a central role in this domain (Zilberman, 2023). Thus, rather than focusing directly on large-scale scientific R&D investment, European public policies have mainly relied on the promotion of public–private partnerships to stimulate innovation within the agricultural sector (Cristiano and Proietti, 2024).

Innovation has always been a fundamental driver of structural change, as emphasized by evolutionary economic theory. While manufacturing and service industries have long benefited from innovation dynamics fostered by public–private collaborations, it remains less clear whether similar mechanisms have been effectively established within agriculture. Innovation has long been recognized as a key driver of agricultural productivity, sustainability, and territorial development. Over the last decades, policies in Europe such as the Common Agricultural Policy (CAP) and related national frameworks have progressively emphasized cooperation and learning as essential tools to foster innovation in rural areas. This evolution has been accompanied by a shift in governance models, moving away from a view of the state as a mere regulator toward one that actively shapes innovation-ecosystems (Mazzucato, 2021).

At the European level, the Agricultural Knowledge and Innovation System (AKIS) provide a conceptual and operational framework for understanding how knowledge exchange and innovation occur through dynamic, multi-actor interactions (Hall & Clark, 2010; Knierim et al., 2015; Fieldsend, 2021). AKIS fosters learning processes that connect research, advisory services, policymakers, and producers to address complex challenges such as productivity stagnation, climate change, biodiversity loss, and food security (European Commission, 2024; FAO, 2024). Within this perspective, the innovation capacity of agriculture depends not only on technological advancement but also on the institutional investments that enable collaboration, experimentation, and knowledge transfer (Cristóvão et al., 2012).

The present Thesis disentangles the relevant policies revealing interesting insights into agricultural innovativeness and acknowledges innovation's crucial role. This hypothesis is explored extensively in the first chapter, where the authors demonstrate the concept's genesis in Agricultural Districts as precursors to contemporary multi-actor arrangements. Indeed, in Chapter 1 we analyse the evolution of agricultural policy instruments and their coherence with the Agricultural Knowledge and Innovation System (AKIS) framework. Specifically, authors examine the role of the new established Food Districts as early forms of multi-actor territorial arrangements that have sought to stimulate learning, cooperation, and innovation in rural areas. This chapter provides the conceptual basis for understanding how public initiatives have encouraged collaboration and knowledge diffusion before the implementation of the most recent CAP innovation measures analysed in the next part of the thesis.

Chapter 2 focuses specifically on AKIS-measures and try to put new light on which are the economic and financial characteristics of farmers that influence their participation in public subsidies for innovation-related R&D. Using microdata from the Italian Farm Accountancy Data Network (FADN), it identifies which types of farms are more likely to engage in innovation-oriented measures, revealing that participation is closely linked to awareness of the long-term benefits of innovation. These chapter indicate that Italian farmers are not merely adopting innovations but increasingly developing their own capacity to innovate.

Lastly, Chapter 3 advances the analysis by constructing and evaluating a novel database of Italian Operational Groups (OGs); public–private partnerships established under the CAP 2014–2020 through the European Innovation Partnership for Agricultural Productivity and Sustainability (EIP-AGRI). By applying large language models (LLMs) to OG project reports, Authors quantifies innovation output and identifies key factors driving higher innovativeness. Results show that innovation within OGs arises from collaborative processes in which farmers, researchers, and other stakeholders jointly co-create new solutions tailored to agricultural needs, rather than simply transferring existing technologies.

Although data limitations prevent this thesis from fully answering the big concern of how far the Italian agricultural sector has transitioned toward a science-based model, two main conclusions can be drawn. First, as highlighted in the first and second chapter, Italian farmers are becoming more innovative-oriented, demonstrating growing awareness of innovation as a strategic element for long-term competitiveness. Second, evidence suggests that the sector is indeed moving in that direction, largely facilitated by the institutional and conceptual framework of AKIS.

The analysis of Operational Groups, in chapter three, further highlights that agricultural innovativeness extends beyond technology adoption, it reflects a creative combination of knowledge, experimentation, and cooperation among diverse actors. Consequently, the agricultural sector (not only in the framework of bioeconomy) deserves renewed attention from policymakers for its capacity to attract knowledge capital and to foster innovation through cross-sectoral collaboration.

Future research should investigate more precisely the evolution of agricultural R&D investments and policy mechanisms in Europe, particularly in comparison with emerging economies such as India and China, which are substantially increasing their public and private investments in agricultural innovation (Fuglie; 2024). Understanding these dynamics will be essential to position Europe within the global transformation toward a more science-based and sustainable agricultural paradigm.

The next part of the introduction is presented to introduce two important concepts necessary for the reader: the evolution of the Schumpeterian innovation into Pavit taxonomies and the European policy trajectory concerning the implementation of the EIP-AGRI framework.

Introduction

From innovation to taxonomy / Innovation in evolving economic systems

Schumpeter, that initially was not much considered by mainstream economics, had the merit of bringing the issues of economic dynamics to the fore. Indeed, in extending, and in analogy with previous studies, Schumpeter in his famous *Business cycle* (1939) affirmed how the "innovation activity" is one of the determinants of the economic dynamics. He declares "innovation is the outstanding fact in the economic history of capitalist society (and) […] it is largely responsible for most of what we would at first sight attribute to other factors." (pp.112). The intuition behind this assumption is that "entrepreneurs-innovators" introduce new products and new processes, improving the organizational structure of firms, creating new markets, or achieving new sources. Their initial risk is repaid by the monopoly income position that innovation temporarily secures. This process is well-known as "Schumpeter Mark I", then extended in the second typology of the innovation process, the so called "Schumpeter Mark II", in which the innovation is driven by monopolistic firms which invest in R&D activities (Schumpeter; 1942). This second way of thought was in line with the postbellum economies in which (mostly in the United States) firms performed the majority of R&D inside the intra-mural of the manufactory industries, bringing the development and improvement of industrial technologies intra-mural (Rosenberg and Mowery; 1998). Actually, according to the recent volume of G. Dosi, Adam Smith begins his *Wealth of Nations* "highlighting the importance of technological advance to economic growth and discusses the processes involved in a way that anticipates modern evolutionary analyses." [1]. The "outstanding fact" is so largely recognized as a driver for economic dynamics and market change. From the first industrial revolution technology is seen as the feature, of the products and industries, to distinguish from high wage countries versus low ones (Nuvolari; 2006). Economists of as diverse persuasion as Adam Smith, Karl Marx, and Joseph Schumpeter have argued that material standards of living depend critically upon the level of technology (Scherer; 1982), but the process of technological innovation is a complex phenomenon consisting in many elements and schools of thoughts. A relevant contribution of studies in the literature points out that the production, adoption, and diffusion of technological innovations are essential factor in economic development and social change. However, in the original neo-classical framework, according to Nelson (1981), new technologies instantly diffuse across total capital. Indeed, the new technologies are associated with the capital that embodies them, and thus, the adoption is limited by the amount of investment. In the "schizophrenia" of contemporary research on productivity growth, the "exogenous" technological innovations are not central in the development of economies, while, according to the Author more attention should be on the variety of sources, nature, and uses of innovations (Nelson; 1981). Technological innovation has a contribution to the whole economy not as an exogenous variable, but as endogenous of a specific context contributing to the evolving of it. A first attempt in this direction is provided by the Austrian school during the Sixties which contribute to claim the importance of structural changes in the economic dynamics. According to Streissler (1969), in that period [of hesitant growth, chronic creeping inflation and intensification of search of economic integration], the changes of the aggregates as a whole was no longer the decisive feature on which attention had to be focussed. Economists must not ignore the new economic uncertainties; thus, the structural changes that takes places within aggregates levels must become the fore. Therefore, the "structuralist" perspective in line with the Schumpeterian hypothesis, started focused

[1] This analysis is beyond the aim of our review. For a deeper study see G. Dosi; *The Foundations of Complex Evolving Economies: Part One: Innovation, Organization, and Industrial Dynamics*; 2023.
Nuvolari, A. (2006). The making of steam power technology: a study of technical change during the British Industrial Revolution. The Journal of Economic History, 66(2), 472-476. (Da metter enelle references)

on the effects of the intensity of market competition, as measured by the degree of market concentration, on the investment in R&D and the innovative performance, measured for example by patents and number of innovations (Marsili and Verspagen; 2002). However, the central importance given to technological innovation to set the boundaries for the meso-level, was developed by Nelson and Winter (1982). They criticised the "Schumpeterian hypothesis" according to which the market structure driven innovation: the direction goes in both ways. They claim how the structure of industries is defined by the technological boundaries emphasizing the nature of the learning process, in this way both innovation and market structure, are endogenous to a specific pattern of "technological regime". This Authors have spread new light to the studies of Schumpeter paving the way to a new strand of contemporary studies: the evolutionary approach, according to which the economic dynamics is shaped by the industrial competition which influence the firm to enter the market via innovation or remain cumulating innovation successes determining the evolving of economies. According to Malerba and Orsenigo (1993) a technological regime describes the technological environment in which firms operate, characterized in terms of opportunity, appropriability, cumulativeness, and the complexity of the knowledge base. Winter and Nelson operationalize their framework in distinguish two regimes "entrepreneurial" and "routinized" to differentiate industries in which respectively, the knowledge is non-cumulative and in which the knowledge is cumulative facilitating the established innovative firms. According to Marsili (2001, chapter 5), the use of taxonomies of innovation finds its theoretical precedent in the concept of the *technological regime*. The intuition behind creating classifications and patterns to understand economic dynamics has been emphasized since the early stages of innovation theory. In this context, taxonomies serve as essential analytical tools for ordering complexity, providing a structured understanding of how industries evolve and differ in their innovative behaviour.

Taxonomy, in general, refers to the empirical method of classification—organizing cases according to their similarities in order to maximize variance between groups and minimize variance within them. The resulting classes must be both *exhaustive* (covering all relevant cases) and *mutually exclusive* (each case belonging to one class only). Within innovation studies, this methodological approach led to the development of the *Pavitt Taxonomy*, a seminal framework that classifies industries based on the sources, patterns, and trajectories of their technological change.

The conceptual roots of this approach can be traced back to Schumpeter's insights on *technological and structural change*, which later evolved into the *evolutionary approach* to economics. As emphasized by Cefis et al. (2024), within evolutionary economics (Nelson and Winter, 1982; Dosi et al., 1988), innovation is understood as a *path-dependent* process, in which firms rely on their prior R&D efforts and accumulated competencies to guide future technological development. Local search—defined as the exploration of innovation opportunities close to a firm's existing knowledge base—represents the dominant mode of innovation. This localness is influenced by past successes and failures and is reinforced by the firm's *absorptive capacity* (Cohen and Levinthal, 1989).

However, this dependence on existing competences also entails risks. As highlighted in the *fitness landscape* perspective, the interdependencies characterizing technologies and organizations can lead firms along "bumpy" or constrained innovation paths. When technological paradigms shift, firms entrenched in obsolete trajectories may face *competence-destroying innovations* (Tushman and Anderson, 1986). Hence, while the Pavitt Taxonomy and similar classifications help capture the regularities of industrial innovation, they also reflect the evolutionary tension between stability through accumulated knowledge and the disruptions brought by radical technological change.

Innovation in the Agricultural Sector

Within the European Union (EU), the transformation of agricultural systems has increasingly relied on the interaction between multiple actors (farmers, research institutions, firms, and public authorities) operating in shared knowledge and innovation ecosystems (European Commission, 2020).

In Italy, the evolution of agricultural innovation policies reflects these broader European trends. Since the 1990s, the promotion of inter-firm cooperation and territorial governance has led to the creation of Agricultural Districts (nowadays in a broader perspective Food Districts), designed to strengthen local production systems and enhance economies of scale through territorial proximity. These multi-actor arrangements integrate private and public stakeholders to address economic, environmental, and social challenges (Proietti & Cristiano, 2023). Food Districts, formally established under Law 205/2017, represent an institutional framework for collective action that links innovation, sustainability, and rural development objectives. Although initially conceived as instruments of territorial competitiveness, we argue they can increasingly function as operational nodes of the AKIS by facilitating knowledge diffusion and cooperation among farmers, enterprises, and local administrations.

Parallel to this institutional evolution, European and national policymakers have devoted substantial financial and regulatory efforts to support agricultural research, development, and innovation. Public investment in agricultural R&D remains essential due to market failures that hinder private incentives to innovate, including high uncertainty, information asymmetries, and difficulties in appropriating returns (European Commission, 2014). Nonetheless, evidence indicates that both public and private R&D yield significant social and private returns (Vollaro et al., 2021; Anderson et al., 2021; Pray & Fuglie, 2015). As a result, public–private partnerships (PPPs) have emerged as strategic tools for enhancing innovation outcomes. In Europe, since the CAP programming 2014-2020, this approach emerged particularly through policy instruments under the umbrella of the so-called European Innovation Partnership for Agricultural Productivity and Sustainability (EIP-AGRI).

EIP-AGRI, introduced under the 2014–2020 CAP programming period, embodies the "interactive innovation" approach by promoting Operational Groups (OGs) that are multi-actor collaborations involving farmers, researchers, advisors, and firms addressed to develop practical solutions to local challenges pinpointed by farmers (SCAR AKIS, 2019; Guerrero-Ocampo et al., 2022; Maziliauskas et al., 2018). These partnerships illustrate how innovation can arise from the intersection of scientific knowledge and experiential learning, often combining traditional practices with modern technologies to create sustainable value chains. The Italian experience, with more than 780 OGs funded across 21 regions, demonstrates the importance of fostering collaboration across diverse agricultural systems, yet also reveals disparities in innovation performance, coordination, and resource allocation (Giarè & Vagnozzi, 2021; Arzeni et al., 2023; del Puente et al., 2024).

Despite this growing institutional and financial support, the effectiveness of agricultural innovation policies ultimately depends on the capacity of local actors to engage in collaborative arrangements and translate policy incentives into concrete innovation outcomes. Empirical evidence shows that farms' participation in AKIS-related initiatives is influenced by their economic and financial characteristics, knowledge base, and entrepreneurial orientation, highlighting persistent differences in access and capacity to innovate. At the same time, recent analyses of OGs and Food Districts underscore that while farmers increasingly recognize the value of cooperation and networking, key dimensions such as digitalization, advisory systems, and innovation services remain underdeveloped.

Overall, the European agricultural innovation landscape reveals an evolving interplay between policy design, institutional capacity, and local dynamics generating good practices of innovation systems across countries. The continuing effort to build a coherent and effective innovative ecosystem, in which public R&D plays a crucial role and where cooperation, knowledge sharing, and investment converge, remains essential for the modernization and the future of the European agriculture (European Commission; 2025).

Chapter 1

Rethinking agricultural district as an innovation system

1.2 Introduction

The growing emphasis on agricultural production systems and inter-firm cooperation has brought discussion on the efficient processes of learning and innovation in rural areas. Over the years, both the Common Agricultural Policy (CAP) and national policies have expanded interventions to promote cooperation among economic actors and public and private stakeholders within the same territory. Notably in the '90s, regulations on agricultural Districts played a key role in fostering multi-actor arrangements for territorial development. During the last decade national legislators have expanded the term of agricultural districts (D.L. 228/2001, art.13), regulating the constitution of the so called: 'Food Districts' (law 205/2017). These multi-actor arrangements between public and private stakeholders serve as essential tools for supporting local productive systems, particularly in addressing economies of scale challenges by leveraging territorial proximity and deal with environmental and food quality issues faced by farmers.

Meanwhile, the European Union (EU) enforces the CAP which can play a critical role in supporting the innovation ecosystems, while standing away from the view of government as mere regulator of markets or a system failure corrector (Stam, 2015). Over the past century, several EU policy instruments, developed to support the establishment of multi-actor arrangements in the agricultural sector, are anchored in the framework of the "Agricultural Knowledge and Innovation System" (AKIS) (Hall & Clark, 2010; Knierim et al., 2015; Fieldsend, 2021). From this perspective, AKIS is understood as a dynamic learning process that fosters innovation through the interaction of multiple actors who share knowledge among stakeholders (see also Morgan, 2007; Cristóvão et al., 2012; Markow et al., 2023).

The existing literature (Touzard et al., 2015; Spendrup & Fernqvist, 2019; Sutherland & Labarthe, 2022a; Proietti & Cristiano, 2023) shows the important role of AKIS for innovation and knowledge exchange within the agri-food sector, and therefore for local development. Studying several case-study projects[2], the authors of previous works in the literature have assessed the impact of these initiatives by examining their practices, innovation profiles, and innovative activities, as well as their efforts to disseminate and diffuse results to civil society.

[2] To cite some Liaison; ProAKIS; i2connect; modernAKIS.

However, only a minority of them (Proietti & Cristiano, 2023; Sutherland & Labarthe, 2022b) stress the alignment of multi-actor arrangements with the European legislator's objective regarding AKIS, demonstrating a difference in views in terms of supporting services and advisors within the territory to improve innovation.

Those differences are extremely enhanced during transitional periods (towards a clear regulation of modalities and criteria), in which both legislators and territorial entities are less aware of the pivotal roles and goals to have in charge. However, those periods can be "windows of opportunity" (Bodenheimer; 2020) to enhance the main important issues and topics embedded in the economic agents.

Thus, referring on the regulatory transitional period, the hypothesis of this study is to frame 'Food Districts' within the AKIS framework. It highlights the significance of both new and existing cooperation policy interventions and emphasizes the need to understand multi-actor arrangements in the agricultural sector as channels for enhancing AKIS at the territorial level.

Towards this research aims, the study seeks to demonstrate this relationship by analysing the 'Strategic Plans' submitted by 'Food Districts' to achieve formal status recognition during the regulatory transitional period. Our relational content analysis reveals a connection between the objectives outlined in the 'Strategic Plans' and the AKIS, supporting the hypothesis that 'Food Districts' can be conceptually and functionally linked to AKIS.

Evaluating "Food Districts" as facilitators in the implementation of AKIS is of great importance to enable policymakers to grasp the embedded needs in rural communities on the one hand, and to direct them toward main goals for territorial development on the other.

Findings indicate that, during this transitional phase, farmers and local organizations were already aware of the importance of establishing networks, which serve as a crucial driver of innovation, not only for improving farm structures but also for enhancing product valorisation. However, significantly fewer needs were expressed regarding advisory services and digitalization, which remained underdeveloped. Consequently, the legislator's role, beyond providing financial support, should be to encourage greater attention to these crucial areas, thereby enhancing rural development.

Indeed, according to Garcia-Alvarez-Coque et al. (2021), agricultural multi-actor arrangements are collaborative legal initiatives undertaken by agents primarily to enhance networks and access external knowledge, which consequences are reshaping the balance between market, State and civil community (Casula, 2022) for territorial development. 'Food Districts' can serve as valuable tools to support this perspective by fostering interactions among actors and enhancing the innovative capacity of territories. As pointed by Toccaceli & Pacciani

(2023), the complexity and heterogeneity of the agricultural sector have contributed to the lack of a clear legal definition for these entities. This ambiguity highlights the need to situate 'Food Districts' within a broader framework that encompasses innovation systems.

To the best of our knowledge, this study is the first to address this issue, highlighting its originality and contribution to the field by advancing the debate on improving and reconceptualizing 'Food Districts' in response to emerging agricultural challenges which necessitate a boost in innovation and the knowledge-sharing capacity of territories.

The paper is structured as follows. Section 2 overviews the background grounding of Food Districts with references to the theories of AKIS and agricultural districts. Section 3 presents the methodological approach, focusing on data collection on an index of co-occurrences that allows to measure the degree of alignment of strategic plans to AKIS goals. Results, presented in Section 4, are finally discussed from a policy perspective in the last Section 5, which also draws conclusions and suggestions for further research.

1.2 Background

In order to support modernization in agriculture, the European Commission is enhancing the importance of AKIS as 'the combined organisation and knowledge flows between persons, organisations and institutions who use and produce knowledge for agriculture and interrelated fields' (EU Regulation 2021/2115). According to Hermans et al. (2015), the strength of the AKIS concept lies in its consistent promotion of a systemic approach, enabling the mapping and evaluation of constituent actors, network structures, communication and interaction dynamics, and governance interventions in terms of their functionality and performance. The AKIS framework has been widely used for diagnostic purposes across territories, but even though various theories have emerged, they often diverge in identifying system components. Early concepts, such as Blum's (1991) agricultural knowledge system (AKS), focused on research, education, and extension subsystems. Rivera et al. (2005) expanded this by incorporating agricultural producers and support systems. The EU SCAR reports (Poppe; 2012, EU SCAR; 2013) further broadened AKIS to include input suppliers, food processors, retailers, and supporting services. Moving forward, Klerkx et al. (2012) proposed an "infrastructural" view of AKIS, emphasizing actor interactions and governance mechanisms. Knierim et al. (2015) focused on five types of service-providing organizations, with particular attention to advisory services that enable farmers to co-produce knowledge and skills. More recently, Sutherland et al. (2023), building on the principles of assemblage theory, focus on the process of formation recognizing the central role of farmers in the innovation process. This aligns with the work of Berthet & Hickey (2018) and Šūmane et al. (2018), which promote "interactive innovation" and multi-actor settings, where farmers actively participate as co-producers of knowledge.

By the 2010s, AKIS was reframed as a system of innovation (EU SCAR AKIS, 2019), with digitalization playing a key role in enhancing knowledge flows through innovative solutions for knowledge collection, management, and dissemination (European Commission, 2023). In this regard, public interventions play a crucial role in managing the complexity of interactions and coordination among actors by establishing supportive legal frameworks, such as multi-actor arrangements, to enhance collaboration (Hekkert, 2023).

Collaboration has long been a cornerstone in agriculture, a sector where small and medium-sized enterprises (SMEs) face numerous challenges related to economies of scale, division of labour and distribution to the local and international product markets. To address these challenges, various forms of governance have been established among actors to enhance supply chain efficiency (Mantino; 2005). These collaborations (Pacciani e Toccacelli, 2014) range from joint efforts in sourcing inputs (such as labour or capital, including machinery) to the distribution of outputs in both local and international markets (this includes the formation of Consortia or cooperatives aimed at improving product quality and enhancing brand image). This paper specifically examines a key example of legislative efforts to enhance interactions and foster innovative collaborations in rural areas: agricultural districts, which emerged as an adaptation of industrial districts.

Recent findings from the JRC report on Boston-Cambridge Innovation Districts can reinforce the relevance of agricultural districts as AKIS as discussed in the present study. Hence Rissola et al. (2019) demonstrates that place-based innovation ecosystems, when grounded in local assets, coordinated through multi-actor collaboration, and spatially configured to foster interaction, are key enablers of sustainable development. Similarly, the manuscript highlights how 'Food Districts' serve as territorial platforms to strengthen AKIS by fostering network-building, knowledge flows, and innovation at the local level. Drawing on the Boston case, it becomes evident that the spatial organization of innovation actors and their embeddedness in a local socio-economic context is not a marginal condition but a prerequisite for effective knowledge circulation. Similarly, Toccaceli (2015) demonstrates that agricultural districts in Italy, have evolved into governance tools capable of coordinating innovation, local development, and agricultural transformation. These rural districts are not only sectoral grounded but also territorially embedded, linking farms, agro-industrial actors, institutions, and civil society in multi-level governance frameworks.

‘Food Districts’, like urban and rural innovation districts, are thus crucial nodes where firms, public bodies, and civil society interact to co-produce knowledge becoming centre of innovation for rural development, based on local resources (Bravaglieri et al., 2025). They exemplify the transition from sectoral to territorial innovation governance, confirming the strategic value of AKIS in aligning policies with local needs and boosting systemic innovation in agriculture. As in Boston, success hinges on empowering districts as relational infrastructures capable of enabling collaborative learning and locally embedded entrepreneurial discovery. These cases together demonstrate how territorially embedded innovation networks, whether urban or rural, are central to sustainable development. However, the district model has a long history, and scholars are still demonstrating how those models can be meant innovation networks within the rural areas (Stortini, 2025).

The concept of industrial districts can be traced back to Alfred Marshall (1842-1924), who observed clusters of firms in the same area that supported local industrial development. Becattini (1987) further developed this idea, defining the industrial district as a “socio-territorial entity” characterized by a community of people and a concentration of enterprises in a specific area. He highlighted that these districts are not just productive organizations, but also local societies defined by cultural heritage, local identities, values, and both formal and informal institutions (Dei Ottati, 2018; Schilirò D, 2008; Storper, 1993). At the turn of the century (Agenda 2000), the European Commission demonstrates a strong commitment to move beyond traditional agricultural support towards a more holistic rural development policy that actively promoted economic diversification and integrated various sectors. Therefore, the approach of industrial districts expanded its applicability to various sectors, including agriculture, thereby laying the groundwork for the development of district-specific legislation in the agricultural domain (Toccacelli 2012). The concept of rural districts, advanced by Pacciani (2003, 2010) was conceived as a political tool for fostering rural-territorial development in response to the CAP Agenda 2000 reform debates (Buckwell, 1997; Philippidis & Hubbard; 2003). Despite its ambitions, the territorial approach was later subsumed into a sectoral framework, limiting its capacity to address the diverse geographical, social, and economic scales of rural areas (Sotte, 2023). To address these shortcomings, scholars (Brunori, 2022; Torre, 2023; Toccaceli & Pacciani, 2023) highlight the need for a cohesive theoretical framework that integrates productive, social, and cognitive dimensions, moves beyond sectoral translations of industrial models, and supports zone-specific agricultural policies (Copus Andrew & van Well, 2015; De Rosa & Turri, 2004; Musotti, 2004).

