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RURAL DEVELOPMENT POLICIES AND FARMS BEHAVIOUR

LA DOTTORESSA

Debora Insolda

IL COORDINATORE

Ch.mo Prof.
Vito M. R. Muggeo

IL TUTOR

Ch.mo Prof.
Davide Piacentino

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"Life is not easy for any of us. But what of that? We must have perseverance and above all confidence in ourselves. We must believe that we are gifted for something and that this thing must be attained."

Marie Curie

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I am truly grateful to life!

Contents

Introduction

Since 1962, the Common Agricultural Policy (CAP) has played a crucial role in the development of European agriculture by providing financial support to farmers in member states. From its inception, the CAP has set specific objectives, including increasing agricultural productivity through technological progress, ensuring a adequate living conditions for farmers, stabilizing markets, and guaranteeing reasonable prices for consumers.

However, the CAP system has faced widespread criticism for encouraging overproduction, leading to storage issues and straining financial resources with negative impacts on local agriculture and at the same time on the environment due to excessive land exploitation.

Following various CAP reforms that recognized the need for change, such as the MacSharry Reforms of 1992 and Agenda 2000, a significant shift occurred in 2003 with the Fischler reform (EC, 1997). This reform decoupled subsidies from production, encouraging farmers to adopt more sustainable and market-oriented practices. Subsequently, the CAP was divided into two main "pillars" addressing different aspects of agriculture and rural life.

The first pillar consists of direct payments to farmers, often based on the size of a farm (direct payments per hectare), market measures, and greening measures in the current and "ecological schemes" in the future CAP effective from 2023. To eliminate any incentive for overproduction, payments are based on the amount of land a farmer owns, not on what they produce.

The second pillar involves rural development policy and includes support for agri-environmental and climate measures, including organic farming. The goal is to achieve balanced territorial development of economies and rural communities, including job creation and maintenance. While the first pillar is 100% EU funds, rural development policy is co-financed by national (and sometimes regional) budgets.

Local Action Groups (LAGs) play a crucial role in supporting more integrated and sustainable development in rural areas. What makes LAGs particularly significant is their LEADER (Liaison Entre Actions de Développement de l'Économie Rurale) program, based on a bottom-up approach. They support local projects aimed at improving the quality of life, allowing local communities to actively participate in the planning and implementation of rural development projects.

However, the CAP has undergone further reforms. The latest reform, effective from 2021, integrates the CAP with the European Green Deal, emphasizing environmental sustainability, climate action, and the Farm to Fork strategy. A more flexible and results-oriented approach has been introduced, allowing member states to adapt their CAP strategic plans to specific national needs and priorities. The new CAP emphasizes ecosystems, climate action, and biodiversity protection, with a significant portion of direct payments tied to environmental and climate requirements. Moreover, the CAP aims to support young farmers by allocating a portion of funds to them, and gender equality in agriculture becomes a specific goal. A financial reserve has been established to address crises (e.g., the COVID-19 pandemic), providing support for emergency measures. The CAP aligns with international environmental goals and the EU's commitment to global sustainable agriculture.

In line with the new CAP, LAGs will continue to play a key role, contributing to environmental goals, promoting sustainable and innovative agricultural practices, natural resource management, and resilience to climate challenges. The bottom-up approach will be maintained, ensuring active involvement of local communities in defining and implementing development strategies. LAGs will also contribute to supporting young farmers and promoting gender equality in agriculture, aligning with the broader goals of the CAP.

In conclusion, the CAP has come a long way from its origins as a mechanism for ensuring food security and market stabilization. Over the years, it has adapted to address emerging challenges, shifting towards sustainability, rural development, and a more market-oriented approach. The future of the CAP reflects a commitment to environmental responsibility, climate action, and a resilient and competitive agricultural sector in the context of a rapidly evolving global landscape. Therefore, the purpose of this doctoral thesis is to provide an analysis of CAP reforms, highlighting key innovations and changes, while offering initial reflections on opportunities and potential challenges. This is done in light of the experiences, strengths, and weaknesses that have characterized the CAP through its evolutions, with a focus on both the agricultural sector and rural areas in Italy.

For this reason, the thesis aims to conduct an in-depth analysis of agricultural policies, with particular attention to the Common Agricultural Policy (CAP) of the European Union, dividing it into its two pillars. Furthermore, it seeks to explore the effect of these policies on Italian regions, focusing on Total Factor Productivity (TFP) and assessing the specific impact of the first and second pillars of the CAP. The goal is also to understand the interaction between direct income support (first pillar) and rural development measures (second pillar), highlighting how they mutually influence each other.

In the concluding part of the thesis, a more specific perspective is introduced, focusing on Sicilian farms, considering the period before and after the onset of the COVID-19 pandemic. The analysis extends to examine the attitude of these farms towards changes, with particular reference to key issues such as digitalization, innovation and sustainability.

The thesis aims to provide a comprehensive overview of agricultural policy dynamics, with a particular focus on the Italian and Sicilian situation, contributing to understanding the effects of these policies on various stakeholders in the agricultural sector. Finally, we conclude by offering an original contribution to academic literature on agricultural policies and their impact on farms, suggesting potential improvements or regulations based on the results obtained.

Chapter 1

CAP evolution: Agricultural policies and rural development

1.1 Introduction

This chapter embarks on a comprehensive exploration of the academic literature pertaining to the European Union's (EU) Common Agricultural Policy (CAP), with a particular emphasis on its two distinct pillars and the LEADER approach adopted by Local Action Groups (LAGs). Over the past sixty years, Italian agriculture has undergone significant transformations influenced by diverse factors such as technological advancements, market dynamics, and evolving consumer trends. A pivotal influence on this trajectory is ascribed to the EU's rural development policy, inaugurated in 2000 through Rural Development Programs (RDPs), constituting the second pillar of the CAP. While the first pillar centered on providing income support to farmers, the second pillar aimed to facilitate the modernization of agricultural production structures and the fostering of multifunctionality.

Multifunctionality, in this context, denotes agriculture's capacity to assume roles beyond its primary production function by diversifying its activities. The agricultural policy, consequently, aims improving environmental sustainability, competitiveness, and the conditions conducive to the creation of rural zones (European Commission, 2003). This evolution affected agricultural income and production methods, initially through price support, subsequently incorporating agro-environmental constraints and incentives. Most notably, it propelled initiatives for rural development. Given the substantial impact of rural development policy reforms and requisite institutional adjustments over the years, this document centers its focus on these pivotal aspects.

The fundamental objectives of agricultural policies have perennially revolved around ensuring an ample food supply and sustaining the livelihoods of farmers. The multifaceted nature of these policies, entwined with economic integration, has played a defining role in shaping the contours of Italian agriculture. As we delve into the nuances of the literature, our review predominantly seeks to unravel the intricate interplay between the CAP, rural development policies, and their ramifications on Italian agriculture.

The subsequent sections are meticulously structured to provide a comprehensive understanding of the phenomenon under study. Section 1.2 furnishes a review of pertinent literature, encapsulating the historical evolution and key components of the CAP. Section 1.3 delineates the objectives and complementarity of the CAP's pillars, shedding light on their interdependence. Section 1.4 propels us into a forward-looking perspective, contemplating the future trajectory of European reforms in the agricultural domain. The concluding section, Section 1.5, serves as the synthesis of our exploration, drawing together insights gleaned from the literature and setting the stage for the ensuing chapters.

1.2 Rural Policy: Origin, Objective and Development

In 1962, within the European Community, the Common Agricultural Policy (CAP) was initiated. Initially, its objective was largely protectionist, aiming to shield domestic productions from foreign imports through imposing high customs duties and supporting farmers' income via subsidies and guaranteed prices. Specifically, the fundamental idea was twofold: to bridge disparities between agricultural and non-agricultural enterprises and, more importantly, to boost agricultural productivity, harmonize competition rules across nations, foster technological progress, protect and support farmers to ensure a reasonable standard of living, stabilize markets, address climate change, and sustainably manage natural resources, preserving rural areas and landscapes across the EU. It also aimed to ensure reasonable prices for consumers, sustain rural economies by promoting employment in agriculture, agri-food industries, and related sectors (European Commission, 2003).

Over the years of CAP implementation, most of these goals were achieved, and the situation of European and Italian farmers began to improve. After initial general reforms to promote both production and productivity in rural areas, the "Mansholt Plan" in 1968 and the "Green Paper" on the prospects of the Common Agricultural Policy in 1985 were introduced to restore market balance and avoid surpluses. The "Mansholt Plan" was named after the European Commissioner for Agriculture, Sicco Mansholt, who presumed that market imbalances could result from overproduction and price support. He proposed comprehensive modernization of the agricultural sector to improve quality of life for farmers, avoid market distortions, and optimize cultivated areas by merging farms into larger units. During the 1970s and early 1980s, agricultural production began to exceed demand, leading to surpluses. Consequently, food products were sold on the world market at much lower prices. To prevent a sharp decline in farmers' income, in 1984, the EU initiated a quota system for products to limit overproduction and manage supply. Each farmer received a quota representing the quantity of food products they could produce, with penalties for exceeding the quota. Simultaneously, external pressures mounted, accusing the European community of excessive protectionism and demanding market liberalization.

As a result, during this period, the European Agricultural Guidance and Guarantee Fund (EAGGF) and Common Market Organizations (CMOs) were established to promote free trade in agricultural products and increase productivity.

Structural agricultural policies were instituted to consolidate farm structures, improve land, develop agriculture-oriented infrastructure, provide subsidies and loans for mechanization, and disseminate more advanced production methods necessary for the proper functioning of the common market (Lowe et al., 1998).

The EAGGF had an "Orientation" section, part of the structural funds, contributing to agricultural reforms and rural development through investments. There was also a "Guarantee" section that financed expenses through the purchase and promotion of agricultural product exports.

A significant reform was the "MacSharry reform" in 1992, aiming to reduce the overall budget and abandon unlimited guaranteed prices. It introduced an innovative concept: diversifying support to farmers through direct payments to their incomes (compensatory payments), unrelated to production but proportional to cultivable land area. It signaled a shift in the CAP's approach, moving away from ensuring that prices could not fall below a certain threshold, regardless of supply and demand levels. After the MacSharry reform, price levels were lowered, aligning them with world market prices to enhance the competitiveness of EU agricultural production. To improve the quality of food products, new environmental protection and incentive requirements were introduced for farmers. These developments led to capital-intensive agriculture, which was less reliant on nature and required less human labor. The modernization outcome resulted in increasing migration of the population to industrial areas.

Subsequently, the "Agenda 2000" was introduced, offering a more holistic approach to agriculture and rural development, aimed at improving agricultural competitiveness, finding alternative income sources in rural areas, and strengthening social cohesion in those regions. This program led to the creation of a second pillar of the CAP dedicated to rural development.

CAP thus gained centrality, although with resources not yet sufficient for proper implementation. For a comprehensive overview, please refer to Figure A1.1 in Appendix C that briefly outlines the CAP evolution.

1.3 CAP and its reforms: The First and Second Pillars

The objectives of "Agenda 2000" included the reorganization and stabilization of spending, the creation of alternative jobs and income sources for agricultural workers, the introduction of the concept of sustainable, multifunctional, and competitive agriculture, achieving a fair standard of living in rural areas, and a greater focus on structural, environmental, and rural development goals. In other words, it established an agricultural model that gave more consideration to the productive function, clearer, more transparent, and more accessible regulations.

However, the limitation of "Agenda 2000" was the insufficiency of resources and operational capacity (European Parliament, 1999). This limitation was overcome with the "Fischler reform" in 2003 and the "Health Check" in 2008 (EC, 2007). The "Fischler reform" aimed to strengthen the second pillar by introducing minimum standards regarding the environment, food quality, animal welfare, and efficient land management. It introduced budgetary discipline and a new financial mechanism to ensure better aid distribution to farmers. It also decoupled agricultural payments from production and created a new fund for rural development. This reform refined the model towards more sustainable agriculture focused on the market, quality, and environmental preservation. The 2003 reform set the parameters for subsequent reforms (EC, 2003).

The "Health Check" in 2008 further refined the CAP. The aim was to simplify payment systems, address global challenges and improve biodiversity conservation.

Following these reforms, the implementation of CAP measures was modified. The Salzburg Conference in 2003 and Regulation (EC) No 1698/2005 reshaped rural development policies. The National Strategic Plan (NSP) emerged, translating European Strategic Guidelines (ESGs) into actionable plans at the member state level. At the regional level, the Rural Development Programmes (RDP) operationalized NSP objectives (EC, 2007).

These RDPs cover different programming periods, each lasting about seven years: 2000-2006, 2007-2013, 2014-2020, and 2023-2027.

In the 2007-2013 programming, the financial provisions of the two CAP pillars were divided by establishing two agricultural funds: (1) the European Agricultural Guarantee Fund (EAGF), which replaced the guarantee section of the EAGGF and funded market measures to regulate and support agricultural markets, and direct payments to farmers for the first pillar, and (2) the European Agricultural Fund for Rural Development (EAFRD), a tool for financing and controlling rural development policy for the second pillar (Council Regulation (EC) No 1290/2005 bis, Articles 2 and 4). The latter provided more support to the agri-food sector and the diversification of economic activities in rural areas.

The legislators' objective in separating the EAFRD from the other funds was to facilitate the use of this type of funding and to facilitate the adoption of an integrated approach in rural areas. The key to success in these changes was to be proper coordination of interventions within the various funds.

However, complementarity between the EAGF and the other funds was considered insufficient due to the lack of this coordination (Kantor, 2011; Andersson et al. 2017).

Following the introduction of these changes, the question arises whether this separation has actually led to a more effective use of the available funding.

Nevertheless, with this new approach, the EU is attempting to give more freedom to the member states, drawing up their own NSPs, but respecting European guidelines. The NSPs are implemented through RDPs that contain a package of measures grouped into four axes: (1) improving the competitiveness of the agricultural, (2) improving the environmental enhancement, (3) rural economic diversification, and quality of life in rural areas, and (4) the LEADER axis. The latter is implemented through local development strategies by public-private partnerships known as Local Action Groups (LAGs).