Recent scholarship has increasingly framed districts as strategic enablers of innovation, emphasizing their role not merely as sectoral clusters but as place-based governance models embedded in specific socio-economic contexts. Yigitcanlar et al. (2020) highlight how such districts catalyse private innovative investments by functioning as hubs of concentrated economic activity, where innovation, and entrepreneurship intersect to produce synergistic growth. Building on this perspective, Rissola et al. (2019) argue that innovation districts should be understood as spatial configurations that integrate economic and social development objectives within broader territorial strategies. Rather than focusing solely on sectoral specialization, these districts support multi-scalar planning efforts aimed at regenerating entire urban or rural areas by fostering cross-sectoral collaboration and embedded knowledge flows (European Commission, 2024).

Recognizing the evolution of agricultural districts, the Italian legislator is regulating them within a broader framework that moves beyond a sectoral approach toward a territorial perspective, emphasizing the importance of funds for collaboration and the diffusion of innovations to local development (Gazzetta Ufficiale, Art.4, com.1. decreto 17 Settembre 2024 n. 288).

In Italy, the concept of districts has always been linked to innovation. First regulated by Law n. 317/1991 to promote innovative solutions for SMEs, they have a long-standing tradition in Italian agriculture. However, in Italy, the 21 Regions and Autonomous provinces have independently legislated about the implementation of districts, resulting in diverse definitions and operational frameworks. Thus, in 2017 (Gazzetta Ufficiale; art. 499, Legge 27 dicembre 2017, n. 205), 'Food Districts' were nationally regulated to provide a more comprehensive framework for these entities, refining the classification of districts previously established under Legislative Decree n.228 in May 2001 (art.13).

Scholars realize that new agricultural paradigms and emerging challenges have revealed that the traditional role of agricultural districts is no longer sufficient to support territorial development (Brunori et al., 2013). As in Toccacelli and Pacciani (2023) the old Districts need to be "relaunch" in accordance with current policies allowing the whole sector toward a just transition within territories. These entities have been recognized to support interactions among actors and to foster innovation, increasing local development, avoiding quality dispersion (of products and processes) in the agri-food sector (Caputo et al., 2020)

In this context, in 2019 the Italian Ministry of Agriculture established a formal agreement to fund ‘Food Districts’. Then, the Legislator has broadening de facto the concept of 'Food District' which, according to the more recent law (art.4; comm.1 decreto 17 Settembre; 2024) aims to advance territorial development, social cohesion, and inclusion by fostering collaboration and integration among local activities and stakeholders. The district fosters sustainable agriculture, innovation, and digitalization, reorganizing relationships to improve market dynamics, share knowledge, adopt technologies, and promote local products for collective growth and environmental preservation.

Despite the strong commitment of the regulator, ‘Food Districts’ fall short in supporting a broader vision for Italian territories (Tarangioli et al, 2024), often overlapping their initiatives with other entities within the local community (Pecqueur et al., 2024) and lacking a clear vision and objectives for local development, as discussed by Toccaceli & Pacciani (2023).

Building on the ongoing debate, the present study emphasizes the need to rethink traditional forms of governance and collaboration through the lens of the AKIS framework. By framing 'Food Districts' within this framework, the study aims to enhance these forms of governance as valuable tools in supporting innovation and knowledge-sharing within rural areas as perceived by the legislator. The analysis of ‘Strategic Plans’ submitted after the 2017 law and before the 2024 regulation, is of great importance in order to enhance embedded needs of territorial actors, that are reinforced by the legislator, and topics less predominant that should be promoted by the legislator to support rural development.

1.3 Materials and Methods

The research question of this study calls for a qualitative approach. Grounded Theory (Glaser & Strauss, 1967) has been followed to analyse documents that ‘Food Districts’ have presented to the Regions to be formally recognized. According to Glaser (1999), Grounded Theory refers to a specific methodology able to produce a multivariate conceptual theory from systematically collected data. This method consists of several inductive strategies for analysing data and not of a preconceived concept or hypothesis (Zhang et al., 2023). It is an emergent process that involves several non-sequential steps in which the researcher continuously moves between them. To achieve information, documents are analysed with an open coding process: coding refers to the process of conceptualising data. It is a form of content analysis that is used to find and conceptualise the underlying issue amongst the documents (Allan, 2003).

In this study, data are selected on the basis of their accessibility, considering that these documents are not publicly available and are archived by Regions or Ministry, therefore are difficult to obtain. Hence, the data collection is based on a convenience sample of 'Strategic Plans' redacted by the 'Food Districts' in order to obtain their recognition by Regions. The Italian Ministry supports 'Food Districts' through the possibility of accessing dedicated funding, through calls issued by each of the 21 Regions and Autonomous Provinces. Data collection has proceeded has as follow: researchers have contacted, in February 2021, the Departments of several Italian Regions to request the Documents of the 'Food Districts'; 28 have been collected out of the 65 recognized in until February 2021.

In line with Bengtsson (2016), if the aim of the investigation is too broad, the risk of touching upon too many aspects may preclude the researcher reaching the desired depth of the studied phenomenon. Therefore, researchers have recognized the importance to focus on two types of 'Food Districts', so called Rural Districts (DIR) and Quality agri-food district (DAQ), defined be the legislator (Law n.205 of Dec. 27, 2017, com. 499)3. Thus, the 6 "Organic Districts" (a specific type of 'Food Districts') also have been excluded from the analysis4; in addition, 3 other Documents have been excluded because their reporting was not compatible with this kind of analysis or due to different format of the documents required. Accordingly, the 19 remaining documents represent the convenience sample of the research. They are formally named: 'Scheme for the submission of the District Plan' (7 documents); 'Final District proposal' (2); 'Territorial Economic Plan' (9) and 'Food District Plan' (1). The documents were mandatory to achieve the recognition by a Regional Law, unfortunately they are not structured in a homogeneous scheme. Therefore, only the sections concerning strategy are being analysed. The sections considered are comparable also in terms of length, indeed they stay in a range between 3000 and 5000 characters.

The analysis process is carried out by coding the 19 Strategic Plans of 'Food Districts' with an open coding method. The analysis has been drawn down in several parts. Firstly, the data are open coded to create items without a preconceived concept according to Hull (2013), in parallel all the analysis is supported with memo-writings, written by researchers in order to specify and elaborate codes and aspects of the process. This allows to conceptualize or to note

[3] DR and DAQ are interconnected respectively to rural aspects within the areas involved, and certified (or pivotal) foods aspects within the areas involved.

[4] According to the national the Law n.205 of Dec. 27, 2017, com. 499; Organic districts are a specific case of Districts designed to improve an organic view in local areas. Hence, 'Strategic Plans' and their goals are mainly focused on organic and environmental aspects. Thus, to avoid any form of bias in the perceptions of strategies, those models are excluded.

important process facets of the analysis. To increase reliability, following Abbate et al. (2023) and Tahmasebi et al. (2020) which use this analysis for the agricultural sector, the approach employs a continual to-and-fro between data collection, coding, memo-writing, from which analysis emerges. At the same time, to increase validity, the process of coding starts randomly (with the 'Penisola Sorrentina e Costa d'Amalfi' one) in order to minimize any bias (of order or chronological) and to facilitate a process of distancing the researchers from the text as the Grounded Theory requires. The sections are coded in English to avoid any translation bias at a later time, and to facilitate the process of analysis. Then, documents have been re-analysed repeating the process several times by several researchers; re-evaluating codes; splitting existing ones and creating new ones until saturation as in Charmaz & Thornberg (2021). Concerning the overall codes, they reflect maximum a paragraph and minimum a sentence of the section. Sometimes sentences are coded with more than one code due to the aim of the documents. It is important to note that the sections analysed were versions prepared to meet the requirements for the recognition of 'Food Districts' under Regional Law. Consequently, the text is structured as a response to open-ended questions but is presented in a summarized and concise manner, deliberately avoiding any spontaneous or unstructured flow of words. This approach ensures that the concepts are clearly synthesized to align with the expectations of the regional authorities.

Considering the validity and reliability of the research, the coding process evolved from an initial set of 11 codes to a final set of 58 codes, capturing key themes in the perception of 'Food Districts.' These codes were subsequently analysed to identify specific topics, according to Armborst (2017), which discuss the purpose of the analysis of thematic proximity: to identify latent patterns in the text that cannot be understood by simply reading it.

Then, in order to verify the hypothesis of the study, according to which 'Food districts' can be framed into an AKIS perspective; the so-called relational content analysis is performed supported by the Jaccard Index, which measures the degree of co-occurrence between codes. The analysis aims at identifying relations between two different units (Bos & Tarnai, 1999), by analysing the frequency and pattern of theme co-occurrences within a given set of documents (Creamer, 2021). Co-occurrences happen every time two codes appear in the same Document. Thus, to evaluate co-occurrences the Jaccard Index is estimated in this analysis. The J-index is used to evaluate the perception of 'Food District' in the implementation of an AKIS. Thus, the 'AKIS' code is taken as the target to which every code is related. The formula in notation is:

$$J = \frac{n_{12}}{(n_1 + n_2) - n_{12}}$$

with n_1 = the number of occurrences of Code A (in our analysis 'AKIS'), n_2 = the number of occurrences of Code B (in our analysis, the other codes in Figure 1), and n_{12} = the number of co-occurrences of both codes. It compares codes from Documents to evaluate those which are shared and those which are distinct with the target code 'AKIS'. It is a measure of similarity with a range from 0 (indicating perfect independence between the two codes) to 1 (indicating perfect relation between the two codes). The higher the percentage, the more similar are the two codes.

1.4 Results

Findings point out the number of words involved by each code per Document. Globally, 17.193 words have been coded in the Documents. This allows to evaluate the percentage of word count utilized per code. In this sense, the weight of each code can be summarized by comparing the percentage of word count with the code frequency in the overall view, within the 19 Documents analysed. Stating the number of Documents in which the code is present, it demonstrates the importance given by 'Food Districts' to each single item, displaying the different preferences among the institutions through the territory. Comparing the percentages of word count with the frequency of each code, it is possible to evaluate the labels more frequently used as compared with those less present in the Documents. Figure 1 shows the comparison among both.

Within the range between 4% and 5%, 'Network building' and 'Territory valorisation' are present both for words count percentage and codes frequencies percentage. Under the level of 4% up to 3%, two more codes are identified for both measures such as: 'Product valorisation'; and 'Environmental impact'. Evaluating only the percentage of word counts, 'Cohesion with European policies'; 'Stimulate innovation process'; 'Territory identity' and 'Integrate fragmented value-chains' are identified in this range.

Thus, in terms of number of words labelled, 'Network building' involves the highest number, while in terms of appearance in the text, 'Network building' and the 'Territory valorisation' are more present in Documents. This indicates the weight of Districts aimed to revitalize rural areas in the analysis. In contrast, less present codes in terms of percentage of number of words and code frequency are distributed as follows. Less than 1% are:

‘Mediterranean Diet’; ‘Digital’; ‘Citizen as promoter of strategies’; ‘Access to credit’; ‘Tourism diversification’; and ‘Access to innovations’. Among them, it is remarkable that ‘Food Districts’ devote little attention to ‘Digital’ aspects in their strategies.

The analysis goes beyond the merely description of the topics emerged from the documents. In line with this perspective, in this study, we adopted a relational content analysis approach employing the Jaccard Index to quantitatively assess the co-occurrence of thematic codes across documents. This analysis enables to investigate the connection among topics and a specific code, which in the case of the study refers to ‘AKIS’ code. This analysis is formulated to question the perception of ‘Food Districts’ and the topics related to AKIS within the territories. Thus, the J-index presented in Section 3 is estimated highlighting the co-occurrences regarding the ‘AKIS’ code as the target. Table 1 illustrates the different codes related to ‘AKIS’; they are ordered by level of intensity.

As shown in Figure 2, the Proximity plot evaluates the co-occurrences of the single code with the targeted, using the Jaccard index. In this plot, all measured distances are represented by the distance from the 0 point. The 0 point represents absence of similarity of co-occurrences. As illustrated in Figure 2, the relationship with 'AKIS' is determined based on the co-occurrence of both codes within the same cases. Accordingly, ‘AKIS’ code has strong relationship with ‘Network building’; ‘Improve firms’ structures’; ‘Stimulate innovation process’ and ‘Shared policies’ (more than 55%), while minor interaction is shared with the ‘Human Capital’ and ‘Social objectives’ that would actually be more appropriate for the ‘AKIS’ linkages (46%). Unexpectedly, the data show that ‘Digital’ and ‘Advisory services’ do not share relationships with the ‘AKIS’ code; it demonstrates a low perception by District plans about the relationships with those issues (33%).

1.6 Discussion

The goals pursued by the agricultural district are assessed by analysing 19 ‘Strategic Plans’ of ‘Food Districts’ formally recognized until February 2021 with law 205/2017. This regulation transitional period is interesting for identifying topics deeply embedded in agricultural district perception, as clear definitions and criteria to identify those entities were still not strictly regulated by the legislator. Thus, the analysis demonstrates the awareness of ‘Food Districts’ perceiving themselves as central tools in the improvement of ‘Network building’. Moreover, the necessity to establish ‘Food Districts’ as organizations related with ‘Territory valorisation’ is also highlighted. In this sense, it can be confirmed that the logic of the legislator in recognizing ‘Food Districts’ as important entities to generate interactions and relation with the territory and the communities in order to ‘Stimulate innovation processes’ is achieved. Furthermore, the perception of districts as models useful to improve the environment, in terms of landscapes, quality of products and of food-chains (Annosi et al., 2022), emerges in their strategies under the codifications of ‘Environmental impact’, ‘Product valorisation’ and 'Integrate fragmented value-chains'. As a consequence, the socio-territorial entities which are driven by the interaction of tangible and intangible assets to which the community belongs (Roberts W.; 2024), are recognized as central by the overall communities in the local areas, potentially recalling the Becattini (1989) view of the district model in fostering the local social capital.

Furthermore, also in terms of a learning process, those organizations perceive themselves as facilitators. In fact, even though a 'learning' code does not emerge from the analysis of the ‘Strategic Plans’, other codes point out the dimension of learning such as ‘Stimulate innovation processes’ and the more highlighted ‘Network building’. Those codes demonstrate the necessity of a vision for a cumulative knowledge that enables learning processes (Knickel et al., 2009; Moschitz et al., 2015).

In contrast, the necessity of a rural tourism improvement does not emerge from the analysis of the strategic documents with low attention in seeking goals such as ‘Tourism diversification’ without relating this in a vision of ‘Multifunctionality’. Furthermore, regarding the issues that have been considered less frequently, it is important to pinpoint that ‘Mediterranean diet’ is a goal highlighted only in the southern Italian ‘Food Districts’; mostly in those recognized in the Cilento area5. At the same time, the necessity to achieve ‘Access to credit’ and ‘Access to innovation’ does not emerge, possibly because those entities access specialized funds also dedicated to innovations through the so-called District agreement regulated by the Agricultural Ministry.

Unexpectedly, ‘Food Districts’ underline a lower centrality of ‘Digital’ issues in their objectives. This could be due to inexperience in implementing digitalization processes in marginal areas. In order to avoid any perception bias, the analysis focuses also on a relative index.

Hence, although topic frequency is a useful tool for demonstrating the goals of these entities, it should be noted that the ‘Strategic Plans’ are either updated versions of pre-existing

[5] This area is recognized globally as the home of the Mediterranean diet thanks to the studies of Ansel Keys

agricultural districts6 or new ones submitted to be formally recognized by Regions as "Food Districts" according to the 2017 law. Therefore, topic frequency does not fully determine the importance of the issues in the documents, but it is a good tool for ranking those topics that have been embedded and deeply perceived as essential by rural economic agents, without the need for these topics to have been defined by top-down regulation.

In a similar way, the study aims to demonstrate how 'Food Districts' could be interesting policy tools in the implementation of AKIS, as indicated by the analysis. Hence, the relational content analysis quantifies with the Jaccard index a connection among topics derived by the 'Strategic Plans' and the AKIS view. The Jaccard index highlights that 'Food Districts' are distinctly recognized as socio-territorial entities with a strong focus on building networks that engage not only farmers and firms, but also citizens for a stimulus into innovation. Nevertheless, as expected, their perceptions of implementing a 'space' for knowledge and innovation diffusion, in an AKIS view, do not emerge. In this view, this dimension could be increasingly supported by the legislator, who could identify agricultural district as place-based systems promoters of innovations for rural development.

In this direction, in revising policy measures, it could be discussed that policymakers consider incentivising or promoting the inclusion, in the strategic goals of 'Food Districts', of all AKIS dimensions, some of which are deeply embedded in the perception of these entities.

1.7 Conclusions

The present study aims contributing to the discussion about agricultural districts as a tool to achieve development in a systemic way. In our focus, the hypothesis is to settle 'Food district' in the framework of AKIS, to stress linkages between multi-actor arrangements policies and the AKIS framework. 'Food Districts' appear valuable tools in the implementation of AKIS within the territory in order to diffuse innovation, because the collaborative, learning and innovation dimensions were already perceived by these organizations also before their main regulation. However, our analysis demonstrates that the agricultural districts fail to integrate assets that a modern approach to innovation needs, such as digitalization.

Multi-actor arrangements have proven to be effective tools for advancing agricultural development (Maryono et al., 2024). Recognizing this, the European Union emphasizes the importance of implementing agricultural innovation systems that foster knowledge sharing and

[6] Some of which were already established as DIRs or DAQs.

collaboration among stakeholders (Arenal et al., 2021; European Commission, 2019). Since before this theoretical framework was affirmed, several forms of organizations have appeared. In Italy, the district model has spread from manufacturing to other sectors, such as the agricultural one, meeting the necessity to implement new forms of organization among actors (Garofoli, 2002). In 2017, the legislator implemented the so-called 'Food Districts', considering them as a multi-actor arrangement tightly related to the territory and the food production. These organizations are recognized by the legislator to have an important role in the development of supply-chains through sharing knowledge and spreading innovations among supply chain actors in the Italian Regions. Nevertheless, the interconnections that these new forms of organization could generate with other actors and entities in the territory, are not well-defined (Toccacelli, 2015). The heterogeneity among regional goals and laws, led to the complexity of agricultural districts, the discussion and the comparison of them with other collective law is rarely explored. Pacciani and Toccaceli (2010; 2024), have deeply investigated these relationships underlying a similarity between the district model principles with other collective oriented policies. This study builds on the ongoing discussion, emphasizing the connections between the district model in agriculture and the AKIS framework.

The present analysis has explored data about the Italian 'Food Districts' using a sample of their 'Strategic Plans' in order to seek a relation with the AKIS framework. Firstly, the analysis quantifies the significance of 'Food Districts' objectives across Italy and reveals potential divergences between the Legislator's envisioned goals and those declared by the district organizations. This analysis points to several aspects that policymakers may consider in order to let the 'Food Districts' strategies and Legislator's objectives converge. Secondly, it stresses the relevance of assessing 'Food District' in a broader framework to enhance innovativeness and knowledge-sharing within the territories in the AKIS view.

Results show that thematic as 'Network building'; 'Territory valorisation'; 'Product valorisation'; and 'Environmental impact', coded in the policy documents, are endorsed by 'Food Districts'. At the same time, the importance given to the 'Integration of fragmented value-chains' and to 'Stimulate innovation process', indicates that the horizons and missions of these organizations are still coherent with European policies, particularly the 2022-2027 programming of the Common Agricultural Policy.

Pacciani (2003), highlighted the district as a blueprint for agri-food districts that foster local development, emphasizing institutional strategies for resilience through service provision, professional training, and inter-firm cooperation stressing the role of institutional bridges in promoting system learning and innovation.

Within this context, the district model could serve as a key legal and organizational system for incentivizing AKIS structures at the territorial level. It enables communities to organize themselves to drive innovation, emphasizing the importance of considering the diverse and heterogeneous nature of the firms involved (Giuliani, 2007), fostering for training and education for an effective knowledge flow within innovation networks (López-García et al., 2022; Roberts, 2024). The Jaccard index results, in Table 1, confirm this view demonstrating that 'Food Districts' relate AKIS to the need of generating processes of learning and innovation supporting infrastructure, integration of value-chains and networks. The relationship between agricultural districts and AKIS emerges as pivotal for promoting a holistic, place-based approach to rural development, one that integrates economic, environmental, and social sustainability dimensions. By fostering multi-actor collaboration, knowledge sharing, and territorial cohesion, this relationship contributes to overcoming the traditionally fragmented and sectoral governance of rural areas. The ‘Food District’, introduced by the Italian government, represents a concrete policy tool that translates these principles into practice. Positioned at the intersection of innovation policy, rural development, and agro-industrial strategy, ‘Food Districts’ function as territorial platforms that could operationalize AKIS, facilitate systemic innovation, and strengthen the capacity of local actors to co-develop solutions adapted to their specific socio-economic and ecological contexts. Thus, while the strategies of ‘Food Districts’ align with theoretical models for agricultural territorial development, the analysis also uncovers additional relationships between AKIS and ‘Food Districts’ that deviate from more recent rural development theories. Indeed, more recent literature emphasizes that the implementation of AKIS is crucial not only to improve infrastructures but also for enhancing digitalization within territories (Klerkx et al., 2019; MacPherson et al., 2022). However, the role of advisory services and digitalization remained underdeveloped. As a consequence, the role of the legislator, beyond mere financial support, could be to solicitate greater attention from farmers to these critical issues in order to strengthen rural development.

Ultimately, this transitional period is crucial in understanding how the development goals rooted in local needs emerged from the bottom, rather than being imposed from above.

This study has a main limitation which may be suggestion for further research: the sample, focusing on the regulation transitional period of ‘Food Districts’, could be expanded to analyse their modifications and evolution over time.

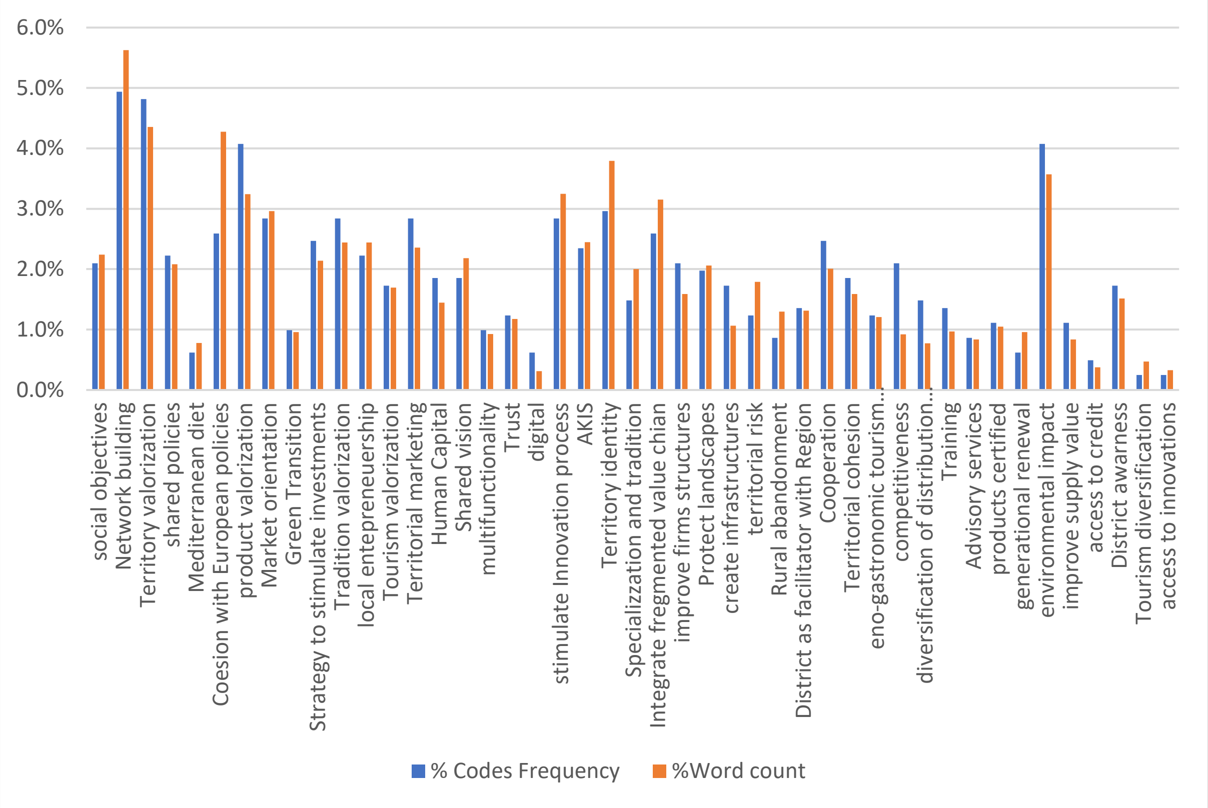
In conclusion, policy-makers should adopt a clearer overall framework and enable actors to implement plans more in line with a systemic approach, monitoring policies throughout the entire process. The present study contributes to the literature by emphasizing the similarities between the AKIS framework and the 'Food District' model. It identifies a still traditional, outdated perspective on AKIS, which focuses on firm infrastructures in rural areas, and that overlooks the issues of digitalization. This finding is of significant relevance for future research, encouraging further studies to explore and identify barriers to digitalization in rural areas, not only from the perspective of Food Districts. We can conclude, accordingly with Giuliani (2024), emphasising the role of regional development policies with socio-environmental conditionalities to create socially and environmentally “safe spaces” for the whole community.

Summary

The European Union ensures the ‘Agricultural Knowledge and innovation System’ (AKIS) framework trough policy tools such as multi-actor arrangements. The paper focuses on a notable example of the efforts made by the legislator to foster interactions and innovative collaborations in Italy: the so-called ‘Food Districts’; established to support interactions among actors and to increase local development in the agricultural sector. Thus, referring on the regulatory transitional period, the hypothesis of this study is to frame ‘Food Districts’ within the AKIS framework. implementing a Grounded Theory on regional ‘Strategic Plans’. Findings indicate that, during this transitional phase, farmers and local organizations were already aware of the importance of establishing networks, which serve as a crucial driver of innovation, not only for improving farm structures but also for enhancing product valorisation. However, significantly fewer needs were expressed regarding advisory services and digitalization, which remained underdeveloped. Consequently, the legislator’s role, beyond providing financial support, should be to encourage greater attention to these crucial areas, thereby enhancing rural development. Results confirm this view, demonstrating that 'Food Districts' relate AKIS to the need of generating processes of learning and innovation supporting infrastructure, integration of value-chains and networks.

Chapter 1: Tables and Figures

Figure 1 Comparison between percentage of Codes Frequency and Word Count



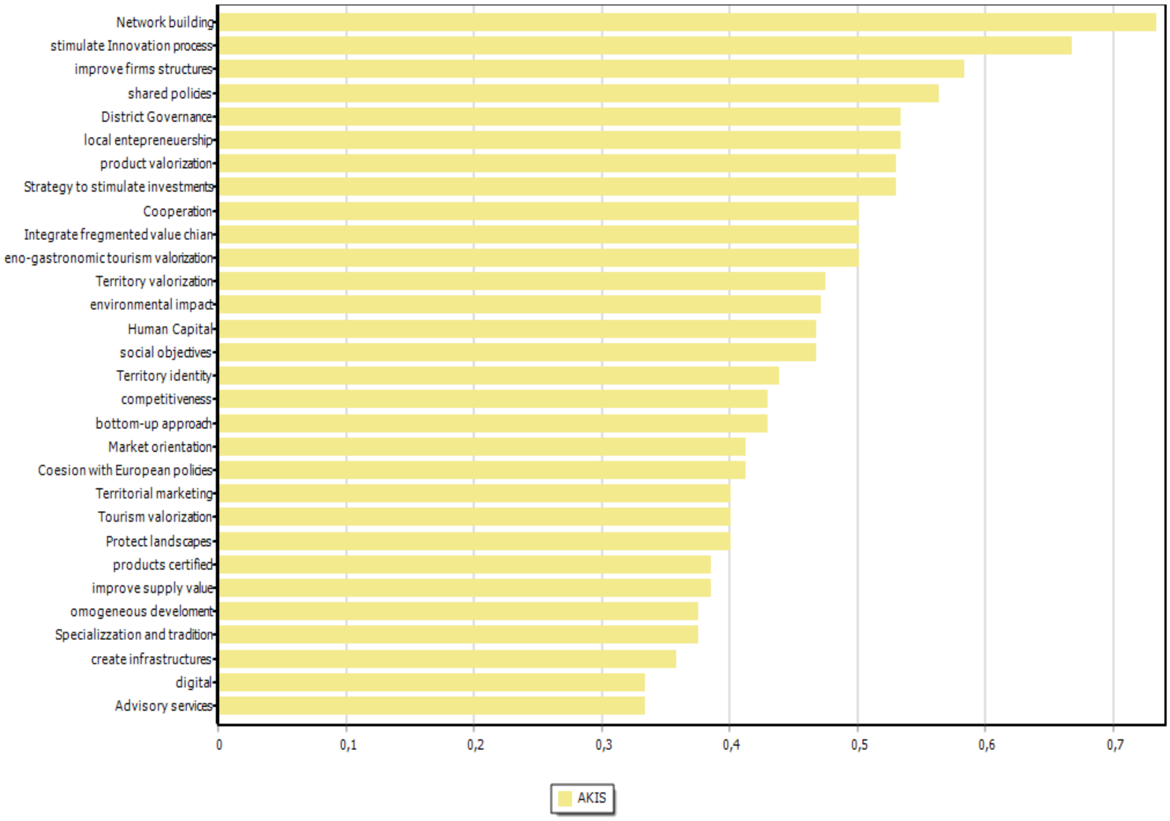
Source: our elaboration. Note: This table presents the frequencies of word count and the percentage of Items (codes). Per each item with a low presence (<0,2%) in 'Strategic Plans' are hidden

Table 1 Jaccard Index co-occurrences in respect to AKIS code.

TARGET	CODES	CO-OCCURS	DO NOT	IS ABSENT	Jaccard	STRENGTH
AKIS	Network building	11	4	0	0,733	
AKIS	Stimulate Innovation process	10	4	1	0,667	
AKIS	Improve firms' structures	7	1	4	0,583	
AKIS	Shared policies	9	5	2	0,563	
AKIS	District Governance	8	4	3	0,533	
AKIS	Local entrepreneurship	8	4	3	0,533	
AKIS	Product valorization	9	6	2	0,529	
AKIS	Strategy to stimulate investments	9	6	2	0,529	
AKIS	Cooperation	8	5	3	0,500	
AKIS	Integrate fragmented value chain	9	7	2	0,500	
AKIS	Eno-gastronomic tourism valorization	6	1	5	0,500	
AKIS	Territory valorization	9	8	2	0,474	
AKIS	Environmental-impact	8	6	3	0,471	
AKIS	Human Capital	7	4	4	0,467	
AKIS	Social objectives	7	4	4	0,467	
AKIS	Territory identity	7	5	4	0,438	
AKIS	Bottom-up approach	6	3	5	0,429	
AKIS	Competitiveness	6	3	5	0,429	
AKIS	Market orientation	7	6	4	0,412	
AKIS	Cohesion with European policies	7	6	4	0,412	
AKIS	Tourism valorization	6	4	5	0,400	
AKIS	Territorial marketing	6	4	5	0,400	
AKIS	Protect landscapes	6	4	5	0,400	
AKIS	Improve supply value	5	2	6	0,385	
AKIS	Products certified	5	2	6	0,385	
AKIS	Specialization and tradition	6	5	5	0,375	
AKIS	Homogeneous development	6	5	5	0,375	
AKIS	Create infrastructures	5	3	6	0,357	
AKIS	Advisory services	4	1	7	0,333	
AKIS	Digital	4	1	7	0,333	

Source: our elaboration (e.g. in order to read the table in terms of the formula used: n12= co-occurs; n1 = (co-occurs) + (is absent); n2 = (co-occurs) + (do not). NOTE: codes with a J-index less than 0,31 are hidden

Figure 2 Proximity plot targeting 'AKIS' item



Source: our elaboration from Jaccard index results

Chapter 2

Farm to tech: evidence on the demand for R&D subsidies in Italian agriculture

2. Introduction

The financing of R&D and innovation activities in agriculture is particularly vulnerable to market failures. These failures largely stem from the intrinsic uncertainty surrounding innovative projects, the difficulty innovators face in fully appropriating the returns from their efforts, and the pervasive issues of asymmetric information and moral hazard in the relationships between borrowers, lenders, and equity investors (European Commission, 2014). Despite these challenges, substantial empirical evidence suggests that R&D investments in food and agricultural research systems produce new knowledge and technologies that fuel improvements in agricultural productivity (K. Fuglie, 2018). European countries are increasingly promoting R&D investments to establish public-private partnerships as a strategic tool to maximize the impact of those investments for innovation investments and knowledge transfer (Fieldsend et al., 2021). According to Zilberman (2022), this can lead to the constitution of borders *innovation supply chains*, which are essential in the agricultural sector because they enable the transformation of scientific discoveries into scalable, market-ready solutions, aligning production with consumer needs, enhancing efficiency, and fostering resilience especially under risk, regulatory constraints, and evolving global demand.

EU countries implement this view with national and regional rural development Programs (RDPs), which are co-financed by the European fund for rural development (EAFRD) and national budgets, in order to establish public-private partnerships framed in the so-called Agricultural Knowledge and innovation System (AKIS). The European Commission, with a budget amounted to roughly €100 billion for the 2014-2020 programming period, invests in technology transfer and innovation systems in the agricultural sector implementing several measures to establish, according to Touzard et al. (2015), strong AKIS in order to better connect science and practice and to boost knowledge exchange and innovation for the benefit of European farmers and foresters (EU SCAR AKIS; 2019).

There is substantial evidence AKIS play a critical role in fostering innovation in agriculture (Spendrup & Fernqvist, 2019), facilitating the adoption of new technologies and practices (del Puente et al., 2024; Guerrero-Ocampo et al., 2022), and supporting sustainable rural development, particularly in relation to food security, landscape preservation, and social innovation (European Commission, 2024; Robinson, 2024; Maziliauskas et al., 2018).

A great example of AKIS cornerstone is the Operational Groups (OGs), which support the development of innovations by groups of relevant actors in a bottom-up manner. Those multi-actor partnerships epitomise the interactive innovation approach. At least in principle, agricultural partners in OGs are not mere adopters of a new product, technology, or organization form, but play an interactive and possibly a proactive role in the process.

An interesting dataset on Italian OGs has been compiled by Arzeni et al. (2023), based on responses to an online survey by respondents belonging to 10 OGs localised in 6 different regions. Among the questions, one focused on the role played by OG partners within the projects. Statistics reported by Arzeni et al. (2023) show that farmers in over 20% of the cases were the promoters of OGs; 20% of them facilitated the diffusion of the innovation, but the large majority (more than 40%) engaged in experimentation of the proposed innovation. Moreover, in 77% of cases, farmers were consulted during the project design stage in order to analyse innovation's needs.

Hence, participation to OGs can be seen as a proxy for innovative efforts by farmers, although it should be clear from the cited evidence that not all farmers provide the same contribution to the outcomes of OGs, and their participation is often passive, and indeed, the interactive innovation perspective allows for a *division of innovative labour* among partners in a multi-actor arrangement.

European Commission is increasingly emphasizing the central importance of AKIS measures as a cross-cutting objective in order to promote knowledge, innovation and digitalization among farmers. Particular attention is given by public authorities, to describing knowledge flows among the individuals and organizations participating in AKIS, as well as to clarifying how advisory services and research institutions collaborate with farmers (EU SCAR AKIS; 2019).

However, this focus raises important questions regarding who the farmers involved actually are. This point European Commission and Member States assess AKIS effectiveness without adequately accounting for the characteristics of the actors engaged in these systems.

Thus, this study aims to identify the type of farmers involved in AKIS measures, recognizing the characteristics that may either facilitate or hinder their participation in achieving the goals of knowledge sharing and innovation, being active in R&D in agriuclture.

Our analysis builds on the assumptions outlined in the economic literature using a large and rich dataset on Italian farmers called Farm Accountancy Data Network (FADN). This dataset enables us to disentangle the economic and financial characteristics of farmers who benefited from AKIS-related measures during the 2014–2021 CAP programming period.

We assume farmers who report having received public support under AKIS related Measures: 1, 2, 16 and 19 in the FADN dataset can be considered as active in R&D, although it's important to underline that information alone does not clarify how autonomous they were in the innovative process (e.g. recruiting research institutes to solve a problem they did identify vs. being recruited by research institutes to experiment a new product or process).

Moreover, while the network of actors described by the World Bank (2006) which "focus on bringing new products, new processes and new forms of organizations into social and economic use, together with the institutions and policies" have considerable attention in literature, how actors "affect their behavior and performance" in participating, remain insufficiently measured. More reliable estimates evaluating farms' behavior engaging in R&D policies would be valuable in guiding public investment decisions.

Therefore, understanding which economic and financial features of agricultural firms affect their decision to participate in AKIS-related policies, and therefore to pursue innovations through multi-actor arrangements is crucial for providing valuable insights to policymakers. We estimate econometric models on a dataset of the Italian FADN (Farm Accountancy Data Network), including the "public-aid" dataset that allows identifying farms that were beneficiaries of the Measures under evaluation, namely Measures 1, 2, 16 and 19. The dataset involves several balance-sheet variables that we employ as explanatory variable in logit models of the probability to participate in AKIS and related innovation-oriented measures. The explanatory variables are selected having in mind hypotheses concerning the role of farm size, its economic efficiency and profitability, its knowledge base and the entrepreneurial age and sex on the propensity to take part in multi-actor arrangements for innovation.

Section 2.2 descends from the economic literature, the main hypothesis that for the Authors can impact the participation of farmers to AKIS initiatives. Following Section 2.3 described dataset and variables used for the analysis explained deeper in Section 2.4. Findings in Section 2.5 are finally Discussed in Section 2.6. Main Conclusions for both theoretical and political aspects are revised in Section 2.7.

2.2 Previous literature

Radical technological and organizational solutions are needed to address a sustainable transition in agriculture favored by the implementation and definition of network models (Brunori et al., 2013) such as the Agricultural and Knowledge Innovation System (AKIS). Supporting the adoption of innovations through AKIS has been one of the main issues addressed by the European Union's structural policies for the competitiveness of farms and rural areas (Mirra et al., 2020). In fact, multi-actor arrangements, stressing the importance of knowledge-sharing among parties, are thus powerful tools in improving innovation within the agricultural sector (Garcia-Alvarez-Coque et al., 2021). Therefore, investment in knowledge sharing is recognised as a primary driver in the creation and diffusion of innovation (Cristóvão et al., 2012).

The AKIS concept has increasingly been conceiving attention by the European policymaker and has been operationalized and regulated during the programming period of the Common Agricultural Policy 2014-2020. In order to establish innovation-systems and paving the way of creating multi-actor arrangements, the Rural Development Program (RDP), within the several European Member States, address specific innovation-systems related Measures: to implement knowledge transfers among actors (measure 1); advisory services to improve adoption (measure 2); and establish the creation of public-private partnership for innovation (Measure 16 and 19).

Studies in literature cover aspects of farmers' interaction among actors in AKIS partnership, mostly from the sociology and psychology fields (to cite few Brand and Blok, 2019; McAdam et al., 2018; Carayannis & Campbell 2009; Etzkowitz & Leydesdorff, 2000). Hermans et al. (2015), analysing innovation-systems, found that social interactions are tackled by lack of funds, combined with horizontal and vertical fragmentation and the lack of proper evaluation criteria. The Authors suggest promoting policies to regulate and incentives collaboration and social learning. In another study, using Social Network Analysis (SNA), Hermans et al. (2017) investigate the collaborative efforts and interactive linkages between actors involved presenting a strong fragmentation among different countries. Similarly, Charatsari et al. (2024) reported a framework to illustrate stakeholder engagement based on trust to strengthen interactions. In that fields, while some projects develop instruments to accelerate AKIS implementation within the territories (Cristiano & Proietti, 2018), others evaluate their interaction with entities within the territory, as Knierim & Prager (2015), which present a comprehensive view on EU countries AKIS' implementation, revealing the fragmentation and decentralization of it in some countries (as in Greek, Portugal, Romania, Italy and Spain) due to different resources availability. Most of those studies show the essence of co-innovation among actors in these multi-actor partnerships (Fieldsend et al., 2020) and their relationship with actors' dynamic capabilities of larger farmers (Teece; 2007). The contribution of this strand of literature lies in rethinking innovation in the agricultural sector from a broader perspective. Therefore, innovation is neither isolated nor occurs with isolated change agents but can be “co-produced” among the interaction between farmers, researchers and intermediate stakeholders. In this sense, actors collaboratively identify problems and co-develop solutions through a collective learning process based on knowledge exchange (Fieldsend et al., 2021). These aspects requires understanding the types of farms that participate in collaborative initiatives, in order to provide policymakers with insights to better target their support efforts and enhance the effectiveness of public R&D and AKIS-related subsidies.

Following, to support our hypothesis, although, to the best of our knowledge, no studies have specifically examined farmers’ behavior in leveraging AKIS-related policy measures, we rely on a substantial body of literature that has addressed the broader issue of the effectiveness of R&D subsidies for small and medium enterprises (SMEs).

The qualitative research on AKIS demonstrates how agriculture is also given back importance by moving it away from the mere concept traditional one, which sees it as a low-tech sector, by engaging in innovation modes that rely on external sources of knowledge, rephrasing the famous work of Pavitt (1984) in the light of an evolutionary approach on agriculture.

Pavitt categorised agriculture among the supplier dominated sectors, wherein firms mostly rely on external sources of technical change, a view that extends to sectors downstream in the value chain, such as food and drinks (Martinez and Burns 1999). Yet, owing to the emergence of biotechnology first, and to digitalisation later, there are reasons to analyse agriculture in the perspective of knowledge-intensive sectors. And indeed, pushing farmers to collaborate with scientists in the innovative process, as AKIS does, aligns with a shift towards science-based innovation-sources and modes, at least for a subset of the agricultural sector. Whether this assumption is correct, only data analysis can tell. Evolutionary economists have long emphasise the reasoning of Pavitt taxonomies in economic studies (Pianta; Marsili), demonstrating the relevance of examining sectors and firms into a broad scenario towards technological trajectories and the evolution of markets.

The Evolutionary Approach views economic systems as dynamic and constantly evolving (Nelson and Winter,1989). Rooted in Schumpeter’s view on innovation, it emphasizes processes of variation, selection, and retention among firms by markets. Economic change arises through innovation, learning, and adaptation, where agents operate with bounded rationality and routines guide behavior (Dosi;2024). Instead of assuming perfect competition or optimal outcomes, the evolutionary perspective focuses on how economic diversity and experimentation drive technological trajectories. In this approach the Pavit taxonomy highlights the importance of historical paths, institutional contexts, in shaping economic development and technological progress of sectors.

Standing from the Evolutionary Theories and the innovation dynamics, we aim at understanding the possibility to study agricultural participation in R&D public subsidies from an evolutionary perspective. Although the dataset does not include information on innovation inputs and outputs at the farm level, limiting the ability to directly assess innovation dynamics, we seek to shed light on the importance of rethinking agricultural studies through an evolutionary lens.

Thus, relying on Pavitt taxonomy, we assume that participation in R&D subsidies to implement AKIS within the territories, is affected by the size and the economic efficiency/profitability of the farm. In particular, we expect that a negative correlation underlines participation for public subsidies as substitute to private funds. Thus, less large and efficient farmers participate in public funds because of their impossibility to acquire private credits. In contrast a positive association will underscore two different aspects of farmers. Firstly, as in Arzeni et al (2023) large farmers could participate in order to cover capital aspects, farmers can lead their own land or barns and livestock for experiments. Secondly, it could be a first correlation with farmers that are more prone and have incentives to innovate in their farms, hence those policies require that the farmers present their needs and how they want the innovation to answer, suggesting a participation of farmers, at least at the beginning of the innovation process.

H1 *The demand for R&S subsidies depends on farm size and economic efficiency.*

Financing gaps in R&D are widely studied through the lens of market failures. Among the many market failures affecting the innovative process, the most relevant in determining a financing gap are information asymmetries between firms and financial intermediaries, and market power in credit supply (Catozzella e Vivarelli;2016). A farm's capacity to provide collateral and the local credit market conditions are credible factors influencing participation in public R&D funding programs. Although the literature has yet to reach a consensus on the relationship between public and private R&D investments, several authors suggest that public subsidies for innovation may act as substitutes rather than complements to private R&D efforts (David et al., 2000), potentially undermining their role in promoting sustainable innovation (Schäfer et al., 2024). On the contrary, Silva & Carreira (2017) basing their analysis on this strategy, estimate the importance of financial constraint to receive subsidies. The authors find that the degree of financial constraint faced by a firm does not significantly influence the likelihood of receiving public funding, raising serious doubts about the effectiveness of such support in alleviating firms' financial limitations for R&D investments as it was suggested by others (Bannò & Sgobbi, 2010; Latruffe et al., 2010). From an agricultural perspective, it is therefore essential to identify which types of farmers are more likely to participate in these policies. Our hypothesis aims to assess whether farmers facing higher financial constraints are more inclined to apply for public R&D subsidies. Two possible outcomes may emerge: a positive association would indicate that policymakers should reconsider the design of such programs to avoid favouring well-established farms and substituting private investments; conversely, a negative relationship would suggest that public subsidies are not effectively reaching financially constrained farmers, highlighting a potential bias in policy implementation.

H2 *The demand for R&D subsidies depends on farm's Financial constraints*

In order to deeply underscore the dynamics of farmers participation in R&D public subsidies for innovation, we aim at examining their likelihood also in the lens of factors availability. We rely on the theory of factor-ratio induced innovation, according to which the direction and intensity of technological change depend, not because of capital knowledge, or the economy of the farms, but on external factors endogenous to their production function (Funk, 2002). Thus, the relative scarcity (and cost of production factors) induce agricultural firms to innovation path.

Applying this reasoning to the context of the study, farmers facing higher scarcity in key productivity factors (whether due to limited labour availability, high input costs, or constrained access to capital) will have a stronger incentive to seek external support for innovation.

Following the theory of induced innovation (Ruttan, 1985; Hayami & Ruttan, 1985), farmers' decisions to engage in innovation are shaped by the relative scarcity of production factors. In contexts where key inputs such as labour or capital are constrained, the incentive to participate in innovation policies increases[7], as these programs provide opportunities to offset such limitations. To capture this mechanism, our model specification includes a factor-scarcity

[7] Note that in our assumption an innovating farm or a farm that participate in R&D public subsidies for innovation is interchangeable.

ratio as an explanatory variable in the participation equation, testing whether resource constraints induce farmers to participate in R&D and innovation initiatives.

Hence, based on this theoretical assumption, we hypothesis that farmers experiencing greater scarcity in productivity factors are more likely to participate in public R&D subsidy programs for innovation.

H3 *The demand for R&D subsidies depends on farm factors-scarcity ratio*

From a macro-level perspective, Fuglie (2018) highlights the critical role of R&D in agriculture, emphasizing the importance of knowledge capital in securing financial support for the adoption of new technologies. The author argues that the slow pace of technological adoption is not solely attributable to farm heterogeneity or the predominance of small-holder structures but is also influenced by the lag between R&D investments and their results. This underscores the persistent need for both growth in agricultural R&D and the need for knowledge capital within the farms. Similarly, in other papers Authors (Cerulli and Poti, 2008; Czarnitzki and Delanote, 2014; Silva et al., 2017), using Italian, German and Portugal data, find that technological co-operation, previous R&D experience, and a high firm skill intensity are positively correlated with participation in publicly sponsored R&D programs, underscoring the importance of knowledge capital within firms. The European Commission (2019) highlight the essence of knowledge to participate in AKIS related measure, underscoring the relevance of accessing external knowledge and internal knowledge as in Jalotjot & Tokuda (2024). Participation in R&D subsidies has also attention in the literature regarding the past participation in applying for funds. Building on Cantner & Kösters (2012) 'picking the winner' strategy, this line of research highlight the need to retrieve firms' behaviour and characteristics that high the probability to participate in R&D policies. In line with this strategy, authors suggest the policymakers are more prone to fund firms that already have an increase in export and productivity, have past experience in obtaining funding and show high managerial practices (Bannò & Sgobbi, 2010; Busom et al., 2017; Santos et al., 2019; Martinez Cillero et al., 2021) This implies that participation itself can be viewed as a cumulative form of knowledge, built and reinforced through successive funding calls. Thus, based on this literature we assume that internal knowledge affects participation in R&D innovation subsidies. We proxied internal knowledge in terms of the age of farmer entrepreneur, the human capital skills needed to ensure diversification of economic activities within the farm, and organic activities (following Cristiano et al., 2015; Cristiano and Proietti, 2019).

H4 *The demand for R&D subsidies depends on farm Internal Knowledge capital*

2.3 Dataset and variables

For the purposes of this paper, we rely on the Italian FADN dataset which contains detailed balance sheet and farmers information. The dataset includes an overall number of 20,028 farmers, over the period 2014-2021, totaling 76,989 observations. Each farm was observed, on average, for 3.8 years in a row. For each farmer, we have balance sheet data and, most interestingly for our research goals, the public subsidy programmes that each farmer benefited from. However, the limited number of beneficiaries constrains the analysis, leading us to treat the dataset as a cross-sectional sample covering the period 2014–2021.