LAGs are composed of public and private entities with the aim of promoting local development through Local Action Plans (LAPs). They play a fundamental role in achieving cooperation objectives through financial contributions from the EU. These funds are utilized to back a range of projects spanning agriculture, rural tourism, farms development, environmental conservation, and social and cultural services. LAGs emerge as crucial contributors to the sustainable development of EU rural areas, leveraging their ability to tailor strategies to local needs and actively engage communities. In addition, LAGs motivate communities to help design a local development strategy and are responsible for initiating and financing projects for local communities. LEADER advocates for a "bottom-up" approach to local development, focusing on cohesive areas (10,000-150,000 inhabitants) with a distinct local identity. Local communities form local partnerships to promote networking (EC, 2002). LAGs collaborate on common projects to address similar challenges ("cooperation"). Multisectoral integration and bottom-up approaches are expected to unlock local potential, enabling groups to identify and implement innovative solutions for sustainable development. Participation in local decision-making aims to generate enthusiasm and commitment, contributing to better and more sustainable local rural development (Council Regulation (EC) No 1303/2013a).

In the 2014-2020 programming (European Parliament, 2017), rural development policy had a budget of 99.587 billion euros, and the substantial sums involved made it particularly important to ensure that the money was used efficiently, with evaluations ideally contributing to goal development.

Member States are obliged to monitor the use of funds and assess the effects of the support provided (Council Regulation (EC) No 1698/2005b, Article 84; Council Regulation (EC) No 1303/2013a, Articles 55 and 56, and (EC) No 1305/2013b, Article 66).

The impact assessment of measures requires a sort of counterfactual analysis, i.e., comparing the outcome for beneficiaries with the outcome for non-beneficiaries. This should improve the prospects of making RDPs more efficient by learning from each other's experiences.

In particular, further changes were made between the second (2007-2013) and third (2014-2020) periods. The program structure changed from four axes to six priorities: (1) knowledge transfer and innovation; (2) farm viability and competitiveness; (3) food chain organization, animal welfare, and risk management; (4) restoring, preserving, and enhancing ecosystems; (5) promoting resource efficiency and supporting the shift to a low-carbon and climate-resilient economy; (6) social inclusion and economic development.

The shift in structure from four axes to six priorities appears to be the result of the need to integrate the main policy objectives set out in the Europe 2020 strategy (EC, 2010c).

However, this policy gives rise to some negative consequences. Financially, CAP allocations decreased from 43% in 2006 to 13% in 2013 and to 33% in 2020. This reduction was due to the first pillar, which went from 36% of the EU budget in 2006 to 25% in 2020, but at the same time, the planning and evaluation of the second pillar were strengthened.

While some researchers (Sotte, 2012) advocate for structural policies, the shift of the CAP toward the second pillar and the LEADER approach reflects a commitment to growth, employment, and sustainability. On the contrary, other scholars (Shucksmith et al., 2005) point out that CAP resources are not allocated more extensively to the poorest regions. In reality, it is the opposite, as the CAP tends to favor wealthier regions, a viewpoint confirmed by Segrè (2005), who deduces that the CAP has led to even greater inequalities between the richer and poorer European regions. However, in a study by Esposti (2006), the issue is directly addressed, with results showing that the CAP has no impact on regional growth. Nevertheless, the CAP remains the EU's primary sectoral policy. Unfortunately, the EU's most significant budget allocation does not benefit all regions equally; some regions continue to receive more support than others (Shucksmith et al., 2005; Copus, 2010; Crescenzi et al., 2011; Camaioni et al., 2013). The reasons for these territorial disparities are manifold, ranging from the consequences of reforms like the Fischler Reform to national political choices and varying degrees of rurality due to the presence or absence of agricultural activities (Camaioni et al., 2013). Additionally, the allocation of European funds at the local level, such as the FEAGA for the first pillar and the FEASR for the second pillar, plays a crucial role. Nevertheless, territorial disparities persist, and the CAP's evolution has not uniformly benefited EU regions. In addressing these issues, the CAP's pillars must be complementary, integrating the first pillar's focus on public goods with the second pillar's emphasis on territorial needs.

1.3.1 Key factors and complementarities between CAP pillars

The Common Agricultural Policy (CAP) of the European Union (EU) faces several significant challenges, which have evolved over time and continue to shape the policy's development. Some of the main challenges of the CAP include: (1) Sustainability agriculture tops the list, demanding practices that are economically viable, environmentally sustainable, and socially responsible; (2) Climate Change adds complexity, necessitating CAP adaptation to evolving farming conditions; (3) Biodiversity conservation, crucial on a global scale, requires integrated measures such as organic farming promotion; (4) Income inequality among EU farmers persists, demanding equitable subsidy distribution for small and medium-sized farmers; (5) Market volatility, trade complexities, and technological innovation are additional hurdles. The CAP must balance the interests of EU farmers with global trade rules and encourage innovation for agricultural competitiveness. Global challenges like food security and Sustainable Development Goals (SDGs) add another layer of complexity (FAO, 2021); (6) Rural development stands out as a pivotal challenge, calling for diversification, infrastructure improvement, and support for local businesses. The CAP, with its two pillars, addresses these challenges comprehensively.

Coordination between the CAP's pillars is essential, with the first pillar, centered on direct income support and market stability, aligns with economic objectives. The second pillar focuses on rural development, encompassing economic diversification and environmental conservation. This dual-pillar approach tailors strategies to regional and national priorities, recognizing the diversity of EU rural areas. Indeed, the integration of these pillars ensures the achievement of economic growth, environmental sustainability and social cohesion in rural areas.

The second pillar, emphasizing the multifunctionality of agriculture, involves creating local partnerships like Local Action Groups (LAGs). These groups, funded through EAFRD, play a pivotal role in addressing local development needs, with LEADER strategies promoting community-led planning and implementation. They also execute local development strategies covering agriculture, rural tourism, small farm development and more. Their role promotes the sustainable development of the EU's rural areas.

To effectively address the challenges faced by rural communities, the CAP must meet changing agricultural, environmental, and societal needs. It should aim to promote rural development by diversifying economic activities, improving infrastructure, supporting local businesses and improving the quality of life in rural communities.

Indeed, the interaction between the two CAP pillars is crucial for a flexible and adaptive policy. Complementarity in objectives, agricultural competitiveness, environmental sustainability, and a territorial approach underpin the necessity for a coordinated CAP. This integrated approach, promoting competitiveness, sustainability, and rural development, ensures the CAP's relevance in addressing the challenges and opportunities shaping the future of European agriculture and rural areas.

1.4 New trajectories: CAP 2023-2027, Agenda 2030, Farm to Fork Strategy

In 2018, the European Commission presented a proposal to reform the Common Agricultural Policy (CAP), and after negotiations between the European Parliament, the EU Council, and the European Commission, an agreement was reached on December 2, 2021. The implementation of the CAP reform started on January 1, 2023 (EC, 2023).

The new CAP represents an opportunity to rethink and outline comprehensive strategies for agri-food and its most important value chains. It is built on a policy that is fairer, greener, more animal-friendly, and more flexible.

In more detail, the CAP will have a robust long-term budget. Approximately €387 billion in funding has been allocated to the CAP for the 2021-27 period. This will come from two different funds: the European Agricultural Guarantee Fund (EAGF), which has been set at approximately 290 billion euros (current prices), of which about €265 billion is for direct payments and around €25 billion for market measures; and the European Agricultural Fund for Rural Development (EAFRD), which will amount to around €95 billion (EC, 2020f). The first fund mainly finances income support for farmers and market measures. It supports EU farmers through several payment schemes, including a basic payment scheme, a payment for sustainable farming methods ("green direct payments"), and a payment for young farmers. All payments are subject to compliance with EU rules on food safety, environmental protection, and animal welfare. Additionally, the EAGF finances measures aimed at supporting and stabilizing agricultural markets.

The second fund finances the second pillar, which contributes to the EU's rural development objectives, such as improving the competitiveness of agriculture, encouraging sustainable natural resource management and climate action, and promoting balanced territorial development of rural economies and communities. These objectives are achieved through national and regional rural development programs (RDPs) co-financed by the EAFRD and national budgets of EU countries.

The new CAP will strengthen cooperation between producers and encouraging farmers to work together. It will maintain the general market orientation of previous reforms, encouraging EU farms to align supply with demand in Europe to cope with future crises.

Additionally, the CAP will include increased support for young farmers starting their agricultural businesses. Gender equality and increasing women's participation in agriculture will also be part of the objectives of the CAP strategic plans. It will better address the income needs of small and medium-sized family-run farms. Support for small farms will be strengthened by the option to replace various direct payments with a single payment for small farmers. However, only active farmers will be eligible for certain support. Furthermore, EU countries can continue to allocate a limited part of their direct payment allocation to support specific sectors or types of agriculture within their territory more efficiently. Coupled support will aim to address difficulties by improving quality, sustainability, and competitiveness. CAP payments will be linked to compliance with certain provisions of EU labor law regarding transparent and predictable working conditions for safety and health on farms.

Therefore, CAP beneficiaries will have their payments tied to a stronger set of mandatory requirements. Part of the direct payment will be allocated to eco-schemes, providing stronger incentives for environmentally friendly farming practices and animal welfare improvements. There will be funds will be allocated to climate, biodiversity, environmental, and animal welfare support measures.

Each EU country will develop a national CAP strategic plan, combining funding for income support, rural development, and market measures. In developing their strategic plans, they will contribute to achieving the ten specific objectives through a package of wide-ranging policy measures provided by the Commission, which can be tailored to national needs and capacities. This new model will tend to reduce EU involvement, seen by critics as a step towards giving more powers to individual countries in the CAP. In fact, the EU sets the ground rules and member states create national strategic plans with realistic objectives. There is more flexibility to consider local conditions and needs.

These changes aim to encourage farmers to use resources efficiently, adopt technology and access credit. Agriculture is expected to grow by over 4% annually over the next two decades under the policy (OECD, 2021).

The CAP is one of several EU policies that contribute to the prosperity of rural areas, and it must improve its complementarity with other EU policies, such as cohesion policy, which also provides substantial EU funding in rural areas, and with the mechanism to connect Europe and other national funds and strategies. Better coordination between these policies would simplify implementation mechanisms and reduce bureaucracy for administrations and citizens.

Compared to the 2014-2020 programming period, the Commission estimates a contraction of CAP resources by approximately 5%, affecting both rural development and direct payments. However, direct payments remain an essential element of the CAP, aligned with the obligations under the EU Treaty, as they bridge the gap between agricultural income and income in other economic sectors (EU, 2022b).

Nevertheless, their role in stabilizing agricultural income is not always effective because many CAP beneficiaries are very small farms, and most payments are directed toward medium-sized family-run professional farms. Efforts should be made to promote a more balanced distribution of support.

There is a clear need to boost investment in farm restructuring, modernization, innovation, diversification, and the use of new technologies and opportunities based on digital technologies, such as precision farming, big data utilization, and clean energy, to improve individual farm sustainability, competitiveness, and resilience and to counteract the negative effects of climate change.

Therefore, to address the various criticisms, the Commission proposes a radical change in the way agriculture is supported. Indeed, from 2023 onwards, the CAP will support the transition to more sustainable food and farming systems, in line with the European *Green Deal* outlining how making Europe the first climate neutral continent by 2050. This may be possible defining a new strategy for sustainable and inclusive growth to boost the economy, improve people's health and quality of life, and take care of nature (EC, 2020c; 2020d; 2020e).

The new approach includes the enhancement of the Farm to Fork and Biodiversity strategies (EC, 2020, which aim to address the sector's crisis and promote it in the medium to long term through innovative and context-specific actions, all while aligning with the Sustainable Development Goals of the Agenda 2030 action plan (for a comprehensive overview, please refer to Figure A1.2 in Appendix C that briefly outlines the CAP future).

A sustainable food system can provide environmental, health, and social benefits, offer economic advantages, and help farmers recover from the COVID-19 pandemic and economic recession.

The COVID-19 pandemic has highlighted the need to focus on sustainability practices in agriculture, shift towards a "producer-to-consumer" strategy, accelerate the transition to a sustainable food system with a neutral or positive environmental impact, and contribute to mitigating climate change, reversing biodiversity loss, ensuring food security, nutrition, and public health, ensuring that everyone has access to sufficient, safe, nutritious, and sustainable food while preserving the economic affordability of food. This should generate fair economic returns, promote the competitiveness of the EU supply sector, and support fair and sustainable trade (EC, 2020c; 2020d; 2020e). The pandemic has emphasized the importance of a strong and resilient food system that works in all circumstances.

Leveraging lessons learned from the COVID-19 pandemic, the Commission will also develop an emergency plan to ensure food supply and security.

The EU will support the global transition to a fair, healthy, and environmentally friendly food system. Consultancy services, financial tools, research, and innovation are instrumental in resolving tensions, developing and testing solutions, overcoming barriers, and discovering new market opportunities.

Now more than ever, people are paying increasing attention to environmental and social issues, checking the foods they consume, preferring fresh, less processed foods from sustainable sources. All actors in the food supply chain should consider sustainability as an opportunity to strengthen their competitiveness in both foreign and local markets. Investing in nature protection and restoration is crucial for Europe's economic recovery from the COVID-19 crisis.

To address future crises, the reformed CAP will include a new financial reserve, amounting to at least about €450 million annually, which can be allocated to measures such as emergency purchases and private storage aid (EC, 2022a).

The Council, the European Parliament, and the Commission have adopted a joint declaration recognizing the need to proactively engage at the multilateral level to increase ambition regarding international environmental goals when applying and improving international trade rules.

In line with the European Commission's communication on the review of trade policy, they confirm that it is appropriate for imported agricultural products to comply with certain EU production requirements to ensure the effectiveness of EU rules on health, animal welfare, environmental sustainability, and to contribute to the full implementation of the "European Green Deal" and "Farm to Fork" strategy.

Therefore, the European Green Deal is the strategy for recovery and biodiversity conservation. Biodiversity allows farmers to provide safe, sustainable, nutritious, and affordable food.

Organic farming should be further promoted as it has positive effects on biodiversity, creates jobs, and attracts young farmers. In addition to the measures under the new CAP, the Commission will present an action plan on organic farming, helping EU countries stimulate the demand and supply of organic products and ensure consumer trust (EC, 2020a; 2020b; 2020c).