For the estimation analysis, we focus in particular on Measures 1, 2, 16 and 19 which deal with R&D for innovation and are defined by the European law as the AKIS related measures (see European Commission Regulation (EU) 2021/2115)[8].

Thus, the variable AKIS is a dummy equal to 1 for farmers who benefited from Measures 1, 2, 16, or 19 in the years when they received the corresponding subsidies. A value of 0 indicates farmers who did not participate in these specific AKIS measures (although they may have received other non-innovation-related subsidies). Some may have applied for those Measures funding but were not selected. While the exact number of such cases in the Italian FADN dataset is unknown, a review of regional calls suggests that selection criteria for AKIS measures do not rely on financial performance or balance sheet indicators. Instead, the main eligibility criteria are general and widely applicable across farm types (see Table 1.a in Appendix A). This suggests that access to R&D innovation subsidies was broadly open and not restricted to a select group of farmers based on economic performance. Moreover, as shown in Table 1 the AKIS dummy covers a poor set of observations (78 treated on 76,989 non-treated) leading to problems of identification bias described in section 3.

Regarding the hypothesis formulated following, we describe the hypothesis and the variable used as a proxy form the FADN dataset, note that each formula is referred to each individual (farm) in each period of time (t0).

H1 Size and Economic efficiency/profitability

[8] Articles art.15; art.114; art 127. Note: For the older see Regulation (UE) n. 1305/2013, art.5.

In this study, farm size is measured using total sales, which more accurately reflects the overall economic scale and productive capacity of each farm. While we acknowledge, as in Helfand and Taylor (2021), that farm size in agricultural studies can be expressed with other proxies rather than total sales (or in terms of farms' agricultural utilized area); we argue that economic revenue better captures a farm's organizational dimension for two key reasons. First, total sales encompass the combined output of both crops and livestock, providing a holistic measure of farm activity that aligns more closely with our hypothesis regarding eligibility for R&D funding. Second, total sales reflect the economic value of the farm, the aspect we aim to analyze in the context of innovation subsidies, rather than merely its physical size in hectares[9]Table 1 reports the descriptive statistics of this variable in logarithmic form. The average total sales (€63,446) indicate that the agricultural sector is predominantly composed of Small and Medium-sized Enterprises (SMEs), as expected. The values range from €1 to €21,900,000, highlighting the considerable heterogeneity among farms included in the Italian FADN sample.

In farms, economic efficiency usually means how well a farm converts inputs (land, labour, capital) into economic output (revenues, profits). Thus, a negative correlation would indicate that public R&D serves as a substitute for internal investments, whereas a positive correlation would suggest that larger and more efficient farmers are becoming more innovative as they increasingly take part in the innovation process, as noted by Arzeni et al. (2023).

Following the economic accountancy literature we use the farmer's Return on Assets (ROA), as a proxy for a farm's economic efficiency and profitability because it captures how effectively the farm transforms its total assets (including fixed and circulating capital) into net income. In our dataset (Table 1) farmers generate, on average 4,8 cents every euro of asset managed. The variable is constructed as:

$$ROA = \frac{Net\ Income + \ Entrepreneur's\ Withdrawals\ and\ Self/Consumption}{\text{Fixed Capital} + \ \text{Working Capital}^{10}}$$

H2 Financial Constraint

The Return on Investment (ROI) and Indebtedness index are used to capture a farm's financial constraints, as these indicators reflect complementary dimensions of financial health

[9] Some may argue that hectare or livestock numbers could serve as a proxy for identifying farmers more willing to dedicate land or animals to experimentation. However, we contend that this is not an appropriate measure, as on-farm experimentation depends on the type of innovation for which each farmer receives funding.
[10] Working Capital (current assets, without subtracting current liabilities)

commonly evaluated by lenders and investors. In particular, ROI measures a farm's ability to generate profits relative to the capital invested, thus indicating its internal capacity to finance new investments. Conversely, the indebtedness index reflects reliance on external financing and the weight of debt obligations, indicating potential limitations in credit access. As reported in Table 1, the average ROI is 0.88, meaning that for every euro invested, the farm earns 0.88 cents. The indebtedness index ranges from 0.6 to 19, with an average suggesting extremely high financial leverage. On average, for every €1 of equity, farms hold €11.53 in debt. Together, these two measures provide a comprehensive picture of the financial constraints that may restrict a farm's operational and investment capacity. The formulas below detail how these variables are constructed following Italian accounting standards:

$$ROI = \frac{Standard\ Farm\ Production}{\text{Liabilities to third parties} + \text{Current Assets}}$$

$$Indebtness = \frac{Equity + \ Medium/Long\ term\ Debts}{\text{Equity}}$$

H3 Factor Scarcity

We construct a Factor-scarcity ratio usually used when dealing with induced innovation theory (for a deeper study on the theory see Schulz & Börner, 2023) between Capital intensity and Labour input. The data (Table1) shows a highly diverse sample of farms in terms of production methods. The majority of farms cluster around a moderate level of mechanization (around 4.161), but the large spread (3.4 SD) and extreme minimum/maximum values confirm that the sample includes more small, traditional, labor-intensive operations than large, modern and highly automated farms. The hypothesis is formulated constructing a variable that captures the hours worked and the machine kw use, so to accurately reflect the true intensity and availability of these inputs, emphasizing the role of labour time and capital utilization in shaping production constraints and innovation incentives on the farm as in Binswanger (1978):

$$Factor - scarcty\ ratio = \frac{Kw\ Machine\ use}{\text{Hours worked}}$$

H4 Internal Knowledge

The qualitative research described above in the previous literature suggests internal capital knowledge can be formulated, not only with the usual variable of farmer age and educational level (Cristiano et al., 2015) but also in terms of farmers capability to enhance economic activities within the farm. Although we added as a variable the age of the farmer, we are not able to construct a comprehensive variable on educational level due to data constraints. Thus, we rely on two dummy variables which proxies managerial skills and higher knowledge acquisition within the farm. The first address whether the farmers have diversified the core activity (e.g. implementing agrotourism, hospitality, biofuel/energy production plants etc.), the second whether the farm produces (at least a part of the production) in an organic regime, requiring an increase of internal knowledge for both activities. In particular the dataset involves farmers with an age ranging from 17 to 97, with an average of 54 years-old, in line with the ISTAT permanent census on population and households from 20214 to 2020[11.] Farmers in the Italian FAND presents a discrete level of diversification, among all 18% produce in an organic regime and 13% have diversified the economic activities of the farm.

Controls

Finally, ISTAT-based variables are used as controls for the farmer sex and its' external environment (population density and a social norms index). Firstly, we collected the attitude toward cooperation in association activities in each year per region. In this direction, a social norms index is constructed by a Principal Component Analysis among activities regarding: Ecological, Volunteers, Labour Unions and Financing no-profit entities. Appendix B presents in detail the PCA, and the variable used to construct the social norms index. Furthermore, we include as a control, the annual population density to determine the access to external capital and the relative sex of farmer to account for potential heterogeneity among farmers behavior rooted in sociology and psychology fields as described in Section 2.1. To account for potential unobserved heterogeneity related to both temporal trends and geographical characteristics, Year Fixed Effects and Regional Fixed Effects were incorporated into the model specifications. This approach allows us to isolate the effects of the primary variables of interest by controlling for stable, systematic differences across time and location.

All non-dichotomic variables are included in the regressions after taking logarithms, to reduce their variability as customary in the econometrics of firm-level data and lagged one year before the policy subsidy. Table 2.a in Appendix A shows that cross-correlations among the

[11] Web browse https://www.istat.it/en/statistical-themes/population/population-and-households/ Access: 10-10-2025 Time: 10:15 UTC+2

variables to be included in regressions are low, suggesting multicollinearity is not a significant concern.

2.4 Econometric design

The following econometric setting is devoted to testing which are the farmers in the agricultural sector in Italy that are beneficiaries of public subsidies for R&D (in order to adopt AKIS measures) and the role of economic characteristics in determining their participation in AKIS policy measures.

In our estimation strategy, the dependent variable is dichotomic, and our dataset is organised as cross-section from 2014-2021; therefore, we construct the strategy following several steps until estimating a fixed effect logistic regression for rare events with a likelihood penalized following Firth (1993).

Our first economic specification is a logistic regression with control variables:

$$Pr\left(AKIS_{i,t} = 1 | \, X_{i,t-1}, Z_{i,t-1}\right) = f\left(\alpha + \beta KNW_{i,t-1} + \gamma SZEF_{i,t-1} + \delta INDB_{i,t-1} + \theta FCT_{i,t-1} + Z_{i,t-1} + \varepsilon\right) \quad (1)$$

where function f(.) is a logistic CDF, α refers to the constant $\beta, \gamma, \delta, \theta$ are the vectors estimates used to test the four research hypotheses regarding: Internal Knowledge (KNW), Size and Economic Efficiency (SZEF), Financial Constraints (INDB), and Factor Scarcity (FCT) (named X in the right side of the equation) in Eq1, Z_i refers to the control variables and dummies (for fixed-effects) to account for unobserved heterogeneity among farmers and ε is the error term.

However, the efficient estimates for Eq. 1 may be biased, for a number of reasons regarding endogeneity and identification issues which, following, we address in detail.

Firstly, while farmers obtain R&D subsidies, they may have different characteristics which could have affected their participation. This issue arises because of different timing during the application process. For example a farm in time t, when receiving the subsidy, could have different characteristics when applying to the subsidy in time t-1, moreover given the time lag between the submission of the application, the publication of the results and the actual availability of funds, the probability that the company will benefit from aid at time t depends on characteristics prior to t. Thus, to avoid this simultaneity bias (that could happen if estimating the covariates and the participation in the same period of time), we lag all explanatory variables measured the year before, under the assumption that the expectation of receiving the AKIS subsidies did not influence the size, the economic financial variables, the internal knowledge and the factor availability of the farm.

A further suspect of estimation biases includes measurement errors that could derive from the different ratio variables that we use as proxies. To address this issue, we formulated, as a check on measurement errors, different models' specifications as in Table 3. Stepwise we estimate coefficient with White-sandwich standard errors, then with Bootstrapped SE (with 50 repetitions and with 100 repetitions).

Moreover, the most important endogeneity comes from the selection bias due to the decisions made by farms and the lack of information on regional rankings and applications. This arises due to the inability to have information about the farmers who did apply to calls for those measures, but the proposed projects were not selected. Thus, we are not able to clearly split the non-treated with the treated farmers.

Indeed, our AKIS dummy is upper bound because for non-treated (AKIS=0), it refers to both non-applicants and failed applicants for AKIS subsidies. In econometric estimation this is an important aspect when dealing with policies that (normally) are not randomly assigned. Thus, in our case the coefficients could be biased because the AKIS variable depends not only on the covariates in Eq.1, but also on unobservable, that are involved in the error term ε, and are so correlated to the covariates. This problem led to a selection bias because it violates the conditional mean independence assumption and leads to biased estimates of the parameters $\beta, \gamma, \delta, \theta$:[12]

Moreover, a risk of selection bias is encountered because the criteria used by funding agencies to select beneficiaries are often closely aligned with the unobserved factors that also influence firm behaviour making it difficult to distinguish between them (as in Bannò & Sgobbi, 2010). While the empirical analysis relaxes this issue, by assuming that the selection is driven by broader national criteria in the applications which reflect subjective and non–economically based considerations (see Table1.A in Appendix A for more details), endogeneity due to unobservable cannot be entirely addressed.

Indeed, although econometric strategies exist to avoid selection bias by capturing unobserved factors and accounting for endogenous selection (as, to cite few, Heckman selection model or Instrumental variable regressions, for more details see in Heckman &

[12] $E(\varepsilon | X_{i,t-1}, Z_{i,t-1}, AKIS_i = 0) \neq 0$ (2)

Vytlacil, (2007); Wooldredge (2020)) , these approaches are not feasible in our case due to another key characteristic of the dataset: the treatment group is very small relative to the non-treated group.

The rare-events lead to estimator inefficiency, as the limited number of observed occurrences reduces the precision and reliability of the estimated coefficients (Firth,1993; King and Zeng, 2001; Leitgob 2013, Beiser-McGrath 2022) this issue happens when the number of treated is really rare (small observed numbers) compared to non-treated. In our dataset over 76,989 observations, 78 farmers are treated. The logistic regression has in this case a non-accurate and non-efficient Maximum Likelihood Estimator (MLE) as it can be biased away from zero. Thus, Firth penalized logistic regression is a method used to increase efficiency and accuracy in logistic regression MLE particularly when dealing with small sample sizes or separation issues (Tomz, King & Zeng; 2003). In particular, in small datasets, logistic regression often yields unstable parameter estimates, biased coefficients, and unreliable *p-values*. These issues stem from the reliance on Maximum Likelihood estimation (MLE), the standard technique in logistic regression. MLE aims to maximize the likelihood function to estimate model parameters, but its effectiveness diminishes when data is sparse, and events are rare. However, traditional logistic regression underestimates the probabilities associated with rare events because the model exhibits a bias toward zero, making it challenging to assess the likelihood of such occurrences accurately. These datasets are characterized by a substantial imbalance between the events (ones) and non-events (zeros), and this disparity presents unique statistical challenges. For example, Rahman and Sultana (2017), shows that separation can almost fully discriminate the presence or absence of the outcome in question, based either on a single predictor variable or a linear combination of several predictor variables. In our dataset there is no perfect separation between firms that applied and do not apply to the AKIS policies. In order to address this issue, we have assessed the statistical differences in the empirical distributions of the main variables used for the estimation by applying the Fligner-Policello test (1981). The Fligner–Policello (FP) test is a nonparametric test for location shift (differences in central tendency), designed as a robust alternative to the Wilcoxon–Mann–Whitney test, when sample sizes and variances are unequal all characteristics encountered in our data.

Due to the asymmetries in our sample, this approach is particularly appropriate for our analysis, as it operates under minimal assumptions: it does not require equal variances, accommodates asymmetric distributions, and remains robust in the presence of unequal sample sizes, all characteristics observed in our dataset. Unlike standard tests focus on a specific location shift (e.g., differences in means or medians), the FP test evaluates stochastic dominance by examining which of the two distributions is more likely to exhibit greater probability mass in the upper tail. Moreover, while FP is appropriate for continuous or ordinal variables, it is not suitable for binary (dummy) variables, therefore, for the latter, we employ a Z-test for proportions to compare group differences (evaluating the central tendency on the mean). Then, we can assume that predictors are not perfectly correlated with the outcome variable as the logistic regression model postulates. Thus, the estimation principle underlying Firth's regression involves introducing a penalty term into the standard MLE function used to generate parameter estimates and standard errors for a logistic regression model. Furthermore, to increase the credibility of estimates we performed a Propensity Score Matching is estimated in Appendix B.

2.5 Findings

In order to avoid any problem of collinearity, a standard correlation test indicate that all the variables have are independent each other as in Tabel 1. Then the FP test is addressed to understand the tendency distribution of the key variables.

Results of the FP and Z tests are presented in Table 2, a significant and positive value indicates a higher probability for non-treated groups to have more mass to the right tail. The significance highlights that both balance-sheets internal characteristics and environmental external behaviours of farmers matter in participating in R&D innovation subsidies.

We observe that non-treated farms are more likely to be managed by elder heads and tend to exhibit stronger return on investments (this is reflected in a higher probability mass on the right tail of the ROI and Head age distributions).

Contrary, farmers that participate in R&D innovative subsidies, while are larger in size (more probability to present high right mass for total sale) display a propensity to invest more despite achieving relatively low returns. Indeed, the contrasting signs for ROI and Indebtedness highlight an important feature of farmers participating in R&D innovation subsidies. Farms appear to be large enterprises that, while risk-averse in their investment behaviour contracting high rate of long-medium-term debts, may exhibit weaker managerial performance, as evidenced by their relatively low return on investment. The regression analysis could reveal further nuances in the profile and performance of subsidy recipients. Although not significant, the negative value of Factor-scarcity-ratio, suggests coherence with the induced innovation theory revealing treated farmers to be in the right part of the tail (indicating farmers presenting an unavailability of factors). Regarding external environment characteristic, those variables plays a role in participating in AKIS related measures revealing that farms located in high density areas (Pop density) that present regional fixed attitudes toward cooperation and association (Social Norms index), have higher probability to participate in public policies to fund R&D for innovation (showed by the negative and significant parameter of both Social norms index and Population density).

Lastly, for dummy variables the Z-test assesses the significance in differences among the two groups relying on their relative mean. Thus, the negative value, while it underscores a relation with the participation of farmers and their internal knowledge (proxied by the presence of Diversified and Organic) and for Female entrepreneurs, its direction needs to be better clarified by the logistic fixed effect analysis. Indeed, the FP and Z-test aid to understand the differences among the two groups without levering on which independent variable increases the probability to participate in R&D innovation subsidies; thus, a fixed effect logistic regression designed for rare events is estimated. Figure 1 shows the kernel densities of the variable used in the estimation strategy in order to present the differences in terms of distributions among treated and non-treated groups of farms, confirming the FP and Z-test results.

As described in Section 2.4, our estimation strategy follows several steps due to endogeneity and sample size issues.

The first issue could arise due to measurement errors; to avoid this particular source of endogeneity, several models have been estimated in order to check the robustness of standard errors (SE). Thus, the model has been re-estimated by using different techniques, in particular the usual sandwich White type robust SE, and SE bootstrap computed over 50 and 100 replications, respectively. Table 3 reports the results, showing similarities in both the magnitude and significance of the covariates across the three models.

Because of the similarities among the measurement errors specifications, the model with bootstrap SE is the one used in the paper, furthermore, because of computational reasons the bootstrap with 50 runs is presented in the rest of the study.

Although we acknowledge that potential endogeneity concerns may affect our estimation, a series of robustness checks indicate a high degree of consistency in the results. Hence, while causal inference cannot be firmly established, the analysis reveals a strong and significant correlation between these variables and farmers' participation in public subsidy programs. Table 4 presents the main results across different model specifications. Indeed, we compare the logistic regression, and we re-estimated it for rare events computing the firth's penalized weight on the MLE, adding stepwise year and regional fixed effect for fixed characteristics over time.

Findings in Table 4 indicate that, while participation in R&D innovation subsidies is higher among larger farms, with coefficient estimates differing by only 0.07 points across models and strong statistical significance in all specifications ($p < 0.01$), it is not correlated with ROI levering negative and not statistical coefficients in the model specifications. Similarly, the financial constraints, measured through the level of indebtedness and ROA, show no correlation with participation in public R&D subsidy programs, suggesting that the investment performance of farms is not associated with their likelihood of participating in these policies.

Conversely, younger (and female) entrepreneurs are more propense to participate in subsidies for innovation showing significant estimation coefficient for all the model specification (at <0.01 level) and same estimates coefficients. The internal knowledge within the farm also plays an important role in the likelihood of participation. Indeed, proxied by the capability of the farms to present diversified economic activities (such as Agrotoruism, Bioenergy activities, Recovery activities, direct product sales etc.), and the presence of an organic activity in the field (as described in Section 2.2) as the entrepreneur age; farm internal knowledge is positively correlated with their participation in AKIS and related Measures showing a strong significance and similar estimation coefficients in all the model specifications (p-value<0.01).

Unexpectedly, the factor scarcity ratio, while capturing the important relationship between factor availability and the likelihood of participating in innovation subsidies (with negative coefficients across all model specifications), exhibits a low level of statistical significance ($p < 0.1$) not present for the firth penalized estimation of the MLE.

External environment controls present interesting insights, while the density of population undercover an increase in the participation of measures, this is confirmed by the social norm index even though not significant in all specifications. Thus, while the two environmental proxies indicate a positive relationship between farmers and a qualified, conscious knowledge capital within the territory, as suggested by the Flinger-Policello test, the estimated coefficients of Social Norms index, should be interpreted with caution due to their lack of statistical significance.

Lastly, in Table 5 we present models incorporating different covariate specifications as a robustness check. Specifically, we replace Total sales with gross value of output, we added instead a dummy indicating young (if less than 40 years old as from the FADN database), lastly, we resume Net Indebtness by Invested Capital.

The results reveal no significant differences across specifications, supporting the robustness of our main findings. Then, although a causal effect is not possible to attest, a strong correlation among those variables and farmers' behaviour in participating in public subsidies for innovation emerged.

2.6 Discussion

In our results some takeaways for policymakers can be outlined. The evidence based on our econometric estimates identifies that female, relatively young entrepreneurs in large farms, endowed with knowledge assets, are the ones that are more willing and/or best positioned to participate in R&D innovation subsidies.

As noted in the Methodology section, we cannot identify farms whose projects were not financed, hence our results mix up the effects of size and age in motivating demand for publicly funded R&D, and their effects in fostering the success of R&D funding applications. Still, if policymakers had in mind different farm targets when designing programs to finance innovative multi-actor arrangements, our results may stimulate reflections about why other farm types did not (successfully) participate in AKIS Measures, and what should be done to foster their participation.

Moreover, it is worth reminding that our estimates align with Literature Arzeni et al. (2023). Farms in Operational Groups partnerships (OGs) are mostly involved downstream in the innovative process, in activities such as experimentation of new technologies, an activity which may not need capital outlays as large as needed by R&D proper. At the same time, research entities may prefer experimentation of agricultural innovation in larger farms, for at least two reasons: large farms allow for larger "samples" to experiment new techniques; and they may be part of a larger network (through rural associations or buyer-customer relationships), thereby facilitating the diffusion of the experimented innovation.

Besides, it is worth noting that although larger farms receive public funding, they exhibit relatively low levels of economic efficiency and profitability. This suggests, on the one hand, a potentially beneficial involvement in training and advisory support programs (Measures 1 and 2), learning managerial skills to increase efficient investments. But on the other hand, the negative value of the ROI variable may indicate that farmers participation is driven more by the opportunity to access public financing than by a genuine intention to complement R&D subsidies with private economic investment (Measures 16 and 19). Indeed, farmers which already presents high return on investments, showing greater managerial skills and planning capacity, are less likely to participate in public R&D subsidies for innovation. Even though further studies could better investigate this issue, it seems that the complementarity of public and private investment in innovation as illustrated by Fuglie (2016), seems to be loosening in the Italian agricultural sector.

Moreover, the strong relation with total sales and participation in R&D measures, while could reveal a tendency to “picking the winners” (Cantner & Kösters, 2012) in selection, may reaffirm the farmers' tendency to participate in public policies in order to increase their productivity (Quiroga et al., 2024).

Additionally, it is worth noting that these farms are typically engaged in organic and/or diversified activities, indicating a strong commitment by such farmers to adopt or explore new innovations, in line with the priorities outlined by the European Commission, (2023). Thus, the results provide strong evidence of alignment with the Sustainable Development Goals (SDGs), highlighting public policies that effectively support farms engaged in sustainability challenges and demonstrating the significant role of internal knowledge capital in guiding investments through public programs, as suggested also from the variables concerning external environment behaviour (Social Norms and Population density) indicating the strong role of the social territorial community in the participation of R&D measures as perceived in the analysis by Guerrero-Ocampo et al. (2022). Similarly, Arzeni et al. (2023), using data on Operational Groups (Measure 16) in Italy, found strong involvement of external freelancers in these projects, while Partalidou et al. (2023) identified the participation of citizens in initiatives under Measure 19 supporting our positive correlation with the external conscious knowledge.

Lastly, our hypothesis concerns the availability of inputs in determining farmers participation in public policies, according to the induced innovation theory (Hayami and Ruttan, 1984). For agriculture, Ruttan and Hayami (1984) posits that technical change is endogenous to a country's development process, driven by relative factor scarcities. Specifically, it suggests that capital-saving innovations are induced in environments where capital is scarce (and thus expensive relative to labor), while labor-saving mechanical innovations emerge where labor is scarce (and relatively costly). Ruttan and Hayami's original framework emphasized that this endogenous technical change is primarily generated by public research agencies responding to evolving factor prices.

Our empirical findings align with the core mechanism of the hypothesis by confirming a tendency for public R&D investments to be directed toward, or adopted by, farmers facing specific factor scarcities. Specifically, the observed negative value for the farmer Labour–Capital ratio among participants in public R&D subsidies strongly indicates a predominance of highly mechanized farms. These farms, by virtue of their substantial investment in labour-saving mechanical capital, exhibit a high degree of capital-to-labor intensity, consistent with a strategy induced by high labour costs.

Consequently, this high level of mechanization among R&D participants suggests that their greatest marginal returns would come from complementary investments. In this context, enhancing labor skills becomes crucial to effectively managing and maintaining updated and new, capital-intensive technologies.

2.7 Conclusions

The present study aims at understanding which farmers participate and successfully obtain public funding for R&D innovation in the agricultural Italian sector. To the best of our knowledge, it is the first study which analyse farmers' characteristics benefiting from the so-called AKIS measures of the Common Agricultural Policy (programme 2014-2020 Measures, 1,2,16 and 19) using the Farm Accountancy Data Network (FADN) which for our estimation analysis cover 52,000 farmers from 2014-2021.