The future of the Union cannot do without European farmers, who must continue to be the social and economic core of many of our communities. Support and incentives are needed to transition to fully sustainable practices, making the sector more resilient to climate change, environmental risks, and socioeconomic crises while creating new jobs, such as in organic farming, rural tourism, or recreational activities.

1.5 Conclusions

The first chapter of this doctoral thesis has provided a comprehensive review of the literature on the Common Agricultural Policy (CAP) of the European Union (EU), with a particular focus on its two distinct pillars and the LEADER approach of Local Action Groups (LAGs). This analysis explored the origin of the CAP, its evolution over the years, and the future perspectives emerging from recent reforms, integrating the CAP with the European Green Deal and the Farm to Fork strategy. Since its inception, the CAP has played a crucial role in the development of European agriculture, facing a series of challenges and transformations over the years. The main objective of the literature review was to analyze the birth and evolution of the two pillars of the CAP, as well as the significant role played by LAGs. From the literature review, it is clear that the CAP has been subject to criticisms and significant adaptations over time, transitioning from a system that incentivized overproduction to one more oriented towards sustainability and the market. The division into two distinct pillars, focusing on direct payments to farmers and rural development, has introduced greater flexibility in the agricultural sector.

Moreover, it is crucial to emphasize the importance of the complementarity of the two pillars to address the multiple challenges of the rural sector. While the first pillar aims to ensure a stable income and maintain competitiveness, the second pillar aims at promoting rural development while mitigating environmental impacts.

Furthermore, the introduction of LAGs with their LEADER program, based on a bottom-up approach, has significantly contributed to promoting more integrated and sustainable development in rural areas. LAGs have proven to be key actors in implementing local projects, actively involving rural communities in the planning and implementation of development initiatives.

The connection between the literature review and the subsequent objectives of the thesis is crucial. The second chapter will focus on the analysis of Total Factor Productivity (TFP) for Italian rural farms, examining how the two pillars of the CAP and their interaction impact entrepreneurial outcomes.

This analysis is essential to evaluate the effectiveness of implemented policies and understand how they influence rural enterprises.

The third chapter, on the other hand, will focus on the long-term vision of Sicilian farms in terms of key-drivers of rural development such as digitalization, innovation, and sustainability. In that chapter, it is also investigated the attitude to change of farms due to the pandemic shock of COVID-19.

The analysis in this thesis aims to provide a comprehensive framework, connecting the history of the CAP with the current operational context of farms. Reflecting on the future perspectives of the CAP, in light of past experiences and current challenges, will be crucial to draw meaningful conclusions in terms of impacts and opportunities.

In summary, the literature review has contributed to outline the context in which European agricultural policies operate, laying the foundation for empirical analysis for this thesis' subsequent contributions to a deeper understanding of the role of agricultural policies in the EU and local contexts.

Chapter 2

Impact of CAP on farms productivity: The Italian Case[1]

2.1 Introduction

In the previous chapter, we looked at the evolution of agricultural and regional development policies and in particular on the different but complementary role of the two pillars of CAP. In this chapter, we empirically investigate the impact of CAP on Italian farms' productivity.

The effectiveness of CAP incentives in increasing the productivity of European farmers has long been a subject of discussion, considering that the EU annually invests approximately 50 billion euros in this policy. This investment aims to support farmers' income, improve agricultural production, and ensure a stable food supply, this is in the framework of facing climate change. The fundamental question we pose is whether these investments indeed translate into an enhancement of productivity for farms.

[1] I would like to thank Dr. Sara Maioli for her guidance and support in writing the second chapter during my visiting period at Newcastle University Business School (UK).

Numerous previous studies (Latruffe et al., 2009, 2011; Mary, 2012; Carpentier et al., 2012; Rizov et al., 2013) have investigated this complex relationship between agricultural subsidies and productivity using different estimation methodologies. They observe that CAP support could have contrasting effects on farms productivity depending on the nature of subsidy and farms' characteristics.

Considering the unclear evidence so far provided by empirical research, this chapter attempts to contribute to the literature with a robust analysis based on a large sample of Italian farms ("Rete d'Iinformazione Contabile Agricola" - RICA) over a long time span (2009-2019) that looks at the impact of the two pillars of CAP and their combination on Total Factor Productivity (TFP). To estimate the TFP at farm level, we employ consolidated approaches provided by Levinsohn and Petrin (2003), and Ackerberg et al. (2015).

We find the novel evidence that subsides from the two pillars negatively impact on productivity when they are employed separately but positively when they are combined by farms. Therefore, to maximize the public investment we can say that should be encouraged the complementary use of the two funds. We remember that while Pillar 1 primarily works to ensure a stable income for farmers, Pillar 2 focuses on promoting rural and sustainable development through local initiatives, such as the well-known LEADER approach of Local Action Groups (LAGs). For example, investments in infrastructure and local initiatives can amplify or mitigate the effects of direct payments on productivity, creating a complex network of relationships that goes beyond a separate assessment of the two pillars. In this way, our investigation not only contributes to the understanding of the effectiveness of CAP funds in Italy but also sheds light on the necessity of considering the synergistic interaction between diverse agricultural policies. This integrated perspective not only enriches our economic analysis but also provides a tangible contribution to the broader debate on the governance of European agricultural policies, emphasizing the importance of complementarity between different tools to promote sustainable and resilient agricultural growth.

The chapter is structured as follows. Section 2.2 provides a review of the most relevant related literature with a particular focus on studies looking at the Italian case. Section 2.3 describes the empirical strategy. Section 2.4 discusses the data while section 2.5 discusses the results and section 2.6 introduces the robustness checks. Finally, section 2.7 concludes.

2.2 The impact of CAP subsidies on productivity

2.2.1 Literature review

Since the 1990s, the European Union (EU) has undergone a significant transformation in the Common Agricultural Policy (CAP), marking a fundamental shift in the perspective and goals of European agricultural policy. The 1992 MacSharry reform represented a substantial turning point, abandoning the traditional price support system in favor of a compensatory income support system. This transformation reflected a new awareness of the needs of the agricultural sector and the necessity to address emerging challenges more effectively.

With the introduction of the two pillars, the CAP has adopted a more nuanced and goal-oriented approach. The first pillar, the European Agricultural Guarantee Fund (EAGF), focuses on the regulation and support of agricultural markets. Meanwhile, the second pillar, the European Agricultural Fund for Rural Development (EAFRD), aims to promote economic, social, and environmental sustainability in agriculture, along with fostering innovation and digitalization to enhance the quality of life in rural areas. In short, among the current key objectives of the CAP, sustainable and inclusive development of rural areas stands out prominently (European Commission, 2022).

In this context, it is crucial to emphasize that the current agricultural policies of the EU go beyond merely regulating markets; they actively act as engines of development, benefiting both farms and rural territories as a whole.

To fully understand the impact of these policies, it is essential to connect them with Total Factor Productivity (TFP) rather than simple labor productivity. While labor productivity measures production in relation to employed labor units, TFP takes into account the overall efficiency of the production process, considering both labor and capital inputs. Linking agricultural policies to TFP means comprehensively assessing how resources are utilized, how innovation is adopted, and how sustainability becomes an integral part of agricultural practices.

This approach is significant because it recognizes that sustainable development cannot be separated from efficient productivity and the economic well-being of farms. Measuring efficiency through TFP allows us to evaluate economic growth comprehensively and to better understand how agricultural policies contribute not only to food production but also to sustainable development and social inclusion in rural areas. Thus, the CAP becomes a key instrument in promoting a resilient and sustainable agricultural and economic future for the EU.

In the specific context of the agricultural sector, TFP defined as the part of production growth not attributable to the accumulation of production factors, emerges as one of the critical drivers of economic growth and well-being (Solow, 1957; Basu et al. 2022). By definition, TFP is not directly observable but can be influenced by various technological, political, and socio-economic factors. It can be enhanced through innovation, investments, and knowledge. However, excessive regulation or an underdeveloped economic environment could impede it (Khafagy and Vigani, 2022).

This argument gains particular strength in the agricultural sector, where the EU identifies increasing productivity as one of its fundamental pillars (EC, 2019, 2020). Specifically, the EU allocates approximately 50 billion euros annually in the CAP, aiming to increase the productivity of farms in the EU (Massot, 2017; EU, 2022). Therefore, investigating how the CAP influences the productivity of farms remains of paramount political and economic importance today.

Given the aforementioned considerations, there are various studies in the literature on the impact of agricultural subsidies, but they often lead to unclear conclusions. These diverse studies in the literature suggest that the relationship between agricultural subsidies and the productivity of farms can have a net positive or negative impact, with some finding no effect at all (Hennessy, 1998; Ciaian and Swinnen, 2009; Latruffe et al., 2009; Sauer and Park, 2009; Zhu and Oude Lansink, 2010; Latruffe et al., 2011; Zhu et al., 2012; Mary, 2013; Rizov, Pokrivcak, and Ciaian, 2013; Minviel and Latruffe, 2017; Khafagy and Vigani, 2022).

In particular, Latruffe et al. (2009) find a negative impact of coupled subsidies from the first pillar of the CAP on specialized French farms in the production of cereals, oilseeds, and beef. Lakner (2009) notes that agro-environmental investment programs targeting farmers adopting sustainable and environmentally friendly agricultural practices under the second pillar of the CAP have a negative effect on dairy farms in Germany.

Zhu and Oude Lansink (2010) find that CAP subsidies had a negative impact on dairy farms in

Germany and Netherlands between 1995 and 2004, but no significant impact in Sweden. Latruffe et al. (2011) find a negative impact of subsidies on dairy farms in Denmark, France, Germany, and the Netherlands for the period 1990-2007. Minviel and Latruffe (2017) study the impact of public subsidies, including CAP pillars, and find them commonly associated negatively with the technical efficiency of farms.

Kumbhakar and Lien (2010) report a positive link between subsidies and technical efficiency in their study analyzing the efficiency of Norwegian cereal farms from 1991 to 2006. The authors also conclude that subsidies have a negative impact on the productivity of farms. Mary (2013) estimates the impact of various CAP subsidies on French farms from 1996 to 2003, and the results show a negative impact on productivity. Psaltopoulos et al. (2011) measure the impact of the second pillar of the CAP for Greece and Czech Republic. They report that supports for rural development produce rather limited and mixed effects and cannot compensate for the negative effects of decoupling. As the authors emphasize, the effects of these measures tend to be small compared to those of the first pillar.

Rizov et al. (2013) estimate the TFP of farms in EU countries from 1990 to 2008 and compare the impact of subsidies on agricultural productivity before and after the decoupling of subsidies with the 2003 CAP reform. These authors find that subsidies are negatively associated with productivity until the implementation of the decoupling reform. After this reform, the link between subsidies and agricultural productivity becomes better positive in some EU countries.

Biagini et al. (2023) use farm data from 2008 to 2018 for France, Germany, Italy, Poland, Spain, and the United Kingdom and study the effects of different subsidies on the productivity of cereal farms, considering the intrinsic productivity levels of farms (low, medium, and high productivity). Their results highlight how CAP subsidies negatively or insignificantly affect the TFP of farms, except for agro-environmental subsidies, which can increase productivity. They also emphasize that the negative role of direct payments seems more prevalent in low-productivity farms, accelerating their exit from the market.

On the other hand, Sauer and Park (2009) find a positive effect of subsidies for dairy farms in Denmark from 2002 to 2004. Fogarasi and Latruffe (2009) analyze the relationship between subsidies and TFP for farms in France and Hungary.

They find a neutral effect for dairy farms, while for other types of farms it is positive. This result underscores the need to categorize farms based on their specialization.

Garrone et al. (2019) investigate the relationship between EU agricultural subsidies and the growth of productivity in the agricultural sector of 213 EU regions from 2004 to 2014. They find that, on average, individually taken decoupled payments from the first pillar and other payments from the second pillar of the CAP increase the productivity growth of the agricultural sector. However, coupled payments from the first pillar have the opposite effect, slowing down productivity growth. The authors find a positive effect of the second pillar but an ambiguous effect for the first pillar. In more detail, decoupled payments, i.e., those not directly tied to production, have a positive impact. In contrast, coupled payments, i.e., those linked to production and dependent on agricultural activity, have a negative effect on the growth of farms productivity.

Khafagy and Viagani (2022) analyze the impact of the CAP on the productivity of farms using a panel dataset covering 117,179 farms from all EU member states for the period 2004-2015. Their results suggest that higher levels of CAP payments from both the first and second pillars as a percentage of total agricultural income have a negative or null impact on the technical change of farms. However, higher nominal amounts of decoupled subsidies from the first pillar, investments from the second pillar, and subsidies for disadvantaged areas have a positive impact. Moreover, the higher the share of subsidies in total agricultural income, the greater the negative effects of the CAP.

From the review of empirical literature, it can be inferred that the results are conflicting and inconclusive, although negative relationships between CAP subsidies and productivity tend to prevail as emerged from Table 2.1 in Appendix A1. However, few studies focus on Italian farms.

Moving beyond the review, examining the effects and explanations in the literature provides additional insights. In light of the above-mentioned, Mary (2013), Rizov et al. (2013), and Khafagy and Vigani (2022) observe that CAP support may have a negative effect on the productivity of farms, particularly for those with low productivity. However, depending on the model specification and data source, the results exhibit significant contrasts.

Several arguments seek to explain this effect on the Total Factor Productivity (TFP) of the agricultural sector. In general, these diverse outcomes may arise from imperfections in the rural market and the varied nature of subsidies, each with specific aims that result in differentiated impacts on TFP, the behavior, and performance of farms. This partially justifies the contrasting findings in the literature (cf. Mary, 2013; Latruffe and Desjeux, 2016; Dudu and Kristkova, 2017; Garrone et al., 2019; Khafagy and Vigani, 2022).

To delve further, on one hand, trade liberalization can create distortions in agricultural markets due to subsidies, with variable impacts on productivity (cf. Latruffe et al., 2008; Rizov et al., 2013). On the other hand, the expansion of global markets has heightened concerns for food security, translating into a demand to maintain agricultural support, stimulate agricultural investments, and adopt modern technologies to increase productivity (FAO, 2011).

The negative impact of subsidies on productivity can stem from losses in allocative and technical efficiency. Farms may change their production structure and investment decisions, skewing them towards less productive farms or investing excessively in inputs. An excess of funds towards less productive initiatives can lead to inefficient resource utilization (cf. Zhu and Oude Lansink, 2010; Latruffe, 2010; Mary, 2013). Conversely, according to some studies, the positive effect can arise from increased investments, improved management practices, access to credit, and enhanced investments that foster productivity growth (cf. Minviel and Latruffe, 2014; Garrone et al., 2019).

Lastly, subsidies for rural development are presumed to generally have positive regional effects not strictly tied to the agricultural sector but influencing other sectors such as construction or tourism. It is also likely that the net impact of CAP subsidies on agricultural productivity varies based on the geographical region, different factors, and secondary effects.

Moreover, various studies have attempted to assess the link between subsidies and the efficiency of farms using stochastic frontier analysis (e.g., Serra et al., 2008), demonstrating that the impact of subsidies on technical efficiency is ambiguous and depends on production risk and farmers' risk preferences.

The literature on the impact of CAP subsidies on agricultural productivity suggests that the overall effect may vary. Additionally, studies employing diverse methods have sought to assess the link between subsidies and farm efficiency. Existing empirical studies utilize frontier approaches (see Rizov et al., 2013; Kazukauskas et al., 2014; Minviel and Latruffe, 2017;

Akune and Hosoe, 2021), such as non-parametric Data Envelopment Analysis (DEA) and parametric Stochastic Frontier Analysis (SFA). These approaches have the advantage of deriving technical efficiency and technical change, combining them into the Malmquist TFP index (Baldoni and Esposti, 2021). Other methods include dynamic panel estimators, employing a two-stage parametric approach. In the first stage, productivity measures are estimated without controlling for subsidy effects, followed by regressing these productivity measures on subsidies in the second stage (e.g., Giannakas et al., 2001; Latruffe et al., 2009; Lakner, 2009; Sauer and Park, 2009; Zhu and Oude Lansink, 2010; Mary, 2013; Garrone et al., 2019). Additional studies (Pufahl and Weiss, 2009; Chabe-Ferret and Subervie, 2011; Ratinger et al., 2015) employ propensity score matching, enabling a comparison of effects in the treatment group with the control group to evaluate the impact of subsidies on productivity. Still, others (see Minviel and Latruffe, 2014) employ a meta-analysis approach to study the role of subsidies in agricultural productivity, finding that the aggregation of received subsidies leads to a negative effect on firms' technical efficiency.

For instance, Latruffe et al. (2017) assess the relationship between productivity and levels of policy subsidies in dairy farms across nine countries, obtaining contrasting results with policy measures influencing farmers' behavior and, consequently, the production process (Kumbhakar and Lien, 2010).

Zhu and Oude Lansink (2008) categorize measures based on their influence on price levels, agricultural income, investments, and market participation.

Hence, different policies can have varied impacts on agricultural productivity, rendering the assessment of CAP's role challenging.

Rizov et al. (2013) found that overall CAP support generally has a negative impact on TFP in almost all countries, causing losses in allocative and technical efficiency as farmers may invest excessively in subsidized production factors. Similarly, Garrone et al. (2019) noted that CAP does not have well-defined effects on labor productivity.

The assessment of CAP may conceal significant heterogeneity due to the different types of subsidies provided by CAP. For example, decoupled subsidies positively influence labor productivity, while coupled subsidies slow it down (Garrone et al., 2019). This might explain why Minviel and Latruffe (2017) reported a considerable heterogeneity of results in their extensive review of analyses on the impact of CAP support on technical efficiency. This disparity could be attributed to the wide range of subsidy types and the fact that the examined analyses refer to different countries and periods.

Conversely, Mary (2013) and Biagini et al. (2023) follow a three-stage econometric strategy. In the first phase, the production function is specified and estimated; in the second stage, estimates of the production function are used to recover TFP through the System Generalized Method of Moments (SYS-GMM) dynamic panel estimator; in the third stage, the relationship between CAP subsidies and TFP is assessed. Following their methodology underscores the importance of considering productivity as a dynamic process, accounting for the persistence of past events. This strategy can help shed light on the contentious results in the literature regarding the relationship between CAP measures and TFP.

2.3 Empirical Strategy

Few studies have delved into the impact of CAP subsidies at the Italian level, treating enterprises as uniform categories without segmenting them into different OTE (Operational Type of Enterprise) sectors. The most commonly used estimation method relies on the use of the Stochastic Frontier Approach (DEA). However, the limited existing studies have thus far failed to provide reliable insights into Total Factor Productivity (TFP).

To fully comprehend the impact of the pillars of the CAP on farms' productivity, we employ consolidated econometric approaches to estimate TFP.

Estimating TFP is always a challenging task, and various approaches have been proposed in literature (Rizov et al., 2013; Garrone et al., 2019, among others). With the aim to minimize potential distortions in the estimations of TFP, we adopt a "structural productivity estimation approach" (Rizov et al., 2013) based on Levinsohn and Petrin (2003) and Ackerberg et al., (2015). The STATA command "prodest" by Rovigatti and Mollisi (2020) allows to simply implement this approach. Exploiting the dataset "Rete di Informazione Contabile Agricola" (RICA) collected by Council for Agricultural Research and Agricultural Economy Analysis (CREA), we provide estimates of TFP for a large sample of Italian farms for the period 2009-2019 and then explore its relationship with the pillars of CAP.

Commonly, studies on establishment-level productivity assume that output, often measured as value-added, is a function of both the inputs utilized by the firm and its productivity (Katayama, Lu and Tybout, 2005).

The measure of TFP, even at the firm level, could be simply measured as residual of a production function estimated by Ordinary Least Squares (OLS). However, estimates from this approach may be inconsistent and biased due to the fact that input choices (independent variables) are likely to be correlated with TFP levels (error term). In other terms, such an estimation generates problems of endogeneity, violating basic assumptions of the model.

Exploiting panel data may help to overcome these problems. Indeed, fixed-effects estimates may be seen as measure of TFP at firm-level but with the limitation of being time invariant.

Addressing these methodological challenges, the literature has proposed various estimators, both parametric and semiparametric. Nevertheless, traditional methods employed to tackle endogeneity problems, such as fixed effects, instrumental variables, and Generalized Method of Moments (GMM), have proven unsatisfactory when applied to production functions. The probable causes of these estimators is likely attributed to the assumptions they rely upon. Consequently, several semiparametric alternatives have been suggested to address these limitations.

A remedy to these issues has been proposed by Olley and Pakes (1996, henceforth OP), modified by Levinsohn and Petrin (2003, henceforth LP), and consolidated by Ackerberg, Caves, and Frazer (2015, henceforth ACF). OP and LP have developed a semi-parametric estimator that addresses the simultaneity bias (and the selection bias in the case of the OP estimator).

The OP (1996) method is a consistent semi-parametric approach that also controls for selection biases present in the other aforementioned methods. This estimator solves the simultaneity problem by using the firm’s investment decision to proxy for unobserved productivity shocks. The proposed methodology will be discussed only briefly, and the interested reader is referred to Olley and Pakes (1996) for the more technical aspects (and their demonstrations). They were the first to introduce an estimation algorithm that explicitly addresses both the selection and simultaneity problems. They develop a dynamic model of firm behavior that incorporates idiosyncratic productivity shocks, as well as for entry and exit.

At the beginning of each period, each firm decides whether to exit or continue its operations. The firm is assumed to maximize the expected value, and exit decisions will depend on the firm’s information.

Investment decisions are determined as part of a Markov perfect Nash equilibrium and thus depend on all parameters determining equilibrium behavior. To achieve consistency, several assumptions need to be made.

First, the model assumes there is only one unobserved state variable at the firm level, namely its productivity.

Second, the model imposes monotonicity on the investment variable to ensure invertibility of the investment demand function. This implies that investment must be increasing in productivity, conditional on the values of all state variables (as capital variable). Consequently, only non-negative values of investment can be used in the analysis.

Therefore, the OP method considers investments as a proxy variable for unobserved TFP.

However, this variable is not always valid. Firstly, investments may be "lumpy", and they are often observed as null and do not respond to some productivity shocks, making them an unsuitable proxy for productivity. While Olley and Pakes (1996) use the investment decision to proxy for unobserved productivity; LP (2003) propose using a static control, such as intermediate inputs, instead of investments (i.e., a dynamic control). The monotonicity condition of OP stipulates that investment is strictly increasing in productivity. This implies that only observations with positive investment can be utilized, potentially leading to a considerable loss in efficiency based on the available data. Additionally, if a substantial number of firms report zero investment, it raises concerns about the validity of the monotonicity condition. Hence, Levinsohn and Petrin (2003) use intermediate inputs rather than investment as a proxy. Since firms typically report positive use of materials each year, this allows for the retention of most observations. Consequently, the monotonicity condition is more likely to be satisfied in this alternative approach.

Their estimation algorithm deviates from that introduced by OP in two significant ways.

Firstly, instead of using investment as a proxy for unobserved productivity, they employ intermediate inputs, specifically materials. In this case, materials are expressed as a function of capital and productivity. If the monotonicity condition is satisfied and material inputs are strictly increasing, this function can be inverted, allowing the expression of unobserved productivity as a function of observables. Notably, the coefficient on the proxy variable, i.e., materials, is recovered in the second stage of the estimation algorithm, in contrast to the OP approach where it is obtained in the first stage.

The second difference between the OP and LP approaches lies in the correction for selection bias. While OP accommodate the incorporation of survival probability in the second stage of the estimation algorithm, LP do not include the survival probability in the second stage. Aside from using materials instead of investment as a proxy and excluding the survival correction (to correct for the selection bias) in the second stage, the estimation process remains fully analogous to the approach used by OP and outlined above. For a more in-depth understanding of the LP approach, I recommend consulting Levinsohn and Petrin (2003).

While the OP approach is non-parametric, in the LP and ACF approach, the functional form refers to the production function.

However, ACF (2015) argue that previous estimation methods suffer from identification problems and thus criticize these approaches for a collinearity problem between labor and the non-parametric terms during the first stage of the estimation algorithm can lead to the labor coefficient being unidentified.

This issue arises from the need for firms to allocate labor, materials, and capital in a coherent manner. While this collinearity challenge can be present in both OP and LP estimators, it poses a more significant problem for the LP estimator.

For LP, the simultaneous selection of labor and materials implies a potential assumption that they are allocated in similar ways, both dependent on productivity and capital. Consequently, both labor and materials rely on the same state variables, making it impossible to concurrently estimate a non-parametric function and the coefficient on the labor variable in the first stage. This situation results in the labor coefficient being unidentified due to collinearity with the non-parametric function.

ACF attempted to explore plausible assumptions about the data generating process for labor to salvage the LP first stage estimation, but with limited success. While the collinearity problem can also manifest in the OP estimation, the identification of the labor coefficient in the first stage is attainable by assuming that labor is not a perfectly variable input, and firms decide on labor allocation without perfect information about future productivity. This assumption allows OP to identify the labor coefficient in the first stage, unlike LP, where the collinearity problem persists.

The distinction between the two estimators arises from the fact that investment, unlike materials, is not directly linked to outcomes in period "*t*". Consequently, a firm's allocation of labor does not directly impact its investment decisions (Ackerberg et al., 2006).

ACF (2015) propose a new approach by modifying the assumptions about the timing of input decisions and shifting the identification of all production function coefficients to the second stage of estimation where the labor coefficient (in a value-added production function) is not estimated in the first stage but obtained in the second stage. The first stage is solely dedicated to eliminating the error component in the production function.

Like LP's approach (2003), ACF also assumes that labor is a variable input and that material inputs are variable inputs and, therefore, functions of state variables.

This approach allows the construction of the optimal input demand that is monotonic with respect to productivity, regardless of other observable input demand variables. Thanks to these assumptions, the unobserved productivity shock can be controlled, overcoming the simultaneity problem. ACF (2015) procedure, like the previous ones, is a two-stage process. The first step replaces the unobserved productivity term with the inverse of the optimal input demand (intermediate input). Its sole purpose is to cleanse the predicted output from the measurement error (for more detail, see Collard-Wexler, 2013). More specifically, ACF (2015) estimates a production function and this function relates inputs (e.g. labour and capital) to outputs (e.g. farm-level output), taking into account unobserved heterogeneity and dynamics over time. Instead, the second stage of the procedure relies on moment conditions, such as the Generalised Method of Moments (GMM), to account for the time dimension and unobserved heterogeneity. These techniques enable consistent parameter estimation even in the presence of endogeneity.

Throughout our analysis, we undertake a series of essential steps in estimating our model, with the aim of thoroughly examining the factors influencing Total Factor Productivity (TFP) in Italian farms.

Specifically, in the first stage, we estimate a Cobb-Douglas production function using the Levinsohn and Petrin (2003) approach and the methodology of Ackerberg et al. (2007; 2015) to control for simultaneity and selection issues. This include: *(i)* measuring TFP by initially estimating production functions using Solow's Residuals Approach (Ackerberg et al., 2007; 2015). Known for its robustness, this method allows identifying the productivity component not explained by traditional input variables, providing a meaningful measure of TFP. The process incorporates the size distributions of Italian farms and considers several control variables such as the altimetric zone in which the farm is located, diversification over the years, and other relevant factors. This approach enables capturing the complexity of Italian agricultural dynamics and analyzing the impact of various variables on productivity.

From these estimates in the first phase, a measure of TFP is derived as the Solow residual and used as the dependent variable in the second estimation phase.

In the second stage, *(ii)* we then proceed to estimate CAP subsidies and their impact on productivity, using a Pooled Ordinary Least Squares (POLS) model and a Random Effects (RE) model. This is an analysis that includes, as the dependent variable, the residual obtained in the previous stage. Among the independent variables, it considers time lags, enabling for an accurate and dynamic assessment of the effects of subsidies on productivity over time.

This comprehensive methodological approach aims to provide an in-depth overview of agricultural productivity dynamics, taking key factors and incorporating detailed analyses to fully comprehend the influence of CAP subsidies on the performance of Italian farms.