The econometric strategy follows several steps in order to avoid or levering econometric issues, including endogeneity arising from selection bias (specifically, selection on the treated), measurement errors typical of small samples, and identification bias stemming from the rare events nature of "treated" observations (i.e., the small count of participants in AKIS measures) within our dataset.

Although we acknowledge that our analysis cannot demonstrate casual effects, it reveals interesting correlations among the likelihood of farmers to participate in R&D public subsidies, presenting interesting insights for academia and policymakers.

Based on the firth's penalization of the Maximum Likelihood Estimator (MLE) within a fixed- effect logistic regression for rare-event (Firth, 1981), our results demonstrate a clear tendency of large, knowledge-intense farmers with low availability of labour, to participate in public R&D subsidies for innovation.

Results align with our four-hypothesis (Section 2.1) formulated to deeply investigate farmers participation in AKIS measures. The hypothesis stemming from the evolutionary, neo-classical and induced innovation theory, regards farmers size and economic efficiency/profitability (H1), financial constraint (H2), farmers availability of capital/labour factors (H3), and their internal knowledge capital (H4), in determining their participation in public R&D subsidies.

Some conclusions can be drawn upon those results for policymakers.

First, based on our results, apparently farms were not pushed to participate in R&D innovation subsidies by their profitability and economic efficiency. One may argue that the effect of size is consistent with a market failure story, as smaller farms may struggle more on the credit market; however, we also find that larger farms, which typically suffer less from financial constraint, are more propense to participate in AKIS-related measures. An alternative theoretical interpretation, such as the evolutionary one, is also suggested by the positive effects of the knowledge base proxies, consistent with the persistence in innovative paths along technological trajectories, as also the total sales which may suggest farmers more structurally advanced and managerial in their organization.

Second, the combined evidence of large size with diversified activities (such as agritourism, bioenergy initiatives, recycling and recovery operations, and direct marketing of agricultural products or presence of organic activities), being relevant drivers of R&D participation provides mixed support to the view that agriculture is transitioning towards science-based innovation modes as their relations spread from the agricultural to the manufacture and service sector.

Conversely, the model incorporates a factor-scarcity ratio to capture how the relative availability of production inputs influences farmers' participation in innovation-policies. According to this framework, technological change and innovation efforts are stimulated by resource constraints, as farmers seek to overcome limitations in labour or capital through new technologies or external support. Therefore, the inclusion of the factor-scarcity ratio in the participation equation allows testing whether farms experiencing higher input scarcity are more likely to engage in public R&D and innovation programs.

The results indicate that farmers are motivated to participate in public R&D investments by labour-saving innovations, meaning that more highly mechanized farms are more likely to engage in these programs. This aligns with literature (Guerrero-Ocampo et al; 2022; Knierim; 2025) emphasizing the need for training and extension services for farm workers, highlighting the importance of hiring skilled labour in innovative farms. To address this, policymakers could support farmers by creating job opportunities within public universities or offering advanced, specialized public training courses.

Policies ought to push to the extent that innovation goals pursued by AKIS pertain to largely unexplored fields – rather than the mere adoption of existing technologies. Further analysis ought to estimate how the participation in that Measures may be complementary or supplementary to private fundings and should rather be expected from farmers who already invested in new technological and organization knowledge within a certain technological trajectory in order to confirm a new taxonomy of the agricultural sector toward a science-based one. Consequently, as noted by Silva, Grass, and Zilberman (2020), greater attention should be given to the role of private funding. These authors trace the evolution of venture capital in supporting agricultural R&D aimed at generating and disseminating innovative solutions, emphasizing the emerging trend of complementing public funding with a diversified range of private financial actors.

In conclusion, it should be noted that in today's agricultural revolution driven by digital and biotechnological innovations, such as robotics, nanotechnology, synthetic protein, cellular agriculture, gene editing technology, artificial intelligence, blockchain, and machine learning, would and will hardly be achieved without significant public R&D investments in the early stage of technology development (when uncertainty around the returns from innovation is so high as to discourage any private involvement as Mazzucato (2021) highlights).

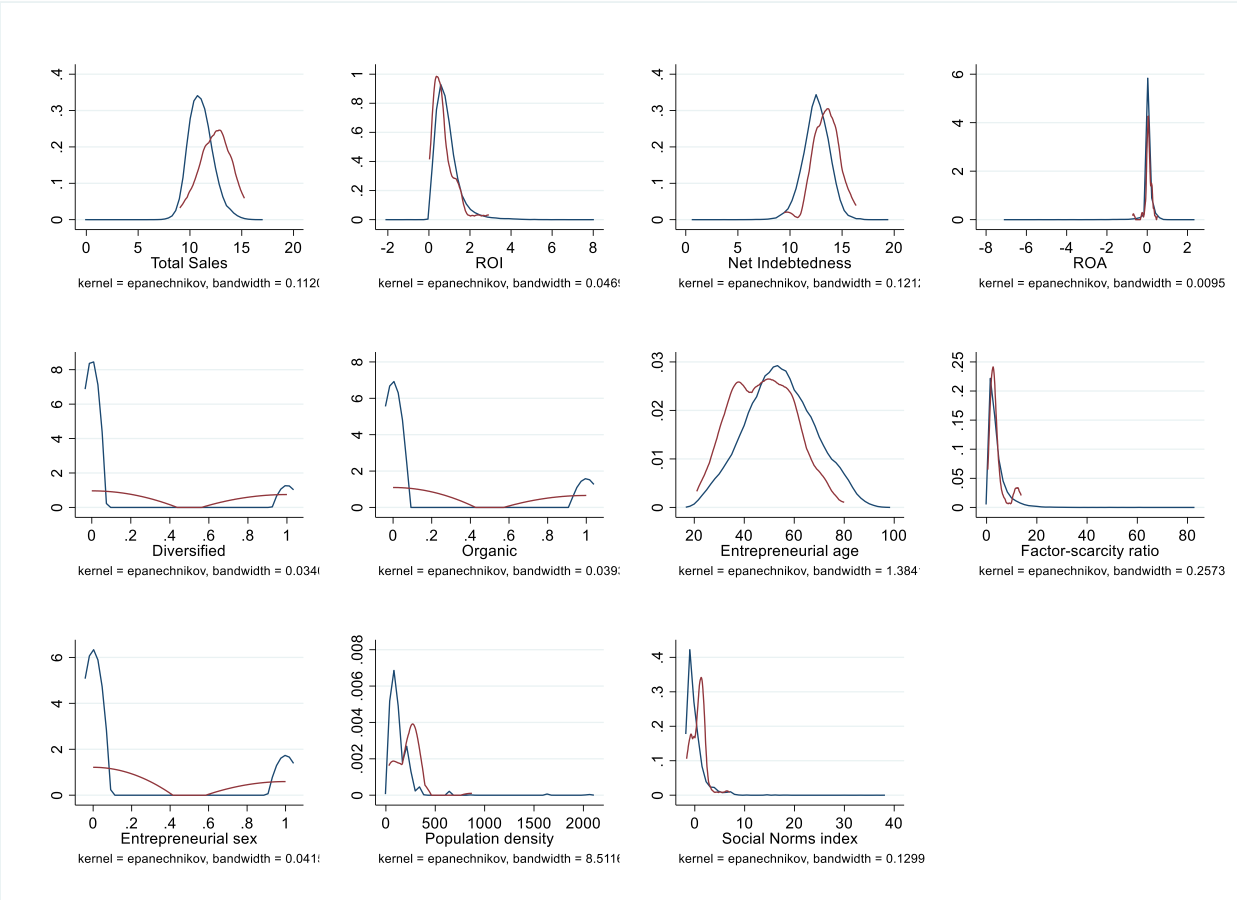
Our study emphasizes the need in the literature to investigate which farmers recognize these opportunities and are therefore more likely to engage in public R&D policies in order to begin to reveal those farmers which (as for non-profit seeking public R&D entities) have grand societal missions necessary in their search for new technological paradigms.

Summary

This paper aims to understand which economic and financial features of agricultural firms affect their decision to participate in Agricultural Knowledge and innovation Systems (AKIS) policies. We estimate econometric models on a dataset of the Italian FADN, including the “aid policy” dataset that allows identifying farms that were beneficiaries from non-beneficiaries. The dataset involves several balance-sheet variables that we employ as explanatory variables in rare event fixed effect logit models of the probability to participate in OGs and related innovation-oriented measures. The explanatory variables are selected having in mind hypotheses concerning the role of farm size, credit rationing, knowledge base and farmer age on the propensity to take part in multi-actor arrangements for innovation.

Chapter 2: Tables and Figures

Figure 1 Kernel density variable used in the estimation strategy treated and non-treated



Note: Treated (red line), non- Treated (blue line)

Table 1 Summary Statistics Covariates and Controls used for the estimation strategy

Variable	Obs	Mean	Std. Dev.	Min	Max
AKIS	76989	.001	.032	0	1
Total Sales	71100	11.06	1.185	0	16.909
ROI	s	.889	.607	-2.068	7.987
Net Indebtedness	55898	12.527	1.264	.693	19.313
ROA	54831	.05	.298	-7.107	2.339
Diversified	55904	.13	.337	0	1
Organic	55904	.186	.389	0	1
Entrepreneurial age	55904	54.359	13.688	18	97
Factor-scarcity ratio	54031	4.161	3.933	.04	82.524
Controls					
Entrepreneurial sex	55904	.215	.411	0	1
Population density	55904	139.082	147.618	3.91	2097.857
Social Norms index	76989	0	1.953	-1.683	38.013

Note: Total Sales; ROI; Net Indebtedness; ROA are transformed into logarithmic form for the estimation analysis.

Table 2 Fligner-Policello test and Chi-square test

Variable	*Non-AKIS*	*AKIS*	*FP*	*p-value*
Total Sales	71,029	71	-8.428	***
Indebtedness	55,840	64	-6.638	***
ROI	55,840	64	3.354	***
ROA	55,840	64	-0.218	
Diversified	55,840	64	-7.310	***
Organic	55,840	64	-3.889	***
Head age	55,840	64	3.605	***
Factor-scarcity ratio	53,967	64	-0.137	
Sex	55,840	64	-2.206	**
Pop density	55,840	64	-5.573	***
Social norms Index	76,911	78	-6.390	***

Note: ([a]) Test of proportions report z-statistics for dummy variables. For equality of distribution among treated and non-treated firms Flinger-Policello test report U statistics. Significance is interpreted as difference in terms of distributions.

Table 3 Standard Error Estimation Under Alternative Robustness Techniques

	Models		
	(1)	(2)	(3)
Total Sales	0.680***	0.680***	0.680***
	(0.146)	(0.135)	(0.143)
ROI	-0.426	-0.426	-0.426
	(0.305)	(0.283)	(0.353)
Net Indebtedness	0.100	0.100	0.100
	(0.148)	(0.135)	(0.139)
ROA	-0.233	-0.233	-0.233
	(0.151)	(0.195)	(0.198)
Diversified	0.979***	0.979***	0.979***
	(0.250)	(0.275)	(0.257)
Organic	0.884***	0.884***	0.884***
	(0.275)	(0.257)	(0.279)
Entrepreneurial age	-0.036***	-0.036***	-0.036***
	(0.010)	(0.007)	(0.011)
Factor-scarcity ratio	-0.051*	-0.051*	-0.051*
	(0.028)	(0.027)	(0.027)
Entrepreneurial sex	0.795***	0.795***	0.795***
	(0.271)	(0.282)	(0.288)
Population density	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
Social Norms index	0.047*	0.047**	0.047**
	(0.024)	(0.021)	(0.023)
Constant	-14.501***	-14.501***	-14.501***
	(1.241)	(1.198)	(1.047)

Observations	52,980	52,980	52,980

Note: This Tabel present different measurement of errors in the model estimated. Specifically, in Column (1) the model is estimated using the conventional White-type robust (sandwich) SE. Column (2) and (3) compute bootstrap SE over 50 and 100 replications, respectively. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 4 Main results Logit regression and firth logit for rare events

	Models				
	(1)	(2)	(3)	(4)	(5)
Total Sales	0.680***	0.674***	0.603***	0.686***	0.610***
	(0.125)	(0.166)	(0.139)	(0.140)	(0.146)
ROI	-0.426	-0.400*	-0.435	-0.396	-0.400
	(0.296)	(0.220)	(0.279)	(0.272)	(0.269)
Net Indebtedness	0.100	0.100	0.110	0.088	0.094
	(0.135)	(0.142)	(0.132)	(0.145)	(0.148)
ROA	-0.233	0.241	0.239	-0.371	0.070
	(0.168)	(0.274)	(0.270)	(0.279)	(0.437)
Diversified	0.979***	0.922***	0.862***	0.979***	0.862***
	(0.241)	(0.226)	(0.257)	(0.266)	(0.272)
Organic	0.884***	0.740**	0.842***	0.900***	0.856***
	(0.256)	(0.287)	(0.269)	(0.268)	(0.273)
Entrepreneurial age	-0.036***	-0.036***	-0.038***	-0.036***	-0.037***
	(0.010)	(0.012)	(0.010)	(0.010)	(0.010)
Factor-scarcity ratio	-0.051*	-0.041	-0.056*	-0.045	-0.050
	(0.030)	(0.037)	(0.029)	(0.033)	(0.036)
Entrepreneurial sex	0.795***	0.837***	0.887***	0.811***	0.902***
	(0.263)	(0.208)	(0.336)	(0.269)	(0.272)
Population density	0.001***	0.001***	0.001***	0.001***	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Social Norms index	0.047	0.045	0.014	0.057	0.027
	(0.029)	(0.031)	(0.025)	(0.041)	(0.046)
Constant	-14.501***	-15.063***	-14.224***	-14.394***	-13.952***
	(1.323)	(1.599)	(1.025)	(1.412)	(1.533)

Observations	52,980	46,328	46,328	52,980	52,980
Control Variables	Y	Y	Y	Y	Y
Year Fixed-Effects	N	Y	Y	N	Y
Regional fixed-effects	N	N	Y	N	Y

Note: The present Table shows different Model specifications for our logistic regression analysis. Stepwise in Column (1) the model presents estimation coefficient with only control variables. Model (2) adds year Fixed-Effects. Model (3) presents also regional fixed-effects. In particular it adds a dummy variable whether the farms are in a southern or northern Italian region, and a categorical variable whether the farms' location is on Hill, Mountain or Plain area. Lastly in Column (4) the model specification adds the firth model strategy to the logistic regression to account for rare events (treated observations). Model (5) adds to the firth logit model year fixed effects and regional fixed effects. Standard errors in parentheses are bootstrapped in 50 replications *** p<0.01, ** p<0.05, * p<0.1

Table 5 Robustness check with different covariates

	Models		
	(1)	(2)	(3)
Gross value output	0.584***	0.607***	0.553***
	(0.187)	(0.153)	(0.142)
ROI	-0.370	-0.365	-0.333
	(0.253)	(0.262)	(0.370)
Net Indebtedness	0.116	0.092	
	(0.162)	(0.130)	
ROA	0.241	0.271	0.325
	(0.387)	(0.327)	(0.484)
Diversified	1.030***	1.056***	1.032***
	(0.284)	(0.275)	(0.274)
Organic	0.867**	0.894**	0.884**
	(0.351)	(0.348)	(0.352)
Entrepreneurial age	-0.038***		
	(0.008)		
Factor-scarcity ratio	-0.059*	-0.056	-0.058**
	(0.035)	(0.038)	(0.027)
Entrepreneurial sex	0.904**	0.914***	0.920***
	(0.397)	(0.306)	(0.297)
Population density	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
Social Norms index	0.016	0.018	0.017
	(0.027)	(0.030)	(0.032)
Young		1.025***	1.041***
		(0.255)	(0.323)
Invested Capital			0.174
			(0.184)

Constant	-14.128***	-16.184***	-16.673***
	(1.402)	(1.395)	(1.966)
Observations	46,328	46,328	46,334

Note: This Table presents the logistic regression using different covariates specifications stepwise added to the models in order to avoid issues of omitted variables and to test the robustness of the main logistic model. In particular, Column (1) add gross value output instead of total sales, Column (2) adds a dummy for the entrepreneurs' age (whether less than 40 years old as form the FADN dataset) and lastly, Column (3) specifies the invested capital (in logarithmic form and expressed within the FADN in total €) instead of the level of net indebtedness. Standard Errors in parenthesis are bootstrapped in 50 replications: ***p<0.01, **p<0.05, * p<0.1.

Chapter 3

Assessing the Impact of Operational Groups policy on Agricultural Innovation in Italy

3.1 Introduction

Agricultural productivity in Italy grew rapidly until 2010 but has since declined (Fuglie et al., 2024). Recognizing the need for innovation to enhance agricultural productivity and promote sustainable agriculture, both European and Italian policymakers have emphasized fostering innovation as a cross-cutting objective (European Regulation 2021/2115 art.77; art.114, art.127). Innovation also plays a crucial role in addressing challenges such as climate change, biodiversity loss, soil degradation, geopolitical instability, energy challenges, and inflation (FAO, 2024). The European Commission's agricultural vision prioritizes innovation through multi-level stakeholder cooperation within an integrated governance framework (European Union; 2024).

The European Innovation Partnership for Agricultural Productivity and Sustainability (EIP-AGRI) is a key initiative to improve agricultural innovation through collaboration. Launched during the 2014-2020 Common Agricultural Policy (CAP) programming period, EIP-AGRI supports innovation and knowledge-sharing through Operational Groups (OGs). Each OG forms a partnership with farmers, food processors, producer cooperatives, consultants, universities, firms, and government entities to develop an innovative project (SCAR AKIS, 2019; Guerrero-Ocampo et al., 2022; Maziliauskas et al., 2018). Within EIP-AGRI, innovation is broadly defined to include both novel practices/products and the application of traditional practices/products to new geographical or environmental contexts (Article 126 of Regulation 2115/2021). del Puente et al., (2024) find that OGs in Italy integrate tradition in their innovation strategies, creating demand for traditional foods and expanding market opportunities. For example, GELSO_net13, with a budget of € 784,244 and a consortium of six farmers, two freelance advisors, and a university, aims to create a new mulberry-based agri-food supply chain in the Piedmont region. This initiative not only expands mulberry sales but also increases their economic value by converting pruning waste into

[13] Gelso-Net project: https://www.innovarurale.it/it/pei-agri/gruppi-operativi/bancadati-go-pei/valutazione-di-innovative-strategie-di-adattamento. Last access on January 29, 2025.

biomass. The 2021-2027 CAP reaffirms EIP-AGRI as the EU's primary strategy for promoting agricultural innovation and knowledge transfer (European Commission, 2023).

Among EU-25 countries, Italy had the highest CAP expenditure during the 2014-2020 CAP period (€ 27 billion - EAFRD funds). As part of this investment, over €267 million was allocated to establish 787 OGs across 21 regions and autonomous provinces, with 183 in the North, 372 in the Centre, and 232 in the South. Despite its policy significance and over a decade of implementation, research on the impacts of EIP-AGRI in Italy remains limited, primarily due to data constraints (Proietti & Cristiano, 2023) and reliance on general information rather than on OG-specific data (Giarè & Vagnozzi, 2021). No quantitative analysis has evaluated OG's effectiveness in fostering innovation. Exiting assessments, mainly from Member State reports, highlight best practices and measure impacts based on the number of funded projects, in line with the EU Regulation 2021/2115 (Annex I p.134). Studies on Italian OGs primarily focus on operational aspects rather than innovation output. For example, Giarè & Vagnozzi (2021) examine financial procedures as a key factor in initiating innovation projects. Arzeni et al. (2023), use surveys and interviews to evaluate participant characteristics, partnership interactions, and satisfaction levels, highlighting strong engagement from farmers and research institutes. Molina et al. (2021) develop a qualitative framework identifying key factors driving participation, such as motivation, commitment, communication, trust, network learning, and knowledge-sharing and co-creation. del Puente et al. (2024) classify OGs' innovation goals using the Oslo Manual and the Community Innovation Survey (CIS), showing a strong focus on green innovations.

This study aims to address these gaps by a) constructing a dataset on OGs and quantifying innovation outputs using a Large Language Model (LLM) based on OG final reports and b) investigating factors contributing to OGs' innovation output using count data analysis.

Based on a newly constructed dataset of 646 OGs completed as of May 2024, developed using web-scrapping and LLM techniques, we discover significant disparities in innovation output across regions, thematic areas, commodities, partner composition, and leadership engagement. Specifically, OGs emphasizing market competitiveness, supply chain management, and resource management are more innovative than those focused on productivity improvement, despite receiving more intensive funding. Regarding commodity focus, OGs centred on forestry products are the most innovative, followed by those focused on industrial crops, vegetables and fruits, and other products (aquaculture, beekeeping, and floriculture). In contrast, OGs focused on main crops and viticulture exhibit the lowest levels of innovation, even though OGs in main crops receive the highest funding. OGs in the centre and northwest regions have lower innovation output than those in the northern region. Regional business diversity related to agriculture is positively associated with innovation output, but regional costs of production and labour are not statistically associated with innovation output. Leadership types and their prior funding experience are not found to affect innovation, whereas leaders actively collaborating with other OGs is significantly associated with increased innovation. Partner composition affects innovation output, with OGs involving farmers, research and education institutes, and training organizations being more innovative than those involving advisories, farmers' associations, and other private sector entities. These findings offer valuable policy insights to enhance the effectiveness of the EIP-AGRI initiative, particularly by refining funding allocation and fostering collaboration among key stakeholders.

This study makes the following significant contributions. First, it is the first to construct a dataset on OGs, including their characteristics and innovation output, using LLM, enabling a comprehensive economic analysis of policy impact on agricultural innovation in Italy. Second, our findings provide valuable insights for policymakers, assessing the effectiveness of the EIP-AGRI in fostering agricultural innovation and highlighting the role of partnership in shaping policy output.

The rest of this paper is organized as follows. The Background section presents a brief literature review on R&D collaboration and its effect on innovation, along with an overview of EIP-AGRI. The Methodology section explains the LLM model used for the extraction of the innovation output and focuses on the estimation strategy used for count-data analyses. The Data section describes the data sources. The Results section presents the findings, followed by an in-depth analysis in the Discussion section. Finally, the Conclusion section provides final remarks.

3.2 Background

The role of R&D alliance in fostering innovation has been extensively explored in the literature (Becker, 2015; Pereira et al., 2023). R&D cooperation has become a cornerstone of innovation and a strategic priority for firms and farmers (Martínez-Noya & Narula, 2018). These collaborations facilitate knowledge exchange, technology transfer, increased efficiency and quality, expanded networks and markets, access to complementary resources, and accelerate time-to-market (Boiko, 2022).

Farmers, however, face significant challenges, including climate change, rural abandonment, the digital divide, resource scarcity, food quality issues, and growing global food demand (FAO, 2024). The literature on the agricultural sector explores R&D collaboration from a strategic perspective, emphasizing the importance of knowledge-sharing and the motivations behind farmers' participation (Klerkx et al., 2012). Aligned with this perspective, the EIP-AGRI initiative follows the broader Agricultural Knowledge and Innovation System (AKIS) approach, in which innovation emerges from interactions among farmers and other stakeholders (Touzard et al., 2015). Innovation is widely recognized as an interactive rather than a linear process, driven by dynamic exchanges among partners, with farmers playing a central role in advancing new solutions (Kok & Klerkx, 2023). These interactions facilitate developing and disseminating innovative practices (Knierim et al., 2015).

However, innovation is inherently uncertain, and collaboration entails significant costs, including externalities that make participation difficult for smaller, credit-constrained farms. Fieldsend et al. (2021) highlight that the EIP-AGRI struggles to engage harder-to-reach groups, such as those with low literacy or digital skills who live in marginalized rural areas limiting its full potential. Policy support is, therefore, essential to facilitate stakeholder interactions (Hermans et al., 2023). Cuervo-Cazurra et al. (2018) emphasize that external financial support, such as governmental funding, can amplify the impact of R&D initiatives.

According to the European Commission, OGs must develop innovative projects addressing various agricultural challenges through diverse partnerships. For example, the VINSACLIMA project in Emilia Romagna (total budget: € 347,870) involved five research partners, two farmers, and three farmer associations. It conducted three on-field trials to improve viticulture techniques and three trials on processed wines to enhance Oenological techniques.14 Similarly, the INPOSA project in Sicily (total budget: € 493,964) brought together five farmers, a university, and a farmer association to develop and commercialize a patented industrial invention for yellow tomatoes.15

Despite these efforts, farmers often remain locked into routine practices and traditional production methods due to limited openness to innovation (Bopp et al., 2019). They tend to collaborate with trusted, familiar partners, which may constrain opportunities for new pathways (Li et al., 2008). Moreover, they hesitate to adopt new practices when changes lack clear incentives or revenue gains (Tensi et al., 2022). As a result, when relying solely on internal

[14] VINSACLIMA project: https://www.innovarurale.it/it/pei-agri/gruppi-operativi/bancadati-go-pei/filiera-agroalimentare-del-gelso-frutto-foraggio. Last access on January 1, 2025.
[15] INPOSA: https://www.innovarurale.it/it/pei-agri/gruppi-operativi/bancadati-go-pei/innovazione-nel-pomodoro-e-sostenibilita-agricoltura Last access on January 23, 2025.

knowledge, farmers are less likely to invest in R&D alliances (Cuervo-Cazurra & Annique Un, 2010).