2.3.1 Measuring Total Factor Productivity

We consider a standard Cobb-Douglas production function (Mundlak, 2000), represented by Equation (2.1) for a given farm *i* at time *t*:

$$Y_{i,t} = A_{i,t} K_{i,t}^{\beta_1} L_{i,t}^{\beta_2} T_{i,t}^{\beta_3} \tag{2.1}$$

With $i = 1, \dots, N$ and $t = 1, \dots, T$

Where, $Y_{i,t}$ is production output and in our case is the value-added, $K_{i,t}$ is the capital input, $L_{i,t}$ is the labour input, and $T_{i,t}$ is the utilized agricultural area. $A_{i,t}$ is the Hicksian neutral efficiency level of farm *i* in period *t*.

While $Y_{i,t}$, $K_{i,t}$, $L_{i,t}$ and $T_{i,t}$ are all observed by the econometrician, $A_{i,t}$ is unobservable to the researcher.

The log-linearization of Equation (1) results, with an usual error term ε_i,

$$y_{i,t} = \beta_0 + \beta_1 k_{i,t} + \beta_2 l_{i,t} + \beta_3 t_{i,t} + \varepsilon_{i,t} \tag{2.2}$$

Where $y_{i,t} = lnY_{i,t}$; $k_{i,t} = lnK_{i,t}$; $l_{i,t} = lnL_{i,t}$; $t_{i,t} = lnT_{i,t}$; $lnA_{i,t} = \beta_0 + \varepsilon_{i,t}$

While β_0 measures the mean efficiency level across farms and over time; $\varepsilon_{i,t}$ is the time- and producer-specific deviation from that mean, which can then be further decomposed into an observable (or at least predictable) and unobservable component.

When estimating Equation (2.2) using ordinary least squares (OLS), this model suffers from a well-known endogeneity problem of explanatory variables in panel data estimation, meaning it would yield biased results. In other words, TFP is not known and incorporated into the error term (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2006, 2015; Rovigatti and Mollisi, 2018, 2020; Ackerberg, 2023).

We then decompose the error term $\varepsilon_{i,t}$ in Equation (2.2) into an observable shock by farmers $\omega_{i,t}$ and an unobservable shock $\epsilon_{i,t}$. More precisely, these represent shocks to production or productivity that are not observable (or predictable) by farms when making their input decisions at time *t* (see Ackerberg, 2023). These could be, for example, actual *i.i.d.* shocks to production or serially correlated measurement errors in output.

$$y_{i,t} = \beta_0 + \beta_1 k_{i,t} + \beta_2 l_{i,t} + \beta_3 t_{i,t} + \omega_t + \epsilon_t \tag{2.3}$$

In other words, given $\omega_{i,t}$ is an establishment specific, time varying productivity shock, that is known to the establishment, but not to the econometrician. It is a state variable and, hence, a determinant of the establishments' decision rules regarding inputs' choices and thus, which induces a simultaneity problem and induces a selection problem.

Instead, ϵ_t it is an unexpected establishment specific, time varying productivity shock, unknown to the establishment and the econometrician. This term does not have an effect on the establishments' decision rules. As stated by Sivadasan (2009), this term "captures all other deviations from the hypothesized production function, arising from classical measurement error, optimizing errors".

In the canonical proxy variable model $\omega_{i,t}$ is assumed to evolves according to an exogenous first-order Markov process (Olley and Pakes, 1996) in fact, it depends on its value at time *t-1* and on an unexpected shock with mean equal to zero; that is: $E(\omega_t|\omega_{t-1}) = \rho\omega_{i,t-1}$, i.e., $\omega_{i,t} = \rho\omega_{i,t-1} + \partial_{i,t}$.

Instead, ϵ_t denotes the idiosyncratic error which is assumed to have zero mean and uncorrelated with the regressors. (see De Loecker, 2011) with $E(\epsilon_t|k_t, l_t, t_t, \omega_t) = 0$. It represents any unpredictable shocks to the production process realized after input choices are made.

Due to the above, the use of Ordinary Least Squares (OLS), Fixed Effect (FE) and Generalized Method of Moments (GMM) estimators is limited due to specific methodological problems.

OLS estimators are susceptible to bias in the presence of simultaneity and selection. Since farms' decisions on input choice and market exit are influenced by their productivity therefore, OLS estimators do not adequately address these problems and expected estimates may be biased because $\omega_{i,t}$ induces both a simultaneity and a selection problem.

FE estimates could only solve the simultaneity problem if productivity $\omega_{i,t}$ be farm-specific and constant over time. However, this assumption is often unrealistic, especially when studying structural reforms.

GMM could address the simultaneity problem but fails to deal with the selection problem arising from the exit of firms.

To overcome these limitations, we follow the methods developed by Olley and Pakes (OP) (1996) and Levinsohn and Petrin (LP) (2003), and their extensions for endogeneity in labor input by Ackerberg et al. (ACF) (2015) using a two-stage semiparametric procedure.

This approach adds a free intermediate input ($m_{i,t}$) to the Cobb-Douglas production function, allowing simultaneity and selection to be addressed more effectively.

$$y_{i,t} = \beta_0 + \beta_1 k_{i,t} + \beta_2 l_{i,t} + \beta_3 t_{i,t} + \beta_4 m_{i,t} + \omega_{i,t} + \epsilon_{i,t} \tag{2.4}$$

where $y_{i,t}$ denotes the logarithm of the output, $k_{i,t}$ denotes the logarithm of the capital input, $l_{i,t}$ and $t_{i,t}$ denotes the row vector of the logarithms of the labor and land inputs. In particular, k is defined as the state variable, l and t as the free variable (following ACF, 2015).

Furthermore, m_t denotes the logarithms of intermediate inputs such as materials. As well, m_t is defined as a proxy for unobserved productivity shocks.

We are interested in estimating the parameter vector $(\beta_1, \beta_2', \beta_3', \beta_4')'$ in this model.

However, criticisms have arisen regarding the use of investments for TFP with OP method: their value is zero for long periods, and by nature, they are multi-year processes, thus not an efficient tool for annual variations in TFP since the monotonicity condition only holds for positive observations.

Levinsohn and Petrin (2003), Ackerberg et al. 2007, and Ackerberg et al. 2015[2] overcome this issue by using materials as an intermediate inputs[3] for TFP instead of investment function like OP (1996). In particular, the LP (2003) and ACF (2007; 2015) approaches use an intermediate input demand function, i.e., $m_{i,t} = m_{i,t}(\omega_{i,t}, k_{i,t})$, to identify the firm's productivity shock $\omega_{i,t}$, substituting it into the Cobb-Douglas production function. This method requires the intermediate input demand function to be monotonically increasing with $\omega_{i,t}$for all $k_{i,t}$.

By inverting it, the productivity shock $\omega_{i,t}$ is expressed as a function of $m_{i,t}$ and $k_{i,t}$ (i.e., $\omega_{i,t} = m_{i,t}(m_{i,t}, k_{i,t})$), allowing for consistent estimates of the Cobb-Douglas production function. Moreover, the use of total costs as an intermediate input ensures the monotonicity condition is met. In our case, the log. of the total costs[4] (i.e. proxy variable) enters equation (2.) as:

[2] Ackerberg et al., (2015) show that the LP methodology suffers from a functional dependence problem. In this approach, both intermediate input and labor decisions within a firm are influenced by its productivity level. Therefore, the labor coefficient faces identification issues during the first-stage estimation. As an alternative solution, ACF proposes the utilization of a value-added Cobb-Douglas production function. In addition, ACF assumes that labor is a deterministic function of capital and intermediate inputs, resulting in a conditional intermediate input demand function. This information is used in the second stage to identify and estimate labour and capital coefficients.

[3] An advantage of the LP and ACF approach lies in the typical positive utilization of intermediate inputs (such as materials) by farms, ensuring the fulfillment of the monotonicity condition. In this study, we use total costs as an intermediate input to estimate equation (2.5). Nevertheless, as mentioned in Levinsohn and Petrin (2003) and Ackerberg et al. 2015, “inputs measured with less error” are generally preferred, specially in non-parametric estimations, and this is the case for total costs.

[4] See Bratsiotis and Robinson (2015) and Schmidt-Ehmcke (2010). The TFP measures the efficiency with which a company utilizes its set of inputs such as land, labor, and capital to produce output. Total costs are closely tied to this concept, as they represent the sum of payments made for all inputs.
In addition, management decisions also influence the total costs of a business.
Therefore, total costs serve as a good proxy because they take into account all the inputs used in the production

$$y_{i,t} = \beta_0 + \beta_1 k_{i,t} + \beta_2 l_{i,t} + \beta_3 t_{i,t} + \beta_4 v_{i,t} + \beta_5 m_{i,t} + \omega_{i,t} + \epsilon_{i,t} \tag{2.5}$$

In its estimation (Eq. 2.5), we use the (log of) the firm's value-added in year t for $y_{i,t}$ (*Value-Added*), the degree of farm mechanization in terms of available power (KW) for $k_{i,t}$ (*Capital*), total working hours for $l_{i,t}$ (*Labour*), and the Utilized Agricultural Area (UAA) for $t_{i,t}$ (*Land*). We use materials as free intermediate inputs ($m_{i,t}$), representing total costs, for LP and LP-ACF methods.

In addition to this standard specification, to enhance the robustness of our findings, we add several control variables ($v_{i,t}$) to Equation (2.5) to control for farm-specific effects and time effects (see Table 2.2).

These include a dummy variable reflecting the age of the businessman, specifically identifying those below 40 years of age (classified as *Young*). We introduce a dummy variable indicating the provision of services for complementary activities, denoting E*xtra-Agricultural Diversification*. Another dummy variable is employed to identify enterprises that undergo a change in Technical-Economic Orientation at least once, signifying *Agriculture Diversification*. Additionally, *Altitude* and *Economic Size* are incorporated as categorical variables, contributing to a comprehensive assessment of farm characteristics.

Consequently, we estimate the unknown parameters in Equation (2.5) by adding the controls and calculate the TFP of farm *i* in year *t*. After specifying and estimating the production function, the TFP (TFP_{ACF}) at the farm level is calculated as the Solow residual (Eq. 2.6), representing that portion of production output not directly correlated with production factors (OP, 1996; LP, 2003; ACF, 2007, 2015).

$$e_{i,t} = y_{i,t} - \hat{\beta}_1 k_{i,t} - \hat{\beta}_2 l_{i,t} - \hat{\beta}_3 t_{i,t} - \hat{\beta}_4 v_{i,t} - \hat{\beta}_5 m_{i,t} \tag{2.6}$$

process. However, it's also acknowledged that this proxy may not capture all production dynamics. Nevertheless, considering the data availability and the specific nature of the agricultural context in question, the choice of this variable remains one of the best options.

2.3.2 The relationship between TFP and Pillars of CAP

As seen in the previous literature review section on the impact of agricultural subsidies provides different results regarding their influence on farm productivity. Numerous studies (cf. Latruffe et al. 2009; Zhu and Oude Lansink, 2010; Latruffe et al. 2011; Mary, 2013; Rizov et al. 2013; Minviel and Latruffe, 2017; Khafagy and Vigani, 2022) in the literature examine the relationship between individual CAP subsidies and the TFP of farms. These studies present conflicting findings, with some indicating a positive or negative impact, and others showing no significant effect. Notable studies highlight negative associations between CAP subsidies and farm productivity, particularly after the decoupling reforms of 2003. Furthermore, the type of subsidies, such as decoupled or coupled payments, can result in divergent effects on productivity. Additional insights emphasize the role of imperfections in rural markets, varied subsidy aims, and global market dynamics, which contribute to the heterogeneous outcomes observed in the literature. The geographical region, farm specialization, and specific policy measures further contribute to the complexity of the relationship.

In particular, Latruffe et al. (2009) identify a negative impact of coupled subsidies in the first CAP pillar on French farms, while Lakner (2009) notes negative effects of agro-environmental programs on farms in Germany. Zhu and Oude Lansink (2010) find negative impacts of CAP subsidies on farms in Germany and the Netherlands, and Latruffe et al. (2011) report negative effects on farms in multiple European countries. Mary (2013) estimates the impact of various CAP subsidies on French farms and the results show a negative impact on productivity. Conversely, Sauer and Park (2009) find positive effects on farms in Denmark. Biagini et al. (2023) show that CAP subsidies negatively affect the Total Factor Productivity (TFP) of cereal farms, except for agro-environmental subsidies. Garrone et al. (2019) find varied effects of CAP subsidies on the growth of productivity in EU regions. Khafagy and Vigani (2022) observe negative impacts on the productivity of farms that depend on the nature of the subsidy and the methodology used.

From the review of empirical literature, it can be inferred that the results are conflicting and inconclusive, although negative relationships between CAP subsidies and productivity tend to prevail and few studies focus on Italian farms.

However, there is still a gap in the literature regarding the understanding of the TFP impact of farms and the complementarity of subsidies under the first and second pillars of the CAP. This study aims to fill this gap delving into the intricate dynamics. In other words, while existing literature has explored the effects of individual CAP subsidies on farm productivity, there is a paucity of knowledge on the effects resulting from the interaction or coordination between subsidies from different aspects of the CAP. This study seeks to provide insights into this specific aspect of agricultural policy and its implications for the productivity of agricultural farms. The relationship between CAP pillars and the TFP of agricultural farms is expressed using Pooled-OLS[5] (see Hansen, 2007; Wooldridge, 2019) as follows:

$$\begin{aligned} TFP_{i,t} = \beta_0 + \beta_1 Pillar1_{i,\,t-1} + \beta_2 Pillar2_{i,\,t-1} \\ + \beta_3 \left(Pillar1_{i,\,t-1} \# Pillar2_{i,\,t-1}\right) + \beta_4 D_i + \beta_5 D_t + \epsilon_{i,t} \end{aligned} \tag{2.7}$$

Where $\boldsymbol{TFP_{i,t}}$ is the residual obtained from the estimates of the production function in Equation 2.6, as described above. Therefore, it accounts for fixed effects over time, such as policy changes within the analyzed period, as well as individual fixed effects. Moreover, the TFP estimated in the model is a dependent variable, according to the econometric results, this is not a concern for standard errors. $\boldsymbol{Pillar1_{i,\,t-1}}$ and $\boldsymbol{Pillar2_{i,\,t-1}}$ are the log of the amount of funds (Pillar 1 and Pillar 2) that farms receive at time t-1; $\boldsymbol{D_i}$ is the set macro-region of dummies and $\boldsymbol{D_t}$ is the set of year dummies. The analysis is conducted both on the overall sample of Italian farms and considering the three categories of Technical Economic Orientation (OTE).