The partner diversity encouraged by the EIP-AGRI strengthens R&D collaborations and offers broad advantages. Since the demonstrated success of their peers highly influences farmers (Wang et al., 2023), collaborating with other farmers and farmer associations could be a key driver of innovation. Additionally, engaging in coopetition--collaborating with competitors--can be beneficial. Mariani & Belitski (2023) find that coopetition positively impacts firms that are not traditionally innovative, mainly rely on imitation, and have little experience in creating new-to-market innovations. Partnering with university researchers in OGs offers mutual benefits (D'Este & Patel, 2007). For farmers, collaboration facilitates the application of university-generated research (Siegel et al., 2003). For researchers, it provides exposure to real-world agricultural challenges and creates opportunities for applied research (Perkmann et al., 2021). Furthermore, collaboration with universities improves human capital (Audretsch et al., 2022), which fosters future innovation and partnerships.

Geographical proximity influences innovation collaboration (Audretsch & Belitski, 2024; Audretsch et al., 2023). Close physical proximity among partners fosters strong local networks, which help build trust, traditions, and routines (Balland et al., 2015). It also enables farmers to observe innovation output firsthand through on-farm demonstrations or structured meetings with partners (Ingram et al., 2018). Recognizing these benefits, the European Commission actively promotes both intra- and inter-regional R&D partnerships within the EIP-AGRI initiative.

The European Commission (2023) emphasizes the importance of national support in disseminating innovative solutions developed by OGs. Each member state publicly shares OG projects through an online database, ensuring visibility. In Italy, the Innovarurale database has been established, requiring OGs to submit standardized project reports (Article 126 of Regulation 2115/2021). However, a key limitation of this system is the lack of quantitative innovation metrics, as project reports are recorded solely as textual descriptions, preventing researchers from conducting rigorous quantitative assessments of OGs' innovation output.

3.3 Methodology

We sequentially employ web-scrapping and LLM techniques to construct a database of Italian OGs based on the publicly available Innovarurale dataset. Web-scraping enables us to collect detailed information on each OG, including project title, objectives, duration, budget, partner characteristics, involved commodities, milestone activities, innovation descriptions, and main results. A thorough data-cleaning process supplements missing information in Innovarurale using data from OGs' websites.

Building on recent advancements in using LLMs to build economic datasets (Devetak & Mandel, 2023), we employ the LlaMa_3 model developed by Meta to extract quantitative information on innovations and OGs. To ensure structured and contextually relevant outputs, we develop a structured system prompt following methodologies outlined by Chen et al. (2024) and Giray (2023). Thus, incorporating insights from agricultural innovation experts, we formulate the prompt to define innovation within the framework of Italian OGs, aligning with the Oslo Manual (IV edition) and the member state reports on OGs' best practices. Specifically, we distinguish between product and process innovations as in the Oslo Manual (IV edition): a new or improved good/service or business process, that differs significantly from the firm's previous and has been introduced in the market or (for process innovations) into the firm. Moreover, due to the context of the Italian agriculture and OGs, we define innovations relating traditional foods and processes. We classify a new approach to bringing traditional foods to markets as process innovation, while revaluing traditional foods falls under product innovation classification. Appendix B details the procedures, prompts, and parameters used to generate the data.

We implement a multi-stage annotation scheme to assess verifiability and detect factual inconsistencies in LLM-generated textual outputs based on established verification methods, as recommended by Wang et al. (2024). Following authors' approach, we assess quantitative outputs through multiple steps. First, we compare a sample of extracted results with findings from a preliminary study on OGs in Italy (del Puente et al., 2024). Second, we conduct randomized tests by submitting both incorrect and correct queries about specific projects and requesting justifications for responses. Finally, we run 13 rounds with the LLM, averaging the extracted values across iterations to construct the final dataset. As a robustness check, we also use the medium values across.

Since our outcome variable--the number of innovations delivered by each OG—is a count variable, we employ count data models, specifically Poisson and negative binomial (NB) regression, to examine the factors influencing OGs' innovation output. Formally, the number of innovations delivered by OG i is expressed as

$$E\left[I_i | OG_i, R_{it_0}, T_i, \tau_i\right] = \mu_i \tau_i = e^{\delta OG_i + \beta R_{it_0} + T_i + \varepsilon_i} \quad (1)$$

where I_i represents the number of innovative projects, OG_i includes OG and project characteristics, and R_{it_0} includes regional characteristics at base time t0. Equation (1) also controls for fixed effects for OG establishment year (T_i). The error term ε_i is assumed to be clustered by region, allowing for correlation within but not between regions. The parameters δ's and β's are to be estimated.

If the unobserved heterogeneity term $\tau_i = e^{\varepsilon_i}$ is independent of regressors conditional on OG_i, R_{it_0}, and T_i, it follows a Poisson distribution with conditional mean and conditional variance $\mu_i\tau_i$. However, the Poisson assumption of equidispersion (equal mean and variance) is often violated due to unobserved heterogeneity or an excessive number of zero values in the dependent variable. In our case, overdispersion is present (approximately 20%), making Poisson estimates inefficient. However, excess zeros are not a major concern, as only 0.15% of OGs report no innovation outputs. To account for unobserved heterogeneity, we employ the NB model, which introduces τ_i as a gamma-distributed random term with mean one and variance α. The NB model assumes a conditional mean of $e^{\delta OG_i+\beta R_{it_0}+T_i}$ and a conditional variance of $\mu_i(1+\alpha\tau_i)$, where α captures the degree of overdispersion.

To determine the appropriate model, we conduct Pearson's chi-squared tests following Poisson estimations. A non-significant result from Pearson's chi-squared test suggests that the Poisson model fits the data reasonably well, while a significant result indicates overdispersion, implying that NB model may be more suitable. After the NB estimations, we evaluate the statistical significance of the dispersion parameter α and conduct likelihood ratio tests. These tests compare the nested models (Poisson vs. NB), testing the null hypothesis that $\alpha = 0$. If the null hypothesis is rejected, the NB model is preferred, confirming the presence of overdispersion. Additionally, we evaluate in-sample prediction accuracy as an additional measure of model fit.

3.4 Data

This study uses two data sources: a) innovation and OG characteristics, constructed using web scrapping and LLM techniques, and b) regional characteristics obtained from Eurostat. Our analysis focuses on 646 OGs established between 2016 and 2024 and completed their projects as of May 2024, representing approximately 84% of all Italian OGs.

OG characteristics include total budget, thematic areas (agricultural productivity, environmental and resources management, supply chain management, and market competitiveness), project duration, year of establishment, number of partners, and involved commodities. For OG members, we capture leader type and partner composition (farmers, research and education institutes, training entities, advisory entities, farmers' associations, other private entities, other public entities, and others). Additionally, we extract information on whether OG leaders currently collaborate with other OGs and have prior experience in securing public funding, Table A1 in Appendix A presents the variables used in the estimation.

To address potential selection bias, we control for pre-OG establishment regional characteristics from 2016, including per capita income, geographical location, agricultural output, percentage of farmers engaged in agriculture-related business activities, production costs, and labour costs. Table AI in Appendix A presents the definitions of the key variables and data sources.

3.5 Results

5.3.1 *Characteristics of OGs and Innovation Delivered by OGs*

We construct the OG data using web scraping and LLM techniques, which help us better understand Italian OGs. Table A2 in Appendix A presents summary statistics for key variables, including characteristics and innovation output of 646 OGs in Italy. We highlight some key features of OGs.

On average, each OG develops approximately three innovations. Figure 1 illustrates the kernel density distributions of the number of innovations, comparing two estimations: one based on the average and the other based on the median across 13 iterations using LLM. The highest density is observed around one to two innovations, indicating that most OGs produce only a few innovations, with fewer OGs achieving high counts of up to 10. Since the kernel distribution based on the mean and median are similar, the OG innovation output process may be less prone to extreme values.

More than half of OGs (55%) were established between 2019 and 2020, while 21% were established in 2016-2018, and 24% in 2021-2024. In our sample, geographically, OGs are primarily concentrated in the Northeastern regions (N = 320), followed by the South (231), Central regions (124), and North (95). Emilia-Romagna leads in the number of OGs, highlighting the role of territorial capital in affecting regional disparities between northern and southern Italy in both innovation and productivity (Castelnovo et al., 2020).

Figure (2) shows significant variations in OG funding across commodity types and thematic areas. In terms of sectoral focus, approximately 22.6% of OGs focus on vegetables and fruits, followed by muti-sector projects (20.1%),16 livestock (19.4%), and viticulture (13.3%). The average budget per OG is highest for those focused on main crops, such as cereals and forage (€408,610), while the lowest average budget is for forestry (€235,805) (Figure 2(b)), while the total budget was highest for OGs focusing on vegetables and fruits and second lowest for those focused on forests (Figure 2(a)). Using Trienekens[17] (2011)'s framework, we classify OGs into key thematic areas: productivity improvement (36.2%), supply chain management (18.6%), environmental sustainability (18.4%), market competitiveness (17.7%), and resource management (8.9%). The total budget per OG is highest for those focused on the productivity thematic area (€96 million), nearly double the budget for supply chain management, market competitiveness, and environmental sustainability, respectively (Figure 2(c)). The average budget per OG is higher for those focusing on market competitiveness and supply chain management than for those emphasizing productivity (Figure 2(d)).

Italian OGs involve diverse partners, with an average of eight types of participants per OG. Figure 3 shows that farmers are the most prevalent, participating in 91% of OGs, followed by research and educational institutes (88%), farmers' associations (38%), advisory consultants (34%), and public and private training institutes (26%). Oher private and public entities each account for 14%.18 Figure 3 also shows that 35% of OGs are led by farmers, demonstrating a strong commitment from agricultural enterprises, while 29% are led by research and education institutes, reflecting a solid alignment with experimental and basic research. Additionally, 26% of OG leaders have prior experience securing funding from EIP-AGRI, and 22% are currently involved in other OGs as a partner.

3.5.2 *Factors Affecting Innovation Outputs Delivered by OGs*

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[16] According to Eurostat, multi-sector crops include a diverse range of commodities, including oilseeds, fiber crops, tobacco, hemp, hops, aromatic and culinary plants, medicinal plants, seeds for herbaceous oilseed plants, linseed seeds (including fiber flax), energy crops, and crops cultivated for renewable energy production.

[17] The framework helps identify the main information flows emphasized by the OGs. Accordingly, the 33 thematic areas are grouped into five clusters, reflecting the dimensions of value addition and chain-network upgrading outlined in Trienekens (2011).

[18] "Other private entities" include environmental and consumer groups as well as other private organizations. "Other Public entities" refer to agencies and functional entities (e.g., environmental protection agencies), development agencies (e.g., agricultural districts), territorial authorities, and garden and park entities.

We employ both Poisson and NB regression models to investigate the relationship between OG's innovation output and contributing factors. The outcome variable is the number of innovations completed by each OG. The total OG budget is used as the exposure variable accounting for factors that increase innovation output. Each model follows a stepwise approach, introducing additional controls at each specification. As shown in Table A3, Models (1) and (4) include only OG establishment year fixed effects and region fixed effects. Models (2) and (5) additionally control for regional characteristics in the base year, including per capita income, production costs per unit of agricultural output, labour costs per unit of agricultural output, and the percentage of farmers engaged in agriculture-related business activities alongside their main agricultural operations. Models (3) and (6) incorporate additional controls for OG-specific characteristics, such as thematic areas, project duration, commodities involved, partner types, leader types, whether leaders have prior funding experience, and whether leaders participate as partners in other OGs. The estimation results for these six models are presented in Table A3 of Appendix A, with the corresponding marginal effects and IRRs (incidence-rate ratios) shown in Table A4. Marginal effects indicate the direction and magnitude of each variable's impact on OG innovation output, while IRRs show the relative changes in innovation output associated with each factor.

As shown in Table 1, incorporating regional and OG characteristics significantly improves in-sample prediction, increasing from 37.78% to 40% for the Poisson models and from 37.01% to 40.13% for NB models. Furthermore, the Pearson Chi^2 tests, the likelihood ratio tests, and the statistical significance of the dispersion parameter confirm the superior fit of the NB models, indicating that the Poisson model's assumption of equal mean and variance is violated due to overdispersion caused by heterogeneity. Additionally, the NB model demonstrates better predictive performance in the full-control specification than the Poisson model (40.13% vs. 40%).

The following section discusses the factors statistically associated with OG's innovation output based on the full-control NB model. Figure (4) illustrates the marginal effects and IRRs associated with thematic areas, partner types, and main commodities. Using the IRRs, we calculate the percentage change in innovation output as follows: (IRR-1) *100%. Figure 4(a) shows that OGs engaged in thematic areas such as environmental sustainability, market competitiveness, supply chains, and resource management have higher innovation counts than those focused on productivity improvement. Specifically, compared to productivity-focused OGs, those focusing on environmental sustainability experience a 38.6% increase in innovations, corresponding to one additional innovation at the mean. OGs emphasizing market competitiveness have a 36% increase (0.95 additional innovations), while those in supply chain management show a 39% increase (0.8 additional innovations). Similarly, OGs focused on resource management experience a 25% increase (0.65 additional innovations). These findings align with the CAP goals set by the European Commission (2024), which prioritizes environmental and market-related challenges in agriculture.

As shown in Table A4 of Appendix A, leader types and their prior funding experience are not statistically associated with innovation output, suggesting a strong and impartial funding process that operates independently of established partners. Additionally, leaders' current participation in other OGs as partners is statistically and positively associated with innovation output, highlighting the importance of collaboration between OGs. This contrasts with existing qualitative literature, which often focuses on the role of leaders in driving innovation within the same organization (Arzeni et al., 2023). Our findings, however, highlight the value of broader collaborative networks that extend beyond individual OG in fostering innovation.

The types of partners involved in OGs influence innovation output. As shown in Figure 4(b), farmer involvement is associated with the highest increase of 0.73 additional innovation counts (a 26% increase), aligning with the goal of OGs to develop innovative solutions for farmers. Participation from research and educational institutes, as well as other public sectors, is linked to higher innovation output, with increases of 16% and 19%, respectively. In contrast, involvement from advisories, farmers' associations, and other private sectors is associated with a 12-14% decrease in innovation output, though these effects are not statistically significant. These results suggest that public sector engagement is more likely to improve innovation of OGs. Additionally, partnerships with training organizations, whether private or public, are associated with a 17% increase in innovation output, corresponding to 0.48 additional innovation counts, which may reflect these organizations' strong connection to certification processes and their role in ensuring compliance with industry standards.

Figure 4(c) shows that compared to the base category (livestock), OGs focused on forestry have the highest increase in innovation output (aside of Others that involves several commodities), with a 67% increase, corresponding to additional 1.79 innovation counts at the mean. This is followed by OGs focused on industrial crops (a 42% increase), vegetable and fruits (a 24% increase), and others (e.g., aquaculture, beekeeping, and floriculture) with a twofold increase in innovation output. However, the lack of significant innovation output in OGs focusing on main crops and viticulture warrants further investigation. Understanding why these well-supported sectors do not exhibit higher innovation output could provide valuable insights into the effectiveness of funding allocation and the structural challenges within these industries. The prominence of forestry aligns with the European regulation (European Commission, 2021) that aims to foster the sector, especially in the northern regions of Italy, with a positive impact on sustainability.

At the regional level, as shown in Table A4 of Appendix A, regional production and labour costs are not statistically associated with innovation output, suggesting it is less likely that OG innovations focus on cost-saving. Furthermore, we find the percentage of farmers engaged in non-agricultural businesses related to agricultural operations, such as agritourism, restaurants, and recreation gardens, is associated with a 2% increase in innovation output. This suggests that regional business diversity related to agriculture is positively associated with agricultural innovation. Additionally, regional fixed effects show that, compared to those in the northern region, OGs in the centre and northwest regions have fewer innovation counts, with 44% and 34% decreases, respectively. The highest innovation output for OGs in the Northeast region highlights a potential limitation for policymakers who may rely solely on absolute project counts as indicators for policy impact within each region without considering the actual innovation output of OGs.

As a robustness check, we re-estimate the models using the median innovation output across 13 iterations with LLM and present the marginal effects and IRRs in Table A5 of Appendix A. The results are consistent with those estimated using the mean values for the main analysis.

3.6 Discussion

One key finding is that OGs focusing on non-productivity thematical areas, especially environmental sustainability, tend to achieve higher innovation output. This aligns with the policy objectives of the European Commission (2024) and existing research on the role of R&D alliances for environmental innovations (De Marchi, 2012). Additionally, our findings reveal a divergence in regional funding priorities. Specifically, OGs with productivity-focused objectives receive the highest level of funding, despite being less innovation-intensive. This suggests that while regional policies align with national CAP objectives, funding allocation disproportionately favours the less innovative "Productivity" theme at the expense of more innovation-driven thematic areas. Future EIP-AGRI programs should provide more support to themes that yield higher innovation output.

From a policymaker's perspective, the relatively low significance of prior funding experience of OG leaders suggests that the funding process is robust and impartial, without systematically favouring or disfavouring established partners. At the same time, collaboration between OGs through shared partners boosts innovation and knowledge sharing, likely due to the strategic selection of collaboration partners based on access to specialized knowledge. These findings align with research on the meso-level influence of firms in fostering innovation. Giuliani (2007) argues that knowledge diffusion occurs within firm-selected clusters--facilitated by local proximity--to improve innovation. Specifically, through network analyses of the wine sector in Chile and Italy, Giuliani (2007) shows that innovation arises from a deliberate and highly selective search process rather than random or widespread knowledge diffusion, leading to the formation of localized knowledge communities.

Un et al. (2010) highlight the importance of accessing external knowledge as a driver of agricultural innovation. Our findings support this by demonstrating that innovation increases in regions where OGs leverage multiple sources of expertise—such as agrotourism, hospitality, and food processing--or partnering with diverse OGs, farmers can better identify sector-specific needs, ultimately enhancing innovation in agriculture.

Partnership diversity plays a crucial role in driving innovation (Yang et al., 2022), as they facilitate learning and accelerate innovation, particularly for firms that rely on imitation and lack prior experience in developing new-to-market products and processes (Audretsch & Belitski; 2024). Moreover, collaboration among farmers is further facilitated by cognitive proximity, which enhances the updating of business routines (Jiang et al., 2024). These dynamics create opportunities for farmers to expand their market reach and adopt technologies from competitors, contributing to overall growth (Mariani & Belitski, 2023).

The involvement of research and education institutes in OGs has statistically significant and substantial positive impact on innovation, highlighting the importance of strong networks that bridge research and practical applications. This supports the hypothesis of Ozdemir et al. (2023), who argue that collaborations with primary stakeholders, such as universities and research centers, improve innovativeness more than partnerships with other entities.

Conversely, our findings indicate that advisory entities (primarily individual consultants) and farmers' associations (such as commodity consortia and farmers' unions) negatively impact OGs' innovation output. This could be due to a 'lock-in' effect, where these partners reinforce existing practices rather than fostering innovation. Advisors in Italy primarily focus on implementing standards and regulations, which can limit OGs' capacity for innovation. This aligns with Allen & Sriram (2000), who highlight the negative relation between strict standards and innovation for low-tech sectors like agriculture. Similarly, Gorman (2019) argues that individual advisors, who often develop technical qualifications through an informal, hands-on approach, may not be as effective, as at fostering innovation. These findings highlight the need for more structured advisory entities rather than individual consultants to better facilitate coordination and support farmers' innovation activities (Lybaert et al., 2022). On the other hand, farmers' associations play a key role in negotiating labor standards and contract agreements within Italy's agricultural supply chain. Their involvement in OGs may constrain cost-saving labor, potentially hindering innovation output. While regional agricultural production and labor costs are associated with an increased innovation output, the results are not statistically significant. Nevertheless, as Hamilton et al. (2022) note, improving agricultural labour productivity requires the adoption of technologies that enhance workforce efficiency and maintain competitiveness, ultimately fostering greater innovation in agriculture.

3.7 Conclusions

This study is the first to construct a unique dataset on Italian OGs by using web-scraping and LLM techniques, based on final textual reports of 644 Italian OGs. This newly constructed database provides better understanding of OGs, investigate factors which facilitate innovation, and address the effectiveness of the EIP-AGRI initiative. On one hand, this study showcases the potential of LLMs as complementary tools for addressing data scarcity and bridging information gaps in agriculture. On the other hand, to further the exploration of policy impact, comprehensive, high-quality quantitative data collected from or documented by OGs are still needed.

OGs serve as valuable platforms for innovation and knowledge-sharing among diverse partners, encouraging farmers, as act as local innovators, as highlighted by Cristiano & Proietti (2018). Our findings reaffirm the important role of public entities, especially research and educational institutions, in fostering innovation through collaboration, as they face fewer regulatory constraints compared to other entities. Additionally, we find that training entities play a significant role in driving innovation, aligning with recent literature (Takahashi et al., 2020). To maximize their impact, the EIP-AGRI initiative should encourage and incentivize the participation of these entities.

Our results highlight the limitations of measures in effectively monitoring innovation. Policymakers may face challenges when relying solely on absolute project counts as indicators of policy impact, as this approach does not necessarily capture the actual contribution of OGs to innovation. For example, consistent with Wesseler (2022) who find a negative relationship between sustainability challenges, the CAP, and agricultural productivity, we find that OGs focused on profitability improvement are heavily funded but show lower innovation compared to others. Similarly, while OGs focused on main crops attract the most funding, they exhibit lower innovation levels. In contrast, forest-focused OGs, despite receiving less funding, are more innovative than those focusing on other crops. The EIP-AGRI initiative should consider balancing funding allocation with innovation output across thematic areas and commodities to maximize the policy impact. Meanwhile, greater attention is needed on funding allocation across regions, as the southern and central regions still showing significantly lower levels of innovativeness compared to the Northeast. This suggests that the policy fails to reduce the Italian south-north divide. In this context, intra-regional collaborations could play a key role in improving effective knowledge-sharing among sector actors.

This study has several limitations. First, it does not rely on Retrieval-Augmented Generation (RAG), a technique that integrates information retrieval with text generation to improve AI responses using relevant external data sources. RAG requires constructing an internal knowledge library to enhance the model's performance. However, the literature on OGs is still quite limited and primarily focuses on best practices and partner commitments rather than innovation, making it challenging to create a sufficiently comprehensive library for defining innovation in the OG context. Future research could address this limitation by developing a more extensive data on OGs as well as other R&D networks, enabling the effective implementation of RAG to enhance AI-generated responses and comparing various LLM to assess their output. Second, while the number of innovations is an important indicator of project effectiveness, we are unable to estimate broader economic impact of these innovations or conduct a cost-benefit analysis due to data constraint. Future research will be needed once such data becomes available.

Summary

This study assesses innovation outputs of Operational Groups (OGs), a key mechanism for promoting innovation in European agriculture. Using a Large Language Model, we construct an Italian OG dataset to quantify innovation outputs and contributing factors. Count data analyses reveal significant disparities in innovation output across regions, thematic areas, commodities, partner composition, and leadership engagement. Higher innovation output is associated with thematic areas focused on market competitiveness, supply chain management, and resource management; commodities like forestry, industrial crops, and vegetables and fruits; collaborations involving farmers, research and education institutes, and training organizations; and OG leaders involved in multiple OGs.