[5] As suggested by Wooldridge (2021) the reason Pooled-OLS (POLS) is considered a good model in this context emerges from the equivalence between the two-way fixed effects estimator (TWFE) and the two-way Mundlak (TWM) regression. This equivalence implies that, even though they may initially seem like different approaches, both lead to the same results in estimating the effects of the variables of interest. Therefore, POLS can be seen as a valid alternative, offering a simpler and computationally efficient, while still maintaining the ability to identify treatment effects. It is a valid model because, in terms of estimating treatment effects, it shows equivalence with the more complex TWFE, while offering practicality and flexibility in application.
In fact, POLS can effectively be employed even in complex situations without compromising the validity of the estimates. Furthermore, restrictions on treatment effects are easy to test and apply, and the POLS/ETWFE approach provides a solution that is simple, flexible, and exhibits exact and asymptotic efficiency properties under certain "ideal" conditions.

We use the Jarque-Bera (J-B) test (1987). It is a goodness-of-fit test of whether sample residuals have the skewness and skewness matching a normal distribution. The J-B test suggests that they are not normally distributed. The same result is obtained with the Shapiro-Wilk test. However, using the graph of the standardised normal probability (pnorm) which tests for non-normality in the mean range of the residuals. In this case, the graph is slightly out of line, but looks correct. In contrast, quintile-normal (qnorm) plots verify non-normality at the extremes of the data (tails). It plots the quintiles of the residuals against the quintiles of a normal distribution. The tails are somewhat non-normal, which is also why we perform robustness tests in the following paragraphs. An important assumption for the regression model is that the independent variables are not perfectly multicolinear. One regressor must not be a linear function of another.
In the presence of multicollinearity, the standand errors may be inflated. By means of the variance inflation factor (vif). The varibials have a vif<10 or 1/vif> 0.10 and so we can state that there is no multicolinearity problem.
We also conduct test for heteroscedasticity using the Breusch-Pagan (1979)/Cook–Weisberg (1983) test and White test (1980). Using both tests, we fail to reject the null hypothesis of no heteroscedasticity. Therefore, we correct for heteroscedasticity by using robust standard errors and/or clustered standard errors thanks to Stata's "vce (robust)” and/or “vce (cluster id)" command, also checking the cluster "id" i.e. at the farm level. You can robustifying/clustering standard errors and account for heteroskedasticity and/or autocorrelation (see Wooldridge, 2002; 2013). Hence, we use Cumby-Huizinga (1992) test and Arellano-Bond (1990) test for autocorrelation and indicates that serial correlation is present at each lags.

To corroborate our analysis, we use a Random Effects (RE) model because, unlike the Fixed-Effect (FE) model, the RE model can estimate coefficients of time-invariant variables (see Gujarati and Porter, 2009). In addition, in this context with a very large number of observations (N) and a small time period (T), individual effects can be considered random, given that there are many entities (farms) randomly sampled from a broad population, and we do not know the specific nature of individual heterogeneity. Indeed, for large N and small T, the FE model has few degrees of freedom (estimates are unreliable), making the RE model a better choice as it allows for significant savings in degrees of freedom, especially for large N. It enables the estimation of the effects of time-varying covariates (e.g., selection bias rules), is suitable for random samples, and allows for inferences about population behavior (forecasts of individuals outside the sample). It efficiently utilizes both within-individual and between-individual variability.

Since we are conducting unconditional inference on population characteristics to assess the behavior of all farms, we choose to employ the RE model.

The FE model is suitable for estimating specific effects considering a panel of countries, industries, or regions rather than specific firms (for more details on the choice between FE and RE, see Greene W.H., 2002 (Ch. 13-14); Wooldridge J.M., 2003 (Ch. 13-14); Verbeek M., 2008 (Ch. 10); Wooldridge J.M., 2010 (Ch. 7-10-11)).

However, when considering the Hausman test, it is crucial to heed the voiced by Johnston and Di Nardo (1998) and Judge et al. (1991) emphasize. When choosing between fixed effects or random effects models, they argue that there is no straightforward rule to guide researchers through the challenges of fixed effects, the pitfalls of measurement error, and the complexities of dynamic selection. Despite being an advancement over cross-section data, panel data cannot serve as a panacea for all the challenges faced by econometricians.

After explaining why we use the RE model, it's essential to note that the data grouping structure controlled by the model is at the farm level (id) and constitutes a random intercept model. This model measures how much each individual/time period deviates from the overall intercept.

In the context of a model like:

$y_{i,t} = a + bx_{i,t} + v_{i,t}$ with $v_{i,t} = \mu_i + \epsilon_{i,t}$ where μ_i represents unobserved heterogeneity and $\epsilon_{i,t} \sim iid(0, \sigma^2)$ idiosyncratic errors. Thus, the heterogeneity represented by μ_i is considered uncorrelated with explanatory variables $x_{i,t}$ and, consequently, is included in the error term, known as the composite error (the RE model is referred to as the "error components model").

It is assumed that the stochastic movements of μ_i are uncorrelated with explanatory variables $x_{i,t}$ and with the error $\epsilon_{i,t}$. Specifically, it is assumed that: $E(\mu_i) = 0$; $E({\mu_i}^2) = {\sigma^2}_\mu$; $E(\mu_i \, \mu_j) = 0$ (when $i \neq j$). In short: $\mu_i \sim iid(0, {\sigma^2}_\mu)$; (for more details, our results can be found in table 5).

Comparing the results with the regression without the robust standard errors, we note that none of the coefficient estimates changed, but the standard errors and hence the *t* values are a little different, and this is true for both the OLS and RE models. Therefore, if there had been more heteroskedasticity in these data, we would probably seen larger changes. However, to ensure unbiased estimates and account for heteroskedasticity, the estimates presented in the analysis tables are reported using robust standard errors.

Besides, caution is needed not to confuse robust standard errors with robust regression. They deal with different problems and in particular, robust standard errors address the problem of errors that are not independent and identically distributed. The use of robust standard errors will not change the coefficient estimates provided by OLS, but they will change the standard errors and significance tests. Instead, robust regression, on the other hand, deals with the problem of outliers in a regression. Robust regression uses a weighting scheme that causes outliers to have less impact on regression coefficient estimates. See section 2.6 for more details.

2.4 Empirical Analysis

2.4.1 Data

The RICA-REA survey, born from the Italian REA and RICA, is a comprehensive sample survey on the economic outcomes of farms, aligning with European regulations. The REA (Risultati Economici delle aziende Agricole) is a statistical survey that employs direct interviews with agricultural operators, focusing on variables essential for estimating sectoral agricultural aggregates. Before 2002, the REA collected a restricted set of variables for estimating economic aggregates. Concurrently, the RICA (Rete d'Informazione Contabile Agricola), managed by the Council for Agricultural Research and Analysis of the Agricultural Economy (CREA), formerly the National Institute of Agricultural Economics (INEA), conducted an accounting survey with a broader set of variables at farm level. Integration between RICA and REA occurred in 2003, enhancing the efficiency and effectiveness of the survey.

Farms in the RICA are selected to take part in the survey, based on the sampling plans established at the level of each region. The survey covers farms that are considered to be of interest due to their economic size. The methodology applied provides representative data stratified along three dimensions: region, Economic Size Unit (ESU) and Type of Farming (OTE) (European Commission, 2010). Economic size, until the 2009 accounting year, was expressed in Economic Size Units, given by the total Standard Gross Income (SGM), in turn obtained as the sum of the SGM of each productive activity present on the farm. From the following year's accounting year, the economic dimension is expressed directly in euros of standard production value.

The current survey is based on a random sample of farms observed at different accounting years and includes about 200 structural, accounting, and non-accounting variables. The dataset, known as the RICA, is an unbalanced panel of data from 2009 to 2019, comprising approximately 118,600 observations across around 31,300 farms. Subsequently, in order to make our analysis more accurate, we decided to consider farms that were present for at least 3 years by eliminating all farms that were present only once or twice in our sample. Hence, our dataset is now an unbalanced panel dataset running from 2009 to 2019 and includes 97,960 observations on approximately 17,000 farms. RICA dataset are sample of farms is chosen to be representative of Italian agriculture. These data offer detailed insights into each farm's production, labor supply, investment patterns, and more. In particular, our analysis focuses four sections of the dataset: *(i)* farms characteristics (e.g., province, region, altitude zone, location, technical-economic orientation, economic size, legal form); *(ii)* the sample; *(iii)* enterprise balance sheets, i.e. balance sheet and income statement (e.g., total enterprise revenues, revenues from livestock farming, revenues from renewable energy sources, revenues from quality products, revenues from agritourism, current costs, direct costs, multi-year costs, mechanization expenses, electricity, health expenses, salaries, net income, gross operating margin, net value-added of the enterprise, fixed and circulating capital, net capital, reserves, profits, losses, public aid divided by funding source, type of agricultural policy, EU aids, and much more), and *(iv)* support (1st and 2nd pillars).

Key factors such as labor inputs, represented by hours worked in total across the enterprise, and the capital stock, denoting the value of machinery and equipment, are instrumental. The land variable represents the total agricultural area utilized, with temporal dummies included for temporal fluctuations. These fluctuations could be due to various factors, and by including time dummies, the analysis aims to control for and capture the effects of such temporal variations. Further details are provided in Table 1.

Table 1: Variables description

Dependent Variables		Definition
	Value-Added	Log. of value-added. Continuous variable. It is the difference between the value of the output of goods and services achieved by individual branches and the value of intermediate goods and services consumed by them.
	TFP	Residual total factor productivity (TFP). Continuous variable.

First Step Independent Variables		
	Capital (k)	Log. of power delivered by the driving machine. Continuous variable in kw.
	Labour (l)	Log. of total hours worked by farm labour. Continuous variable in hours.
	Land (t)	Log. of utilised agricultural area. Continuous variable in hectares.
	Young	Dummy equal to 1 if the businessman is less than 40 years old and 0 otherwise.
	Economic Size	Categorical variable indicating the economic size (by Reg. No. 79/65 et seq. defines the field of observation of the RICA survey as farms with an economic size greater than or equal to a certain minimum dimension): 1 = Medium (25-100,000 €) (*reference*); 2 = Small (< € 25,000); 3 = Large (> €100,000).
	OTE	Categorical variable indicating the Technical Economic Orientation: 1 = Animal (herbivores, dairy cattle, granivores); 2 = Plant (cereal crops, fruit crops, olive crops, horticulture, viticulture, arable crops); 3 = Mixed (crops and livestock).
	Extra-Agriculture Diversification	Dummy equal to 1 if presence of services for complementary activities and 0 otherwise.
	Agriculture Diversification	Dummy equal to 0 if the farm is always specialised in animal (OTE 1) or plant (OTE 2) and 1 when the farm is mixed (OTE 3).
	Gender	Dummy equal to 1 if the respondent is a female and 0 otherwise.
	Altitude	Categorical variable indicating the altitude zone: 1 = Hill; 2 = Mountain; 3 = Plain.
	Years (D_t)	Dummy variables.
	Materials (m)	Log. of total costs that represent current costs. Continuous variable in euros. It is a proxy variable and is an intermediate input in the ACF (2015) specification.

Second Step Independent Variables		
	Pillar II (*EAFRD*)	Log. of agricultural policy measures provided by the European Union to support rural development, promote structural adjustment of farms and territorial development. Continuous variable in euros.

Pillar I (*EAGF*)	Log. of agricultural policy measures provided by the European Union to provide direct financial support to farmers to ensure economic stability and income security. Continuous variable in euros.
Macro Regions (D_i)	Dummy variables Italian macro regions: North-West (*reference*), North-East, Centre, South and Islands.

In describing the data from RICA (see Tables 2 to 3), it is evident that the majority of farms are located in the South and Islands, with a higher frequency in regions such as Campania and Sicilia. A relevant percentage is also found in the North-West, primarily due to Piemonte, represented by over 1000 farms, followed by Emilia Romagna and Veneto in the North-East. In Centre Italy, there is a higher prevalence of farms in Toscana (see *Macro Regions* variable).
Furthermore, it is noteworthy that our sample, approximately 79% of farmers are male, while females constitute around 21% (*Gender*), highlighting a "gender gap". Additionally, only 12% of the agricultural businessmen in our sample are under 40 years old (*Young*), indicating a predominantly mature age distribution in the agricultural context under consideration.
Regarding the geographic distribution of farms, approximately 45% of them are situated in hilly areas, while only 22% are in mountainous regions (*Altitude*). Medium-sized farms constitute approximately 44% of the sample, indicating a significant presence of businesses operating at a moderate scale (*Economic Size*).
Concerning the diversification of farms, few have adopted diversification strategies (see variables on *Diversification*). The majority of farms are concentrated mainly in the South and the Islands, with a lower percentage located in the central region.
Another relevant aspect is that, on average, there is a higher percentage of funds from the first pillar of the CAP (*Pillar I*), suggesting a greater reliance on such funding in the businesses within our sample. These details further enrich the understanding of the context and characteristics of the agricultural enterprises analyzed based on the RICA.