Chapter 3: Tables and Figures

Figure 1. Density Distributions of Innovation Output for Operation Groups based on the Mean or Median of Extracted Values Across 13 Iterations using the LLM Technique

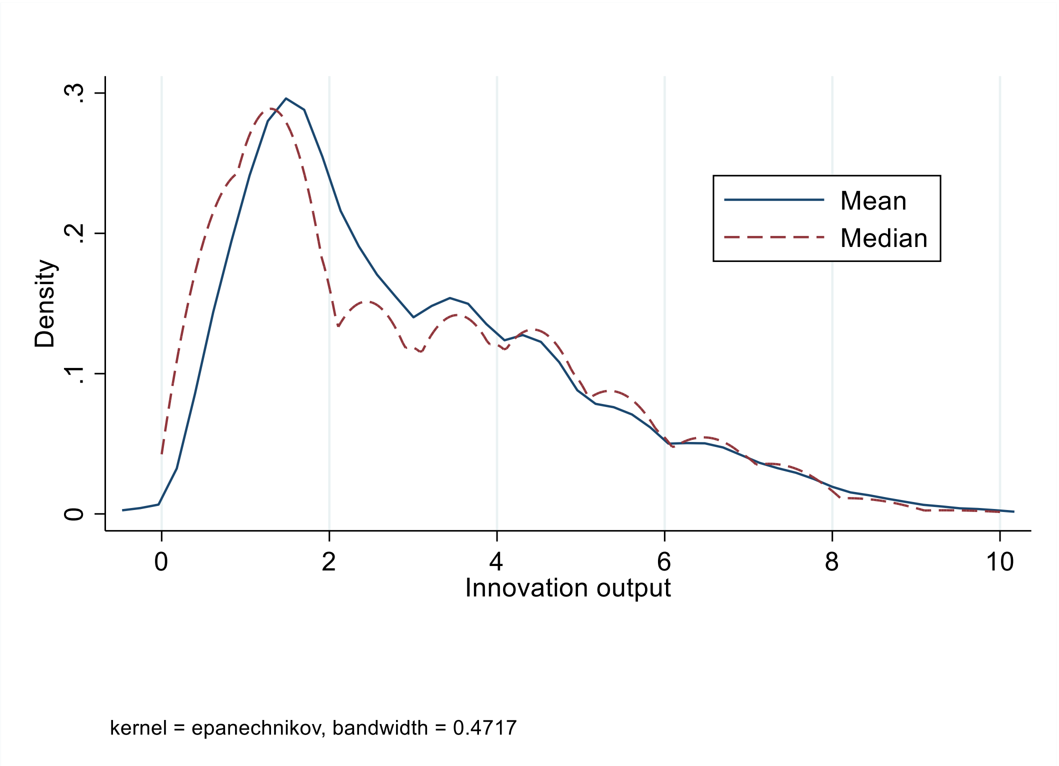
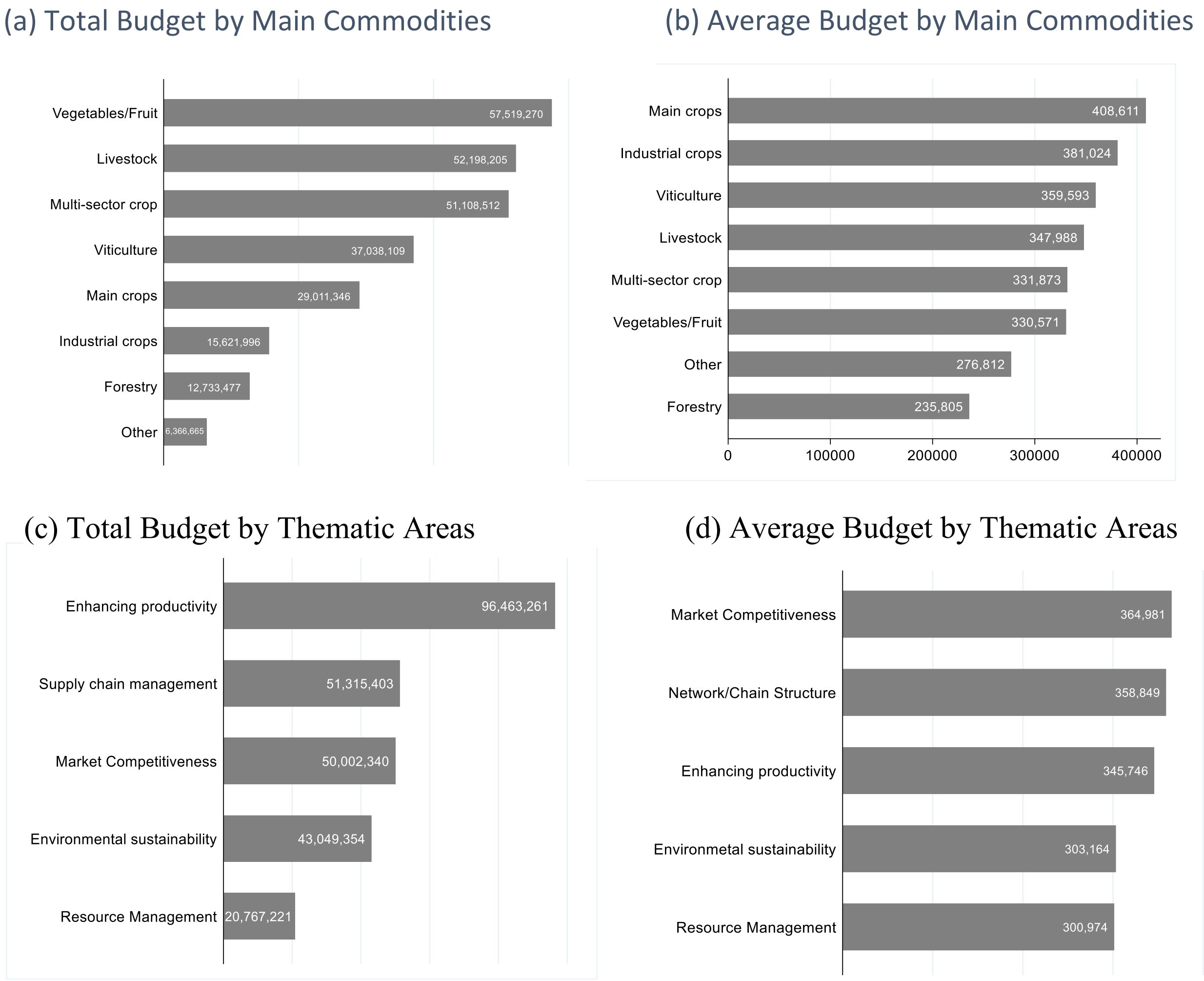
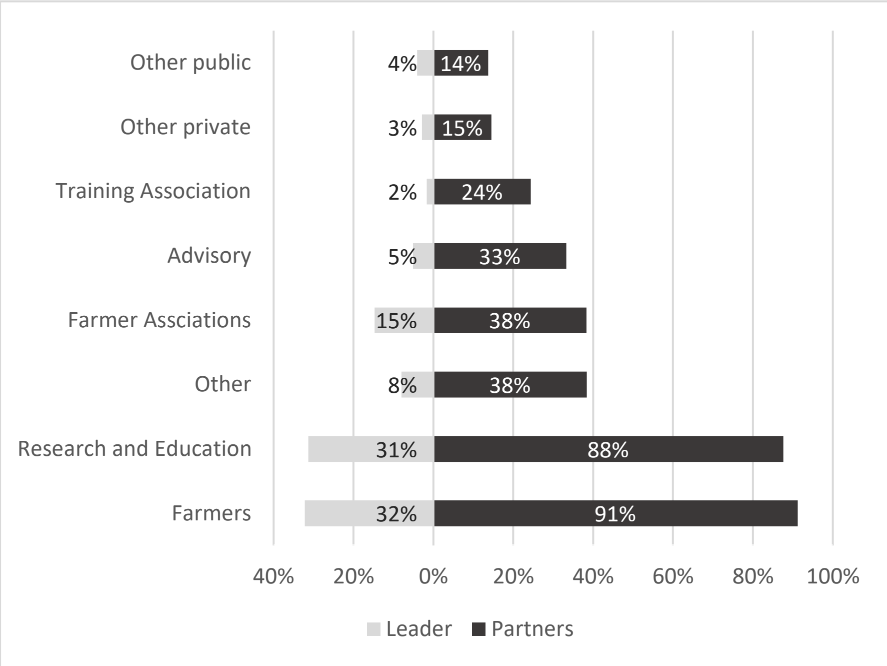


Figure 2. (a) Average Budget and (b) Total Budget per OG by Main Commodities Involved and per OG by Thematic Areas (in €)



Note: The “Other” category for main commodities includes beekeeping, floricultural, aquacultural products.

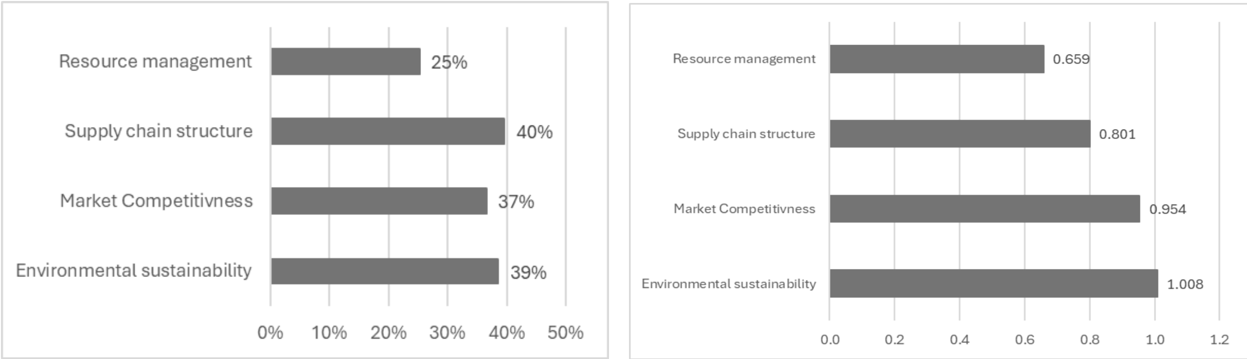
Figure 3. Distribution of Leader and Partner Types among Operation Groups



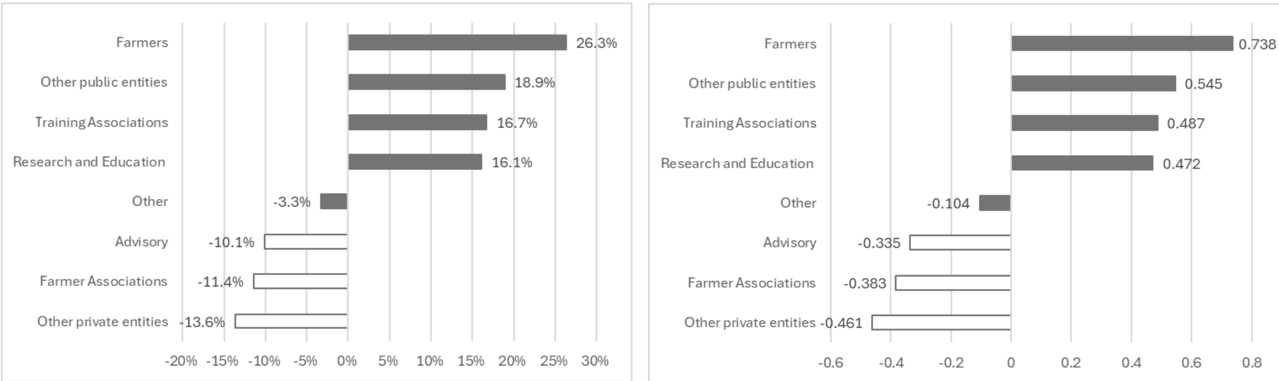
Note: The "Other" category involves OGs with no reference to Partner types

Figure 4. Marginal Effects at Mean and Percentage Change derived from IRR Estimates, Associated with Thematic Areas, Partner Types, and Main Commodities

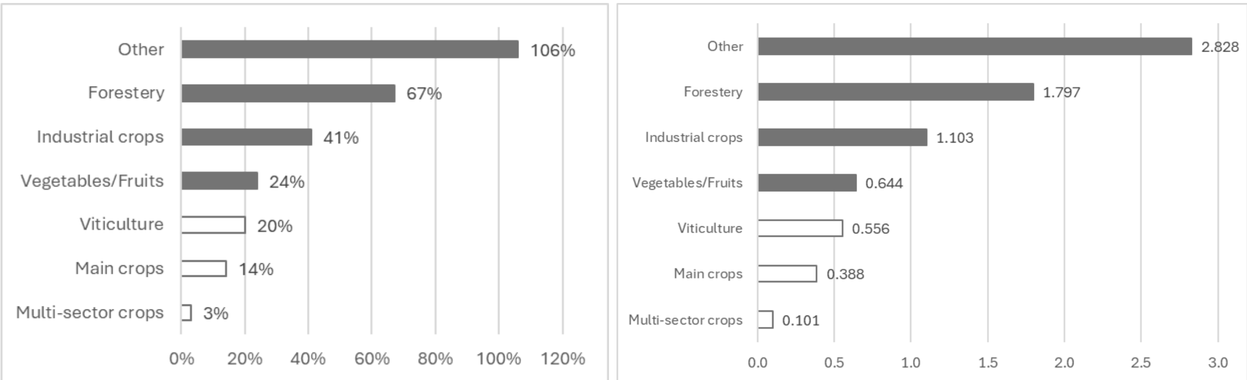
(a) By thematic areas



(b) By partner types



(c) By main commodities



Notes: The solid bars indicate statistical significance at least 10% significance level, while hollow bars indicate statistical insignificance. Percentage changes are calculated based on the following formular: (1-IRR)*100. The base category is “Enhancing productivity” for thematic areas and “livestock” for main commodities. The “Other” category for main commodities includes beekeeping, floricultural, aquacultural products.

Table 1. Model Fit across Different Models (Poisson vs. Negative Binomial) and Specifications

Model	Poisson			Negative Binomial		
	(1)	(2)	(3)	(4)	(5)	(6)
Establishment year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Regional characteristics		Yes	Yes		Yes	Yes
OGs' characteristics			Yes			Yes
Pearson's Chi^2 test	1172.8***	1071***	849.63***			
Ln (Alpha)				0.168***	0.145***	0.066***
				(0.054)	(0.029)	(0.018)
Likelihood ratio test				69.11***	52.58***	13.11***
% correct predictions	37.78%	37.79%	40%	37.01%	37.66%	40.13%

Note: We incorporate the following regional characteristics: per capita income, production costs and labour cost per unit of agricultural output, and the percentage of farmers engaged in agricultural-related business activities alongside their agricultural operations in the base year 2016 before OGs were established. OGs' characteristics are thematic areas, project duration, commodities involved, partner types, leader types, whether leaders have prior funding experience and participate as partners in other OGs.
*** 1%, ** 5%, and * 10%

Main Conclusion

This doctoral thesis explores the evolving landscape of agricultural innovation in Italy, focusing on how public subsidies and institutional frameworks under the Common Agricultural Policy (CAP) influence farmers' participation in research and innovation. Across its three empirical chapters, the thesis provides an integrated understanding of how multi-actor arrangements in knowledge systems environments interact to shape the transition of the agricultural sector from a *supplier-based* to a *science-based* agricultural sector.

The first chapter positions Italy's 'Food Districts' within the broader framework of the Agricultural Knowledge and Innovation System (AKIS). Findings demonstrate that local actors and farmers increasingly recognize the role of collective networks in fostering innovation and territorial development. However, gaps remain in advisory and digital services, underscoring the need for stronger institutional guidance to enhance rural innovation capacity.

The second chapter identifies the key determinants of farmers' participation in R&D AKIS-measures (CAP Measures 1, 2, 16, and 19), using a unique dataset of over 52,000 farms from the Farm Accountancy Data Network (2014–2021). Results show that larger, knowledge-intensive, and mechanized farms are more likely to access public R&D subsidies for innovation. The analysis also reveals that farms engaged in diversified or organic activities align closely with sustainability goals, indicating an ongoing but uneven shift toward science-based innovation. Public and private investments appear increasingly disconnected, highlighting the need for complementary funding models to sustain innovation-ecosystems.

The third chapter deeply investigates AKIS measures, showing new insights on the Operational Groups (OGs) under the EIP-AGRI framework (Measure 16 of the CAP). Through the creation of a novel dataset, Authors, firstly web-scraping OGs characteristics and then undercovering innovative projects using large language model techniques, finds interesting insights to understand factors that are related to the innovativeness of OGs in Italy.

The analysis reveals the crucial role of public entities and training institutions in stimulating innovation and knowledge diffusion. However, policy implementation challenges persist, including uneven funding distribution, insufficient innovation monitoring, and persistent regional disparities between northern and southern Italy.

OGs focusing on sustainability topics tend to be more innovative than those prioritizing productivity, suggesting that innovation potential is not fully aligned with funding allocation.

Taken together, the three chapters depict an Italian agricultural sector in transition, where innovation is increasingly shaped by knowledge intensity.

Institutional support to build efficient multi-actor collaboration for risky R&D projects is essential.

Nevertheless, the persistence of structural inequalities, limited advisory capacity, and regional imbalances hinder the full realization of R&D in agriculture to foster collaborations and knowledge sharing across actors (in the ASKI view).

Future agricultural policies should thus prioritize mechanisms that integrate financial, educational, and digital infrastructures, ensuring innovation processes in all the “innovation-value-chain”.

Finally, this thesis underscores the indispensable role of public R&D investments in the ongoing agricultural revolution, particularly in emerging technological domains such as artificial intelligence, biotechnology, and robotics. As private incentives remain limited in high-uncertainty stages of innovation, public institutions must continue to act as entrepreneurial agents, nurturing the science-based agricultural paradigm necessary for sustainable and competitive rural development.

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Appendices

For

Chapter 2

Farm to tech: evidence on the demand for R&D innovation subsidies in the Italian agriculture

Chapter 3

Assessing the Impact of Operational Groups on Agricultural Innovation in Italy

Appendix A- Chapter 2 Additional checks

Principal Component Analysis (PCA) Results

A Principal Component Analysis (PCA) was performed using four standardized variables which refers to the population density in each Region by year of Association Activities. The Association Activities refers in particular to: Ecological, Volunteers; Labour Unions and Financial activities to no-profit entities. The variables are collected from the Italian Statistical officer (ISTAT) and merged by region and year in the Italian FADN based on 76,989 observations spanning from 2014-2021.

We performed a Principal Component analysis (PCA) in order to extract an index that combine all variables. The analysis extracted four components as in Table 1.B, with the first component (Comp1) having an eigenvalue of 3.82 and explaining approximately 95.4% of the total variance. The remaining components contributed marginally, with Comp2 explaining 3.4%, Comp3 explaining 0.9%, and Comp4 only 0.3%. Given the dominant share of Comp1, the PCA reveals a strong common underlying factor across variables, suggesting high intercorrelation among them. Component loadings in Table 2.B, indicate that all variables contribute positively and relatively evenly to Comp1 (around 0.50), supporting the creation of a single synthetic indicator named Social Norms. Finally, the remaining components capture minor variations related to specific combinations of the variables, but their explanatory power remains limited.

Results of the PCA support the creation of the social norms indicator for our analysis calibrating and controlling for Regional external factors in which farmers operates.

Table 1.A Eigenvalues and Explained Variance

Component	Eigenvalue	Proportion	Cumulative
Comp1	3.81593	0.9540	0.9540
Comp2	0.135898	0.0340	0.9880
Comp3	0.0370084	0.0093	0.9972
Comp4	0.0111649	0.0028	1.0000

Table 2.A Component Loadings (Eigenvectors)

Variable	Comp1	Comp2	Comp3	Comp4
l_at_eco	0.5048	-0.0322	-0.8596	0.0726
l_at_vol	0.5055	-0.3471	0.2465	-0.7505
l_at_sind	0.4864	0.8348	0.2566	0.0259
l_at_fin	0.5030	-0.4262	0.3668	0.6564

Table 3.A Description of Programme Measures (2014-2020) for AKIS implementation

Measure	Description	Major selection criteria
1.Knowledge transfer and dissemination actions	Promotes the acquisition of technical and managerial skills, as well as the dissemination of innovations in various areas of business and the transfer of knowledge between the research and experimentation system and businesses.	- Potential/Quality of the project proposal - Coherence of the proposal with the objectives of the EIP and RDP - Partnership composition - Economic congruity -Applicability/Verifiability of results - Transfer and dissemination of results - Other specificities recognized by the regional office
2.Advisory, replacement and farm management assistance	Farm management consulting, replacement, and support services are support services to farms aimed at improving their efficiency, profitability, and sustainability. These services may include technical advice, replacement of staff during periods of absence or need, and support in administrative and financial management of the farm	
16. Cooperation	It is established with the aim of promoting a partnership between companies, research organizations and other actors, to develop and disseminate innovation in agriculture and forestry.	
19. LEADER Local Development Support	LEADER is a community-led approach to local development that supports private enterprises and community groups who improve quality of life and economic activity in rural areas. These groups are partnerships of public and private entities from a defined geographical area. Local action groups are responsible for local projects in accordance with the local development strategies they develop themselves.	

Appendix B - Chapter 2 Propensity Score Matching

To check the robustness of our results, a Propensity Score Matching (PSM) is estimated. As suggested by Crescenzi et al. (2022) and Cerelli (2022), PSM aims to approximate a randomised experimental setting by eliminating differences between treated and untreated units based on a set of observable characteristics. In this study, PSM was implemented on the pooled sample using a *one-nearest-neighbour* matching algorithm, a logit specification, and a control matrix of firm-level covariates related to Production (in €), Farm Size (Small,, Medium and Big) , Region (21 Regions and Autonomous Provinces) , Disadvantage areas (dummy if farms is located in a disadvantage area according to the Italian Ministry) and Technical-Economic Orientation (FADN categorization among the 59 different Technical- Economic Orientation of the farm).

After performing the PSM, the balancing test in Table 1.b, confirms that the matching procedure effectively reduced differences between treated and control groups. Specifically, the percentage bias for all covariates falls well below the commonly accepted threshold of 20%, indicating a high degree of covariate balance. Furthermore, all t-tests for mean differences are statistically insignificant ($p > 0.05$), suggesting that no systematic differences remain between groups after matching. Additionally, the variance ratios (V(T)/V(C)) for all covariates lie within the acceptable range of 0.64 to 1.57, with none falling outside this interval. These results collectively confirm that the matching has successfully balanced the observed characteristics across groups, satisfying key assumptions for estimating unbiased treatment effects. Furthermore, according to Stuart (2010), p-values can be misleading in this test, especially with small or large samples (small sample = low power, large sample = overly sensitive). Thus, the percentage standardized bias is more informative than p-values. So, while non-significant t-tests support balance, the low % bias is actually the more reliable and recommended a good balance among treated and control groups after the propensity score matching. The Summary statistics in Table 2.b confirm the goodness of the balance, presenting that all indicators (bias, p-values, variance ratios, and global tests like Rubin's B/R and LR test) suggest no meaningful residual differences in the observed covariates. For a graphical presentation Figure 1.b shows the two distributions before and after PSM. In conclusion, Table 3.b presents the results of the logit regression after the PSM compared to the logit results of Model (3) using errors with Bootstrap 100 run.

Table 1.b Balancing test between treated and untreated farms after Propensity Score Matching (AKIS)

Variable	Mean Treated	Mean Control	% Bias	p-value	V(T)/V(C)
Production	€410,000	€450,000	-4.8	0.730	0.89
Farm Size	2.6154	2.6410	-3.8	0.795	1.09
Region	8.1667	8.1410	0.5	0.974	0.90
Disadvantage area	1.359	1.4615	-6.1	0.696	0.95
Technical-Economic Orientation	4022.8	3750.1	14.7	0.368	1.10

if variance ratio outside [0.64; 1.57]

Table 2.b Summary Statistics of Covariate Balance After Matching

Statistic	Value
Ps R^2	0.005
LR χ^2	1.18
MeanBias	6.0%
MedBias	4.8%
B (Rubin's B)	17.3%
R (Rubin's R)	1.38
%Var	0

if B>25%, R outside [0.5; 2]

Figure 1.b Distribution propensity score before and after matching

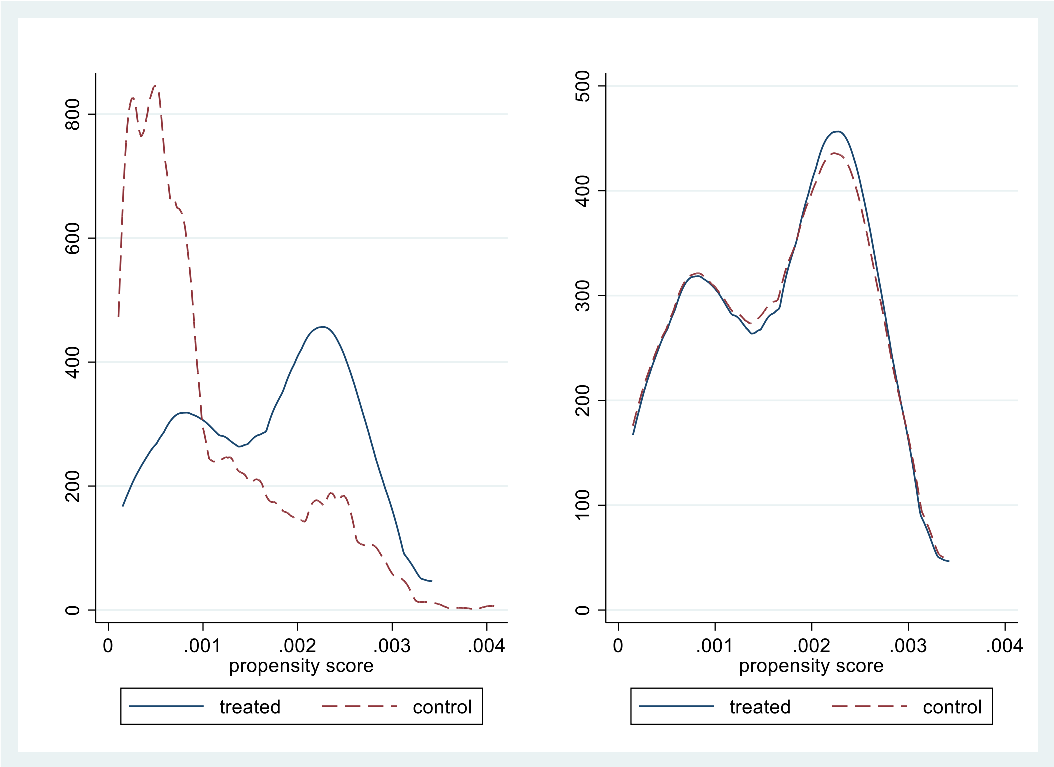

Table 3.b Logit Estimation after Propensity Score Matching

	Models	
	(1)	(5)
Total Sales	0.616**	0.610***
	(0.288)	(0.146)
ROI	0.877	-0.400
	(0.550)	(0.269)
Net Indebtedness	-0.145	0.094
	(0.286)	(0.148)
ROA	-3.179*	0.070
	(1.924)	(0.437)
Diversified	1.221*	0.862***
	(0.647)	(0.272)
Organic	0.408	0.856***
	(0.675)	(0.273)
Entrepreneurial age	-0.019	-0.037***
	(0.019)	(0.010)
Factor-scarcity ratio	-0.080	-0.050
	(0.082)	(0.036)
Entrepreneurial sex	0.686	0.902***
	(0.610)	(0.272)
Population density	-0.001	0.001**
	(0.004)	(0.000)
Social Norms index	0.402	0.027
	(0.302)	(0.046)
Observations	107	52,980
Control Variables	Y	Y
Year Fixed-Effects	Y	Y
Regional fixed-effects	Y	Y

Note: This table present the comparison between Model (1) after the PSM and Model (5) firth logit regression for rare events. Each regression estimates control for year fixed effects, Regional fixed effects and other sets of control variables: Entrepreneurial sex, Population density and Social Norm Index showed in the regression. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Appendix A - Chapter 3 Additional Figures and Tables

Table A1 Variables used in the regression model, definitions and data sources

Variable	Description	Source
(y) Innovations	Number of actual innovation	Extracted with LLM
Total Budget	Logarithmic In Millions €	web-scraped 'Innovarurale'
Thematic	Orientation of the main OG objective (Environmental; Market Competitiveness; Network/Chain structure; Resources; Productivity)	web-scraped 'Innovarurale'
Duration	Number of months	web-scraped 'Innovarurale'
Partners	Number of partners involved	web-scraped 'Innovarurale'
Collaboration	Yes/No head collaboration with other OGs	web-scraped 'Innovarurale'
Past experiences	Yes/No head past experiences in achieving public funding	web-scraped 'Innovarurale'
Leader type	Head Partner typology (e.g., Farmer Research&Education, Training; Advisory; Association of farmers; Other private; other public; other entities)	web-scraped 'Innovarurale'
Actors involves	Typologies of actor involved in the project (dummy for each)	web-scraped 'Innovarurale'
Established Year	number of the first year per OG	web-scraped 'Innovarurale'
Income per capita	in Millions € per region	Eurostat
Geographical location	categorical (Northeast; Northwest; Centre; South)	Eurostat
Commodities	Typologies of commodities (Livestock; Main crops; industrial crops; Veg&Fruits; Viticulture; Multi-sector; Forestry; Others)	web-scraped 'Innovarurale'
Labour costs	Ratio number of labour in agriculture on agricultural costs per Region (in Millions €)	Eurostat
Percentage farmer Other activities	percentage of number of non-agricultural activities Managed by farmers on total number of farmers Per region in 2016	Eurostat
Production costs	ratio of total costs per agr output per region	Eurostat

Table A2 Summary Statistics of Key Variables

Variable	Mean	Std. Dev.	Min	Max
Continuous variables				
Number actual Innovations	3.03	1.91	0	9.7
Established year	2018.9	1.37	2016	2022
Per capita income by region	10.2	.27	9.77	.73
Production costs per unit of agricultural output value	.17	.04	.042	.288
Labour costs per unit of agricultural output value	.56	.38	.179	1.421
Percentage of farmers engaged in agricultural-related business activities	7.87	8.36	1.251	41.894
Duration (month)	31.18	7.69	11	59
Number of partners	8.30	4.36	1	48
Dummy variables				
OG leader collaborating in other OGs	.24	.43	0	1
OG leader past OG experience	.28	.45	0	1
Partner Type:				
Farmers	.91	.28	0	1
Training entities	.26	.44	0	1
Advisory	.34	.47	0	1
Research and educational institutes	.87	.32	0	1
Farmers' associations	.38	.48	0	1
Other public entities	.14	.35	0	1
Other private entities	.14	.35	0	1
Others	.40	.49	0	1
Categorical variables				
Region:				
Mezzogiorno	.254	.436	0	1
Centre	.167	.373	0	1
North-East	.463	.499	0	1
North-West	.116	.321	0	1
Thematic Areas:				
Environmental	.184	.388	0	1
Market Competitiveness	.181	.385	0	1
Network/Chain Structure	.189	.392	0	1
Productivity	.35	.477	0	1
Resources	.096	.295	0	1
Commodities:				
Livestock	.192	.394	0	1
Vegetables/Fruit	.212	.409	0	1
Main crops	.101	.301	0	1
Industrial crops	.054	.227	0	1
Viticulture	.135	.342	0	1
Multi-sector crop	.201	.401	0	1
Forestry	.077	.267	0	1
Other	.028	.165	0	1
Leader Typology:				
Farms	.322	.468	0	1
Training entities	.017	.129	0	1
Advisory entities	.051	.22	0	1

Research and education	.313	.464	0	1
Associations of farmers	.147	.354	0	1
Other private entities	.029	.169	0	1
Other public entities	.04	.197	0	1
Other	.08	.272	0	1

Table A3 Estimation analysis Poisson and Negative Binomial, fixed effects and control variables

	Poisson Models			Negative Binomial Models		
	(1)	(2)	(3)	(4)	(5)	(6)
Region: Base Northeast						
South	0.752	0.830	0.876	0.730*	0.828	0.850
	(0.140)	(0.132)	(0.258)	(0.133)	(0.131)	(0.272)
Centre	0.721	0.724	0.673**	0.708	0.714*	0.663**
	(0.174)	(0.144)	(0.127)	(0.172)	(0.142)	(0.127)
North-West	0.674	0.759	0.547***	0.763	0.788	0.561***
	(0.215)	(0.179)	(0.108)	(0.314)	(0.191)	(0.117)
Regional income per capita			1.461			1.399
			(0.909)			(0.886)
Production costs			1.954			1.896
			(2.401)			(2.371)
Labour costs			1.097			1.102
			(0.206)			(0.215)
Ratio of farmer engaged in non-agricultural activities			1.022**			1.022**
			(0.010)			(0.010)
Thematic: Base Productivity						
Environmental		1.307***	1.384***		1.307***	1.386***
		(0.115)	(0.109)		(0.116)	(0.111)
Market Competitiveness		1.327***	1.358***		1.335***	1.365***
		(0.053)	(0.055)		(0.056)	(0.057)
Network/Chain Structure		1.277***	1.301***		1.279***	1.307***
		(0.095)	(0.105)		(0.096)	(0.106)
Resources		1.190**	1.270***		1.169*	1.252***
		(0.095)	(0.090)		(0.096)	(0.091)
Duration (in months)		0.982**	0.986**		0.982**	0.987**
		(0.008)	(0.006)		(0.008)	(0.006)
Leader collaboration in other OGs		1.166***	1.166***		1.175***	1.171***
		(0.066)	(0.061)		(0.066)	(0.058)
Leader Past Experience in OG projects		1.016	1.005		1.011	1.000
		(0.112)	(0.107)		(0.108)	(0.104)
Base Leader: Research & Education						
LEADER: Farms		0.971	0.996		0.991	1.006
		(0.090)	(0.065)		(0.091)	(0.065)
LEADER: Training entities		0.984	0.918		0.981	0.922
		(0.236)	(0.243)		(0.246)	(0.253)
LEADER: Advisory entities		1.063	1.082		1.051	1.073
		(0.093)	(0.095)		(0.095)	(0.096)
LEADER: Associations of farmers		0.927	0.892		0.927	0.895
		(0.080)	(0.069)		(0.078)	(0.071)
LEADER: Other private entities		1.218	1.154		1.220	1.163
		(0.247)	(0.251)		(0.249)	(0.256)
LEADER: Other public entities		1.077	1.085		1.078	1.086
		(0.138)	(0.137)		(0.138)	(0.137)
LEADER: Other firms		0.945	0.976		0.957	0.988

		(0.096)	(0.107)		(0.096)	(0.107)
Number of Partners		1.007	1.006		1.006	1.005
		(0.010)	(0.009)		(0.010)	(0.008)
Typology partner involved:						
Farms		1.245***	1.255***		1.253***	1.263***
		(0.073)	(0.089)		(0.072)	(0.092)
Training		1.152*	1.165		1.158*	1.167*
		(0.087)	(0.110)		(0.091)	(0.109)
Advisory		0.888*	0.900		0.890*	0.899
		(0.060)	(0.060)		(0.058)	(0.059)
Research&Education		1.184***	1.159**		1.187***	1.161**
		(0.072)	(0.076)		(0.072)	(0.075)
Farmers'Associations		0.879	0.883		0.882	0.886
		(0.070)	(0.071)		(0.070)	(0.071)
Other public		1.178**	1.182**		1.193**	1.189**
		(0.088)	(0.089)		(0.098)	(0.094)
Other private		0.828***	0.866**		0.827***	0.864**
		(0.056)	(0.058)		(0.059)	(0.059)
Other firms		0.940	0.973		0.937	0.967
Base Commodity: Livestock		(0.068)	(0.062)		(0.071)	(0.065)
Veg&Fruit		1.216**	1.239**		1.227**	1.242**
		(0.121)	(0.117)		(0.122)	(0.118)
Main crops		1.125	1.146		1.126	1.146
		(0.117)	(0.111)		(0.115)	(0.111)
Industrial crops		1.403**	1.411**		1.410**	1.415**
		(0.228)	(0.224)		(0.218)	(0.217)
Viticulture		1.182	1.212		1.180	1.209
		(0.167)	(0.162)		(0.165)	(0.162)
Multi-sector		1.043	1.033		1.049	1.038
		(0.082)	(0.085)		(0.080)	(0.082)
Forestry		1.713***	1.662***		1.742***	1.676***
		(0.250)	(0.248)		(0.242)	(0.249)
Other		2.085***	1.998***		2.207***	2.064***
		(0.487)	(0.501)		(0.539)	(0.553)
Constant	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
lnalpha				0.168***	0.082***	0.066***
				(0.054)	(0.026)	(0.018)
Observations	646	646	646	646	646	646
Year Fixed-Effects	Y	Y	Y	Y	Y	Y
% Y predicted count	37.78%	37.79%	40%	37.01%	37.66%	40.13%

Robust SE in parentheses *** p<0.01, ** p<0.05, * p<0.1 Exposure Total Budget per OGs

Table A4 Estimation analysis Poisson and Negative Binomial, IRR and marginal effects

	Poisson Models		Negative Binomial Models	
	IRR (3)	Marginal Effects (3)	IRR (6)	Marginal Effects (6)
Average Number of actual innovations per OG				
Base NorthEast				
South	0.876	-0.453	0.850	-0.560
	(0.258)	(0.993)	(0.272)	(1.083)
Centre	0.673**	-1.192**	0.663**	-1.257**
	(0.127)	(0.607)	(0.127)	(0.642)
North-West	0.547***	-1.649***	0.561***	-1.637***
	(0.108)	(0.583)	(0.117)	(0.639)
Income per region	1.465	1.162	1.399	1.037
	(0.909)	(1.887)	(0.886)	(1.953)
Costs on output	1.954	2.036	1.896	1.973
	(2.401)	(3.740)	(2.371)	(3.860)
Labour on output	1.097	0.280	1.102	0.299
	(0.206)	(0.568)	(0.215)	(0.599)
Ratio farm other activities	1.022**	0.067**	1.022**	0.066**
	(0.010)	(0.031)	(0.010)	(0.030)
Base Productivity				
Environmental	1.384***	0.961***	1.386***	0.979***
	(0.109)	(0.288)	(0.111)	(0.296)
Market Competitiveness	1.358***	0.895***	1.365***	0.927***
	(0.055)	(0.124)	(0.057)	(0.132)
Network/Chain Structure	1.301***	0.754***	1.307***	0.779***
	(0.105)	(0.232)	(0.106)	(0.239)
Resources	1.270***	0.675***	1.252***	0.640***
	(0.090)	(0.216)	(0.091)	(0.223)
Duration (in months)	0.986**	-0.041**	0.987**	-0.041***
	(0.006)	(0.016)	(0.006)	(0.017)
Leader collaboration in other OGs	1.166***	0.466***	1.171***	0.487***
	(0.061)	(0.158)	(0.058)	(0.153)
Leader Past Experience in OG projects	1.005	0.016	1.000	-0.009
	(0.107)	(0.322)	(0.104)	(0.319)
Base Leader: Research&Education				
LEADER: Farms	0.996	-0.012	1.006	0.017
	(0.065)	(0.198)	(0.065)	(0.201)
LEADER: Training entities	0.918	-0.250	0.922	-0.241
	(0.243)	(0.751)	(0.253)	(0.788)
LEADER: Advisory entities	1.082	0.252	1.073	0.227
	(0.095)	(0.284)	(0.096)	(0.292)
LEADER: Associations of farmers	0.892	-0.331	0.895	-0.325
	(0.069)	(0.210)	(0.071)	(0.218)
LEADER: Other private entities	1.154	0.473	1.163	0.504
	(0.251)	(0.768)	(0.256)	(0.792)
LEADER: Other public entities	1.085	0.261	1.086	0.266
	(0.137)	(0.426)	(0.137)	(0.428)
LEADER: Other firms	0.976	-0.073	0.988	-0.038
	(0.107)	(0.331)	(0.107)	(0.332)
Number Partners	1.006	0.018	1.005	0.015
	(0.009)	(0.026)	(0.008)	(0.026)
Typology of partners:				
Farms	1.255***	0.690***	1.263***	0.721***

	(0.089)	(0.220)	(0.092)	(0.229)
Training	1.165	0.464*	1.167*	0.475*
	(0.110)	(0.270)	(0.109)	(0.271)
Advisory	0.900	-0.321	0.899	-0.327
	(0.060)	(0.204)	(0.059)	(0.151)
Research&Education	1.159**	0.448**	1.161**	0.461**
	(0.076)	(0.197)	(0.075)	(0.195)
Farmers'Associations	0.883	-0.377	0.886	-0.374
	(0.071)	(0.253)	(0.071)	(0.255)
Other public	1.182**	0.507**	1.189**	0.533**
	(0.089)	(0.225)	(0.094)	(0.240)
Other private	0.866**	-0.436**	0.864**	-0.451**
	(0.058)	(0.215)	(0.059)	(0.222)
Other firms	0.973	-0.083	0.967	-0.102
	(0.062)	(0.194)	(0.065)	(0.207)
Base commodity: Livestock				
Veg&Fruit	1.239**	0.616**	1.242**	0.632**
	(0.117)	(0.271)	(0.118)	(0.276)
Main crops	1.146	0.376	1.146	0.381
	(0.111)	(0.270)	(0.111)	(0.273)
Industrial crops	1.411**	1.060*	1.415**	1.082**
	(0.224)	(0.559)	(0.217)	(0.547)
Viticulture	1.212	0.547	1.209	0.546
	(0.162)	(0.400)	(0.162)	(0.407)
Multi-sector	1.033	0.086	1.038	0.098
	(0.085)	(0.214)	(0.082)	(0.209)
Forestry	1.662***	1.705***	1.676***	1.763***
	(0.248)	(0.598)	(0.249)	(0.610)
Other	1.998***	2.571**	2.064***	2.776*
	(0.501)	(1.272)	(0.553)	(1.422)
Constant	0.000***		0.000***	
	(0.000)		(0.000)	
lnalpha			0.066***	
			(0.018)	
Year Fixed-Effects	Y	Y	Y	Y
Observations	646	646	646	646

*Robust SE in parentheses *** p<0.01, ** p<0.05, * p<0.1 Exposure Total Budget per OGs*

Table A5 Estimation analysis for median distribution of OG actual innovations, Poisson and Negative Binomial, IRR and marginal effects

	Poisson Models		Negative Binomial Models	
	IRR (7)	Marginal Effects (7)	IRR (8)	Marginal effects (8)
Median Number of actual Innovations per OG				
Base NorthEast				
South	0.968	0.896	0.945	0.821
	(0.314)	(0.989)	(0.343)	(1.027)
Centre	0.691*	0.342*	0.682*	0.322*
	(0.144)	(0.219)	(0.145)	(0.221)
North-West	0.497***	0.175***	0.519***	0.180***
	(0.097)	(0.097)	(0.113)	(0.115)
Income per region	2.148	2.229	2.043	2.134
	(1.333)	(1.815)	(1.338)	(1.963)
Costs on output	2.026	8.218	1.910	7.221
	(2.770)	(33.582)	(2.648)	(30.614)
Labour on output	1.129	1.435	1.149	1.531
	(0.212)	(0.796)	(0.229)	(0.922)

Ratio farm other activities	1.024**	1.074**	1.024**	1.074**
	(0.011)	(0.034)	(0.011)	(0.035)
Base Productivity				
Environmental	1.452***	2.946***	1.456***	3.052***
	(0.130)	(0.937)	(0.132)	(1.019)
Market Competitiveness	1.428***	2.780***	1.439***	2.926***
	(0.070)	(0.369)	(0.071)	(0.408)
Network/Chain Structure	1.350***	2.307***	1.349***	2.350***
	(0.133)	(0.624)	(0.133)	(0.653)
Resources	1.397***	2.585***	1.386***	2.569***
	(0.111)	(0.634)	(0.113)	(0.662)
Duration(month)	0.987*	0.963**	0.988*	0.962**
	(0.006)	(0.018)	(0.007)	(0.019)
Leader collaboration in other OGs	1.116	1.387	1.128*	1.447*
	(0.074)	(0.282)	(0.072)	(0.291)
Leader past Experience in OG projects	1.063	1.198	1.043	1.136
	(0.127)	(0.421)	(0.123)	(0.406)
Base Leader: Research&Education				
Leader: Farms	0.980	0.940	0.986	0.958
	(0.065)	(0.189)	(0.068)	(0.203)
Leader: Training entities	0.929	0.806	0.935	0.817
	(0.257)	(0.637)	(0.278)	(0.714)
Leader: Advisory entities	1.046	1.151	1.036	1.119
	(0.119)	(0.414)	(0.122)	(0.424)
Leader: Associations of farmers	0.894	0.724	0.895	0.722
	(0.094)	(0.209)	(0.097)	(0.220)
Leader: Other private entities	1.064	1.217	1.058	1.199
	(0.244)	(0.903)	(0.249)	(0.930)
Leader: Other public entities	1.101	1.360	1.094	1.340
	(0.196)	(0.824)	(0.191)	(0.806)
Leader: Other firms	0.923	0.792	0.926	0.793
	(0.122)	(0.301)	(0.121)	(0.304)
Number of Partners	1.006	1.019	1.004	1.013
	(0.009)	(0.027)	(0.009)	(0.027)
Typology of Partners:				
Farmer	1.332***	2.353***	1.369***	2.609***
	(0.101)	(0.558)	(0.104)	(0.640)
Training	1.086	1.279	1.078	1.260
	(0.103)	(0.349)	(0.103)	(0.358)
Advisory	0.893	0.713	0.889	0.699
	(0.074)	(0.178)	(0.075)	(0.181)
Research&Education	1.039	1.122	1.038	1.122
	(0.080)	(0.256)	(0.083)	(0.273)
FarmsAssociation	0.869*	0.657	0.873*	0.659
	(0.073)	(0.173)	(0.071)	(0.173)
Other public	1.138	1.472	1.148	1.523
	(0.102)	(0.374)	(0.108)	(0.418)
Other private	0.943	0.840	0.943	0.837
	(0.048)	(0.130)	(0.055)	(0.149)
Other firms	1.037	1.116	1.039	1.124
	(0.066)	(0.212)	(0.069)	(0.225)
Base commodity: Livestock				
Veg&Fruit	1.228**	1.769**	1.240**	1.842**
	(0.120)	(0.473)	(0.123)	(0.514)
Main crops	1.136	1.406	1.141	1.430
	(0.117)	(0.384)	(0.117)	(0.398)
Industrial crops	1.418**	2.847**	1.438***	3.042**
	(0.204)	(1.386)	(0.199)	(1.458)

Viticulture	1.218	1.726	1.212	1.714
	(0.181)	(0.743)	(0.183)	(0.762)
Multi-sector	1.056	1.150	1.067	1.185
	(0.094)	(0.262)	(0.089)	(0.259)
Forestry	1.726***	6.142***	1.761***	6.929***
	(0.260)	(3.694)	(0.263)	(4.324)
Other	2.135***	17.118**	2.256***	24.394*
	(0.584)	(24.380)	(0.656)	(39.777)
Constant	0.000***		0.000***	
	(0.000)		(0.000)	
Year Fixed-Effects	Y	Y	Y	Y
Observations	646	646	646	646
lnalpha			0.120***	
			(0.021)	

*Robust SE in parentheses *** p<0.01, ** p<0.05, * p<0.1 Exposure Total Budget per OGs*

Appendix B - Chapter 3 Definitions and codes for LLM

The selection of the Large Language Model (LLM) was based on the objectives of this study. Specifically, we employed LLaMA 3, an open-source model developed by Meta, designed for text comprehension and generation. Similar to ChatGPT, LLaMA 3 is a general-purpose model, making it well-suited for extracting a specific data variable from unstructured text. However, a limitation of this study is the need to integrate multiple models to assess the accuracy and effectiveness of the generated responses. Future research can build upon our approach by utilizing the code, which is freely available on GitHub, to facilitate comparative analyses.

The present appendix presents the parameters used in the LLM and the definition of innovation. Accordingly, the main parameter underlined is the *temperature* of the model. Results are compared and collected with temperature settled at level 0.3 and level 0.1, while the number of *CPU* used are settled at 32.

To assist the AI in extracting the number of actual innovations within each Operational Group (OG), a clear definition of innovation is provided. The prompt was formulated based on the Oslo Manual (4th edition) and relevant literature on OGs best practices.

The following code snippet outlines the definition of innovation as applied in this study.

```
response_format={ "type": "json_object" },
    messages=[
        {"role": "system", "content": "You are an expert about the
definitions contained in the Oslo Manual 4th edition. You are an expert in
agricultural innovations and agricultural economics. According to the Oslo
Manual IV edition the term "innovation" can be used in different contexts
to refer to either a process or an outcome (product). \
"A product innovation is a new or improved good or service that differs
significantly from the firm's previous goods or services and that has been
introduced on the market." Product innovations must provide significant
improvements to one or more characteristics or performance specifications.
Relevant functional characteristics include quality, technical
specifications, reliability, durability, economic efficiency during use,
affordability, convenience, usability, and user friendliness. Product
innovations do not need to improve all functions or performance
specifications and must be made available to potential users.\
A process innovation is the implementation of a new or significantly
improved production or delivery method. This includes significant changes
in techniques, equipment and/or software.\
"A business process innovation is a new or improved business process for
one or more business functions that differs significantly from the firm's
previous business processes and that has been brought into use in the
firm." A business process innovation can involve improvements to one or
more aspects of a single business function or to combinations of different
business functions. According to Eurostat (2013) the functions can be
divided into: \
•     distribution and logistics: transportation activities, warehousing
and order processing.\
•     marketing, sales and after-sales services: market research,
advertising, direct marketing services (telemarketing), exhibitions, fairs
```

and other marketing or sales services; also included are call-centre services and after-sales services such as help-desks and other customer support services.\

- information and communication technology (ICT) services: information technology (IT) services and telecommunication (IT services including hardware and software consultancy, customised software data processing and database services, maintenance and repair, web-hosting, as well as other computer-related and information services, but excluding packaged software and hardware).\
- administrative and management functions: legal services, accounting, book-keeping and auditing, business management and consultancy, human resources (HR) management (e.g. training and education, staff recruitment, provision of temporary personnel, payroll management as well as health and medical services), corporate financial and insurance services; also included are procurement functions.\
- engineering and related technical services: engineering and related technical consultancy, technical testing, analysis and certification; also included are design services.\

According to Nelson and Winter (1982), technical innovation often emerges as firms experiment and modify their routines in response to competitive pressures and market demands. Thus, in the Operational Group context, innovations often refer to technical innovations that arise from experimental and scientific research and can often be the answer to farmers' needs, bringing the new technology to the local/national market. Technical innovations are not understood as radical innovations, but also as incremental innovations, which improve certain technologies to adapt them to the needs of agriculture. In addition, Italy's relationship with tradition and agricultural culture has led to the view that a new way of bringing into the market traditional foods is a process innovation, while a revaluation of traditional foods is a product innovation.\
The innovation minimum requirement is the novelty. In Italian Operational Groups novelty of innovation can be measured as new for the patterns of the project, or for the entire commodity sector. For Italian operational Groups is not an innovation: routine changes or updates; simple capital replacement or extension; product introductions that only involve minor aesthetic changes; the outputs of creative and professional service firms, such as reports for clients are not by default an innovation for the firms that develop them. "+