Table 2: Summary Statistics (no logarithm)

Variables	***Frequency***	***%.***
Gender		
Male	77,139	78.75
Female	20,821	21.25
Altitude		
Hill	44,231	45.15
Mountain	21,851	22.31
Plain	31,878	32.54
Young		
No	85,949	87.74
Yes	12,011	12.26
Economic Size		
1. Medium (€25,000-€100,000)	42,900	43.79
2. Small (€ 25,000);	22,290	22.75
3. Large (> €100,000)	32,770	33.45
Extra Agriculture Diversification		
No	88,218	90.06
Yes	9,742	9.94
Agriculture Diversification		
No (0)	91,256	93.16
Yes (1)	6,704	6.84
Macro Regions		
North-West	22,736	23.21
North-East	22,015	22.47
Centre	16,492	16.84
South & Islands	36,717	37.48

OTE			
Animals	26,602	27.16	
Plants	62,559	63.86	
Mixed	8,799	8.98	
	Mean	**Min**	**Max**
Value-Added	83902.27	25	10,492,153
Capital	181.83	1	3,390
Labour	4,191.80	20	203,184
Land	33.44	0.05	1,731.29
Materials	63,736.08	142	17,384,457
Pillar II	9,651.33	1	1,000,000
Pillar I	14,861.45	1	2,300,144

Table 2*a*: Summary Statistics (logarithm)

Variables							
	Mean	**Min**	**Max**	***Std. Dev.***	***Skewness***	***Kurtosis***	***Obs.***
Value-Added	10.48	3.219	16.166	1,246	0.122	3,57	97960
Capital	4.79	0	8.128	0.943	-0.385	3.939	94613
Labour	8.07	2.996	12.222	0.675	0.526	4.441	97935
Land	2.66	-2.996	7.456	1.355	-0.178	3.053	97960
Materials	9.92	4.955	16.671	1.327	0.514	3.567	97960
Pillar II	8.30	0	13.815	1.439	-1.211	9.349	35823
Pillar I	8.60	0	14.648	1.401	-0.019	3.072	81963

Table 3: Regional Division of Italy at the NUTS 1 level

REGION	Freq.	Freq.	NUTS 1
Piemonte	9,820	1,184	North-West (22,736 obs) (3,231 farms)
Valle d'Aosta	2,322	351	
Liguria	4,693	759	
Lombardia	5,901	937	
Alto Adige	2,866	432	North-East (22,015 obs) (3,974 farms)
Trentino	2,600	371	
Emilia Romagna	6,028	1,413	
Friuli-Venezia Giulia	4,140	733	
Veneto	6,381	1,025	
Toscana	4,775	919	Centre (16,492 obs) (3,138 farms)
Marche	4,140	697	
Umbria	4,255	742	
Lazio	3,322	780	
Abruzzo	4,782	869	South and Islands (36,717 obs) (6,658 farms)
Basilicata	3,909	578	
Calabria	4,289	916	
Campania	5,590	1,003	
Molise	2,921	527	
Puglia	5,406	952	
Sardegna	4,397	775	
Sicilia	5,423	1,038	
Tot.	97960	17001	

Additionally, in terms of geographical distribution (see tables 2.2 to 2.19 in the Appendix A1), the North-West receives more funds from the first pillar of the CAP compared to other geographical divisions of Italy, with a lower average for the South and Islands. Conversely, for the second pillar, on average, the Centre region receives more funds from the second pillar of the CAP, with a lower average for the South and Islands.

Looking at the years 2009 to 2019, on average, farms in the North-West received more funds from the first pillar in 2014, and the year they received the least was 2018. Similarly, farms in the North-East received more funds from the first pillar in 2014 and the least in 2018. Centre

Italian farms received more funds from the first pillar in 2009 and the least in 2019. In contrast, farms in the South and Islands consistently received fewer funds from the first pillar on average, although they received more funds in 2015 and less in 2009.

For the second pillar from 2009 to 2019, on average, farms in the North-West received more funds in 2019 and less in 2013. The situation is different for farms in the North-East, as on average, they received more funds from the second pillar in 2010 and less in 2017. Centre farms received more funds from the second pillar on average in 2011 and less in 2017. Conversely, farms in the South and Islands consistently received fewer funds from the second pillar of the CAP, despite a considerable number (approximately 38%) of farms being located in this geographical area of Italy. They received more funds on average from the second pillar in 2010 and less in 2016.

In summary, we observe that CAP funds were not distributed uniformly across all macro regions of Italy in different years, with farms in the South and Islands consistently at a disadvantage compared to other geographical divisions, especially in comparison to the North.

Even with the division based on the technical-economic orientation (OTE), we find that, on average, farms classified with OTE 1 received more CAP funds with higher amounts in the North than in the South. Larger farms, on average, receive more CAP funds. However, it is observed that small farms in the South and Islands, on average, receive more funds from both the first and second pillars of the CAP than those in the north.

In our sample, approximately 85% of farms are family-run, and over 86% are individual farms. In the South and Islands, farms are more likely to be family-run than in the North and Centre regions. Being a family-run business, on average, results in receiving fewer funds from both the first and second pillars of the CAP, regardless of geographical distribution. Additionally, individual businesses, on average, receive fewer funds from both the first and second pillars of the CAP, both in the north and the south.

Businesses led by young entrepreneurs (under 40 years old), although representing only around 12% in our sample, have, on average, a higher chance of receiving more funds from both the first and especially the second pillar of the CAP, irrespective of geographical distribution. This suggests the EU's commitment to policies aimed at generational renewal.

Similarly, businesses led by women, despite the low percentage in our sample, on average, receive more funds. In this context, we can observe how policies attempt to foster a cultural shift. Finally, businesses that diversify, on average, receive more funds from both the first and second pillars of the CAP.

The analysis of the RICA dataset is fundamental for understanding the technical-economic evolution of farms in the context of agricultural policy measures. The dataset provides diverse information at the farm level, making it a valuable resource for the evaluation and planning of interventions in the agricultural sector. It is capable of describing the national production system. For each farms, it is possible to analyze costs, CAP contributions, and production with reference to each individual business activity. Moreover, the distribution of funds from the CAP reveals regional disparities, with businesses in the South and Islands consistently facing challenges compared to their counterparts in the north.

The influence of age, gender, and business structure on funding distribution highlights the nuanced dynamics within the agricultural sector. Young entrepreneurs and businesses led by women, although forming a minority in the sample, signaling positive shifts in policy objectives.

The findings underscore the importance of considering not only geographical factors but also socio-demographic aspects in formulating targeted agricultural policies. As the EU strives for generational renewal and gender inclusivity, aligning funding mechanisms with these goals becomes paramount.

Furthermore, the disparities in funding distribution between the first and second pillars of the CAP emphasize the need for a comprehensive and nuanced approach to support different types of agricultural enterprises. Policies should be crafted with an understanding of the diverse challenges and opportunities faced by businesses of varying sizes, orientations, and geographical locations.

In conclusion, this analysis serves as a valuable foundation for policymakers and stakeholders seeking to tailor agricultural support programs effectively. By acknowledging the multifaceted nature of the agricultural landscape, policymakers can implement targeted interventions that contribute to the sustainability and resilience of the Italian agricultural sector.

2.5 Results

As introduced above, the first step of analysis is estimating the production function (equations 2.1 to 2.5) and obtaining a measure of TFP for the sample of Italian farms (equation 2.6).

Table 4 reports the estimates of the production function adopting the ACF model by Ackerberg et al. (2015). Therefore, materials (in our case costs) are used as a proxy. The variables Young, Gender, Economic Size, Altitude, Extra-Agriculture Diversification and Agriculture Diversification are used as controls.

TFP is a measure that takes into account inputs such as labour, capital and land contribute to production. When studying the effect of individual characteristics of farmers, such as gender and age, and farm characteristics, such as OTE - meaning specialization or geographical position (altitude) of the farm - on TFP, it is important to distinguish between production and productivity.

In the context of microdata at the farm level, individual characteristics and farm characteristics can impact the farm's production, but their relationship with productivity will depend on how these variables influence the efficiency of input use. Productivity is often more directly related to the efficiency of resource management than to demographic characteristics or specific business orientations.

Therefore, these characteristics influence agricultural production, but their relationship with productivity can vary. For example, the gender and age of the farmer could impact farm management, access to resources, or the decision to invest in advanced technologies (cf. Food and Agricultural Organization of the United Nations, 2017; Doss, 2018). However, if productivity is measured as production per unit of total inputs, gender or age itself may not be directly correlated with productivity but could influence resource management.

OTE could also influence production, as it determines the type of agricultural activity carried out (animal, vegetable, or mixed). However, the relationship with productivity will depend on how these activities are managed and the level of efficiency in the use of production factors.

The detailed analysis of the estimated production function reveals a significant framework, unveiling considerations that merit careful reflection. As expected, all the inputs (capital, labor, and land) significantly and positively impact the output (value-added) (Mary, 2013; Rizov et al., 2013; Biagini et al., 2023 and others). More interestingly, it is the different magnitude of the inputs. Labour has the highest elasticity (0.778), while Land the lowest (0.0723). This highlights as the sector of agriculture is still labour-intensity. It is intriguing to note that the coefficient associated with the land variable has a relatively low value, a dynamic in line with the literature, as indicated by Mary (2013). This suggests suggest a higher return on labor and a lower efficiency of land and capital, indicating a greater labor intensity on farms. This aspect may be somewhat unexpected, considering the trend towards mechanization that has characterized agriculture in recent years. This result, in harmony with works by authors such as Daron Acemoglu and Zilibotti (2001), Bhattacharya et al. (2013), Pearce and Wu (2022), highlights coherence and rationality in the use of capital, labor, and land.

Control variables add further nuances to the picture. Significant differences emerge concerning the age of the farm owner (*Young*): entrepreneurs under 40 look, on average, to exert a significant positive effect on the value-added. The *Economic Size* of the farm reveals another salient aspect, with larger enterprises (over 100,000 euros of standard output[6]) showing a positive impact compared to medium-sized ones (25,000-100,000 euros). As predicted, the larger the farms and the greater the effect.

Geographical location emerges as a discriminating factor, with businesses situated in mountainous or plain areas showing, on average, incremental effects on value-added compared to those on hills. The presence of complementary services (*Extra-Agriculture Diversification*) also confers a positive impact on value-added, revealing the importance of diversification towards other business activities (e.g., tourism services).

A notable aspect is the clear signal of a gender gap in this context. While requiring further

[6] The economic size of the firm expressed in Standard Output is determined by the sum of the Standard Productions (SP) of each individual production activity carried out on the farm (expressed in euros). PS is defined as the value of production of each agricultural production activity corresponding to the average situation in a given region. PSs correspond to a 12-month production period (calendar year or agricultural year).

investigation, this phenomenon raises crucial questions regarding potential obstacles meet by women in the agricultural sector. This may be the reason why farms led by women have, on average, a lower value-added with respect those led by men (*Gender*).

Furthermore, the analysis has highlighted that mixed farms (OTE 3), compared to those always specialized in animals (OTE 1) or plants (OTE 2), show a significant and negative impact on the value-added of the farm, emphasizing the importance of specialization strategies in optimizing productivity (*Agriculture Diversification)*.

In conclusion, our sample of observed farms over several years provides a basis for long-term analysis. This analysis of estimates from the production function and control variables reveals a complex and articulated landscape, with diverse influences shaping the value-added of farms. An ongoing and in-depth analysis of these dynamics is essential for a comprehensive understanding and to effectively inform agricultural policy decisions and strategic interventions in the sector.

Table 4: ACF Model - Full Sample Italian farms

VARIABLES	Value-Added
Capital	0.115***
	(0.00697)
Labour	0.778***
	(0.00849)
Land (T)	0.0723***
	(0.00725)
Young	
No	*reference*
Yes	0.0335***
	(0.0103)
Gender	
Male	*reference*
Famale	-0.0840***
	(0.0101)
Economic Size	
Medium	*reference*
Small	0.533***
	(0.00894)
Large	1.136***
	(0.0170)

Altitude	
Hill	*reference*
Mountain	0.0661***
	(0.00644)
Plain	0.156***
	(0.00713)
Extra-Agri Diversification	0.157***
	(0.00895)
Agricolture Diversification	-0.185***
	(0.0103)
Dummy year	*Yes*
Observations	94,588
Number of id	16,443
Wald test	490,000***

Notes: Table presents estimates in our baseline sample from proxy-variable methods of Ackerberg, Caves and Frazer (2015) (ACF) (using materials as the proxy). ACF estimate generated by Stata command prodest (Rovigatti and Mollisi, 2018)[7].
Robust standard errors in parentheses from bootstraps with 50 replications *10% level, **5% level, ***1% level.

The analysis of the relationship between subsidies, particularly those from the first and second pillars of the Common Agricultural Policy (CAP), and TFP in Italian farms constitutes a central element of our investigation. To achieve this objective, we first calculate TFP as residual from the production function estimated in the previous step.

Table 5 show the results obtained. To corroborate the results, we use both Pooled model (Table 5a) and a Random Effects (RE) model (Table 5b). We report three different specifications, in which the lagged values of pillars and the interaction terms (combination of the two pillars) are introduced progressively.

It is interesting to note that the results show that the lagged term of European funds have a significant but negative effect on the TFP of Italian farms. This finding aligns with the conclusions of other studies, including Mary (2013) and Rizov et al. (2013), which highlight a negative impact of subsidies on agricultural productivity. This suggests that while subsidies can help farmers in challenging financial times, they may also discourage efforts to enhance productivity.

[7] In each replication the estimated models are **prodest lnva, free(lnl lnt) proxy(lnm) state(lnk) control(years, age, economic size, altitude extra-diversification diversification) va met(lp) value-added reps(50) (acf) id(id) t(year).**

Regarding payments from the first pillar, the issue suggests that, since these disbursements are not tied to specific production quantities, they might weaken farmers' incentive to invest and enhance productivity, potentially proving detrimental to TFP. Interestingly, the depressive effect on productivity could contribute to driving less productive farms out of the sector, as highlighted by other scholars (Chau and Gorter, 2005; Kazukauskas et al., 2013).

Regarding second-pillar payments, they overall reflect a negative impact on agricultural productivity, suggesting that these funds contribute to productivity but with a displacement effect. In other words, the funds seem unproductive and act more as subsidies than investments. This phenomenon may indicate that, despite the financial support provided, productivity is unfavorably influenced, and agricultural enterprises, especially those already facing economic challenges, may not be inclined to actively engage in improving their productivity.

Our results align with some previous research, such as Khafagy and Vigani (2022) and Mary (2013), but contrast with others, like Dudu and Kristkova (2017) and Garrone et al. (2019), reporting non-significant impacts. For example, Biagini et al. (2023) find that European funds for Spanish and German farms are negatively correlated with the value of past productivity.

In contrast, the productivity of French farms has more controversial results, because only highly productive firms show positive significance. As the authors suggest, the negative effects may suggest that these European funds are insufficient to halt the negative productivity trend. Moreover, farms operating at an economic loss may also not engage in other activities to increase their productivity and thus receive the funds while waiting to exit the market.

This heterogeneity in results underscores the complexity of the relationship between subsidies and productivity, offering a contentious picture.

The observed negative effect could be attributed to the temporal misalignment between fund disbursement and the actual implementation of investments. Farms might undergo significant changes in the production system in the initial phase of a new investment, negatively influencing TFP. Furthermore, subsidies might be designed to promote investments compliant with environmental and animal welfare regulations, without necessarily targeting increased productivity (Kirchweger and Kantelhardt, 2015).

However, when we consider the interaction between the two pillars, a surprisingly positive result emerges. The positive effects obtained could be linked to the objectives of payments, which, when considered synergistically rather than in isolation, exert a positive impact on productivity. The mixed nature of these variables may contribute to explaining this phenomenon, highlighting the complexity of the relationship between subsidies and agricultural productivity.

In conclusion, the impact of subsidies is unclear and also depends on the context. Moreover, well-designed subsidy programs aligned with broader agricultural and environmental objectives can negatively and/or positively influence productivity. However, poorly conceived subsidies or those creating market distortions can have unintended consequences on long-term productivity and sustainability. This understanding is crucial to inform targeted and effective agricultural policies, taking into account the nuances characterizing the relationship between financial support and the performance of farms. Policymakers must carefully consider the specific goals and potential consequences of subsidy programs. Therefore, continuous and in-depth investigation of these dynamics is essential to adopt strategies that promote sustainable and resilient growth in the agricultural sector.

Table 5: Full Sample Italian farms

	Table *a*: Pooled Model[8]			Table *b*: Random Effect Model[7]		
VARIABLES	(1) Lag 1	(2) Lag 2	(3) Lag 1 & 2	(1) Lag 1	(2) Lag 2	(3) Lag 1 & 2
L.pillar II	-0.193***		-0.157***	-0.0962***		-0.103***
	(0.0181)		(0.0311)	(0.0188)		(0.0268)
L.pillar I	-0.0749***		-0.120***	-0.0205		-0.0627**
	(0.0168)		(0.0315)	(0.0176)		(0.0271)
L.pillar II # L.pillar I	0.0191***		0.0150***	0.00992***		0.00972***
	(0.00198)		(0.00338)	(0.00205)		(0.00292)
L2.pillar II		-0.180***	-0.113***		-0.0893***	-0.0604**
		(0.0201)	(0.0315)		(0.0206)	(0.0276)
L2.pillar I		-0.0529***	-0.0102		-0.00496	0.00685
		(0.0187)	(0.0324)		(0.0193)	(0.0283)
L2.pillar II # L2.pillar I		0.0171***	0.0110***		0.00887***	0.00584*
		(0.00220)	(0.00348)		(0.00225)	(0.00307)
Macro regions						
North-West	*reference*	*reference*	*reference*	*reference*	*reference*	*reference*
North-East	0.110***	0.117***	0.113***	0.0979***	0.0879***	0.0887***
	(0.0143)	(0.0164)	(0.0185)	(0.0217)	(0.0240)	(0.0270)
Centre	-0.0858***	-0.0709***	-0.0587***	-0.111***	-0.104***	-0.0933***
	(0.0141)	(0.0161)	(0.0175)	(0.0219)	(0.0237)	(0.0256)
South & Islands	-0.00919	-0.00141	0.0189	-0.0351*	-0.0228	0.00106
	(0.0115)	(0.0130)	(0.0141)	(0.0184)	(0.0198)	(0.0212)
Dummy years	*yes*	*yes*	*yes*	yes	yes	yes
Constant	3.512***	3.348***	4.107***	2.968***	2.812***	3.368***
	(0.150)	(0.167)	(0.221)	(0.159)	(0.174)	(0.252)
Observations	24,756	19,054	15,452	24,756	19,054	15,452
R-squared	0.030	0.032	0.030			
Number of id				7,641	6,710	5,469
Wald chi2				290.75***	253.90***	210.44***
Rho				0.468	0.459	0.457
sigma_u				0.498	0.494	0.486
sigma_e				0.531	0.536	0.529
$(sigma\_u)^2$				0.248	0.244	0.236
lambda				0.408	0.356	0.351

Robust standard errors in parentheses, clustered at the farm level. *** p<0.01, ** p<0.05, * p<0.1
Column 1: we use one lag. of the variable Pillar I and one lag. of the variable Pillar II.
Column 2: we use 2 lag. of the variable Pillar I and the Pillar II variable.
Column 3: we use both one and two lag. of the Pillar I variable and the Pillar II variable.
NOTE: Intraclass correlation (rho), shows how much of the variance in the output is explained by the difference across entities; sigma_u = sd of residuals within groups μ_i; sigma_e= sd of residuals (overall error term) $e_{i,t}$;
sigma_u^2= variance between groups .

[8] TFP Estimation using Ackerberg, Caves, and Frazer (2015) Approach.

2.6 Robustness Checks

In our research, we aim to provide a comprehensive analysis of Italian farms. As highlighted by Khafagy and Vigani (2022) in their study on the Common Agricultural Policy (CAP) and productivity, agricultural subsidies exhibit inherent diversities, with specific objectives leading to distinct impacts on TFP and the behavior of farms. Therefore, in this section, we concentrate on examining three subcategories of farms, categorized by Technical Economic Orientation (OTE). Furthermore, the OTE of a farm represents its overall strategy, balancing technical and economic considerations. On the technical side, it involves decisions related to agronomic practices, crop selection, technology utilization, and soil management strategies. On the economic front, it encompasses financial management, including marketing, investments, and diversification of activities to maximize profits. In our analysis, we have categorized farms into three OTE groups: *(i)* OTE 1 "Animals" (includes farms focused only on animal-related activities such as herbivores, dairy cattle, and granivores); *(ii)* OTE 2 "Plants" (involves farms specializing only in plant crops such as cereals, fruit crops, olives, horticulture, viticulture, and arable crops); *(iii)* OTE 3 "Mixed" (comprises farms engaged in both crop production and animal management).

This categorization allows us to specifically analyze how OTE influences productivity in different areas, providing a detailed overview of trends and dynamics specific to each category. It also ensures a more accurate and dependable estimation of impacts.

In Tables 2.20 and 2.21 (in the Appendix A1), Italian farms have been classified according to the OTE at the NUT1 level (Table 2.20) and NUTS2 level (Table 2.21). We observe a higher number of observations for OTE 2, especially in Southern Italy and the islands, with Sicilia and Puglia having higher observations. In Piemonte (North-West), we consistently find elevated observations for all three OTE categories. The situation is different in the Centre region, specifically for Umbria and Marche.

Subsequently, we repeat the above analysis by sub-samples including farms operating in the three categories of OTEs.

Studying the impact of European funds (Pillar 1 and 2) and their interaction on these three categories of OTE is particularly relevant. This allows us to assess how funding from the CAP influences the production function and productivity of farms in different categories. This analysis is essential to understand how European subsidies can affect production processes and the efficiency of agricultural businesses, contributing to the formulation of strategies and policies that address the specific needs of each category.

The estimates for the three different OTEs (see from Table 6 to Table 9 in Appendix A2) demonstrate substantial robustness and consistency compared to the full sample. In the next step of the analysis, the key variables—capital, labor, and land—maintain their significance and exhibit a positive impact across all three categories of OTE. This suggests that, irrespective of the type of agricultural production, these fundamental factors continue to positively influence farm productivity.

The persistent gender gap in the results is a noteworthy aspect emerging across all three technical-economic orientations. This discrepancy underscores the need to delve deeper into the dynamics contributing to this gender disparity in the agricultural sector. Policymakers and those involved in agricultural policy could consider targeted strategies to address and reduce this gap, promoting gender equality and equitable participation of women in the sector.

Regarding OTE 1, the analysis reveals that farms located in mountainous areas experience negative effects compared to those in hilly areas, while the opposite effect is observed for plains-based enterprises. These findings suggest that geographical conditions significantly influence farm productivity, indicating the necessity for differentiated policies based on geographic location.

However, as regards altitude, there are significant differences in the results between the OTE 2 and OTE 3 categories, while maintaining the same impact and significance as the complete sample.

Furthermore, a positive and significant effect is confirmed, similar to the full sample, when agricultural companies opt for diversification, indicated by the presence of services for complementary activities compared to those that do not diversify. Finally, as in the complete sample, a significant and positive effect emerges for small and large businesses, compared to medium-sized farms.

The identification of a negative effect of European funds (Pillars 1 and 2) in the last step of the analysis, considering both the first and second lags, reflects the complexity of the impacts of such subsidies on productivity. This result holds true when considering both the full sample and when breaking down by the three OTE categories, and it is consistent across both the pooled and random effect (RE) models. Applying both models contributes to ensuring the robustness of our analyses.

A common aspect in our estimates is that, for both the full sample and the subsamples, the second lag of the second pillar loses significance in the pooled model. In the random effect model, on the other hand, the first lag of the first pillar loses significance. Furthermore, compared to the full sample, in the pooled model, the southern macro-regions and islands gain significance with a negative effect when broken down by OTE 2 (plants) and OTE 3 (mixed). This contrasts with the effect on OTE 1 (animals), where the variable becomes significant but with the opposite sign. Attributing meaning to the macro-regions could reflect specific regional dynamics or variations in the distribution of funds and resources at the regional level. This could be influenced by a range of factors, such as differences in infrastructure, access to resources, predominant agricultural practices, or other variables not considered in the model. Therefore, the analysis of the significance of the southern macro-regions and islands should be interpreted in the context of specific regional factors that may influence the effectiveness of agricultural funding.

However, the surprisingly consistent positive outcome when considering the interaction between the two pillars indicates that the strategic combination of both could mitigate the observed negative effects when considered individually. This strong result holds for both pooled and random models, and is especially pronounced when examining different OTE categories of farms, as well as the full sample. This suggests the possibility of revisiting and adapting subsidy policies to maximize their benefits.

The insights derived from these estimates could be utilized by policymakers to inform and shape targeted programs. For example, the promotion of best management practices and resource efficiency could be incentivized through specific programs or targeted incentives. Deepening the understanding of how geographic variables and European funds influence productivity could

lead to more focused and tailored policies.
In conclusion, these estimates provide a detailed picture of agricultural productivity dynamics, revealing significant impacts of key variables and European funds. Understanding these relationships is crucial for designing effective and sustainability-oriented agricultural policies aimed at sectoral improvement.

After completing the estimations for both the entire sample and the sub-sample of different Technical Economic Orientations (OTE 1, 2, 3), we conducted additional robustness checks to ensure the solidity and reliability of our results. These checks are thoroughly illustrated in tables 10 to 12 in the Appendix A2.
In particular, we used the ACF method and the LP method for step 1 and 2 estimation, and adjusted the variables with Stata's “winsorize” command (Cox, 2006; Lian, 2020).
The ACF method is designed to address potential endogeneity concerns and improve the precision of estimates in the presence of correlated unobservables. It allows us to account for complex relationships and dependencies within the data, offering a more nuanced understanding of the underlying dynamics. On the other hand, the LP method is selected for its robustness in the face of outliers and influential observations. This method is particularly valuable in scenarios where extreme values might distort the results, leading to biased estimates. By incorporating LP into our estimation process, we aim to enhance the resilience of our analysis against the impact of outliers, ensuring that our results are more reliable and less susceptible to the influence of extreme data points.
The combination of ACF and LP methods contributes to a comprehensive and robust estimation approach, providing a solid foundation for our research findings.
As we mentioned above, we used Stata's “winsorize” command to implement these checks, applying upper and lower limits given by the 1 and 5 percentiles of the distribution of dependent and independent variables. The winsorization process helps mitigate the influence of extreme values or outliers, ensuring a more robust and reliable estimation procedure.
For example, if we use the upper 1 percentile and upper 5 percentile, the command will replace values exceeding the 99th percentile and 95th percentile, respectively, with values

corresponding to these percentiles. This way, the "winsorize" command allows treating extreme data without completely eliminating them, maintaining their influence on statistical results more moderately.

In our analysis, values above the 99th percentile or below the 1st percentile (in our case, 1 and 5 percentiles) are replaced with values corresponding to the limits. Executing this command has helped ensure that the results obtained in our analyses were robust even in the face of potential distortions due to extreme values in the variables involved.

At the end of this robustness process, we arrived at the same conclusions for both the full sample and the sub-sample of OTE. In particular, the negative effects of individual pillars of the CAP on agricultural productivity persisted, confirming the trend identified initially. It is interesting to note, the interaction between the two pillars continued to show a positive effect. This dynamic indicates that, despite the observed negative impacts when the pillars are analyzed separately, the combination of the two forms of European financial support has an overall positive effect on the total factor productivity in Italian farms.

These additional robustness checks reinforce the consistency and validity of our findings, suggesting that the results obtained are reliable and not significantly dependent on the presence of outlier values in the data.

2.7 Conclusions

This chapter contributes in understanding the relationship between the Common Agricultural Policy (CAP) incentives and the productivity of Italian farms. By conducting a comprehensive analysis over a decade 2009-2019 and employing consolidated econometric approaches, we have in particular contributed to unveiled novel insights into the complementarity effect between the first and second pillars of the CAP on the TFP at farm level. Our investigation, rooted in a meticulous review of the literature, addresses the long-debated question of whether the substantial investments made by the European Union in the CAP indeed translate into enhanced productivity in the agricultural sector.

Given the literature gap, this study specifically focuses on the Italian context. The divergence in results from previous studies in other European countries (see Latruffe et al., 2009; Lakner, 2009; Zhu and Oude Lansink, 2010; Mary 2013; Garrone et al., 2019, and many others) led us to explore the unique dynamics of the Italian experience, particularly focusing on the interaction between the subsidies of the first and second pillars.

The literature on the impact of CAP incentives on agricultural productivity in various European countries has produced conflicting results, considering only individual pillars of the CAP. The divergence of results could be attributed to heterogeneity in farm sizes, production methods, and the specificities of each country's agricultural sector, as the effectiveness of CAP subsidies also depends on the strategies adopted by individual countries for the implementation and distribution of subsidies.

For these reasons, in this study, the incorporation of unbalanced panel data from the "Rete d’Informazione Contabile Agricola" (RICA), allows for a nuanced examination of the impact of CAP subsidies on Total Factor Productivity (TFP) at the farm level. The unexpected positive interaction between the two pillars emerged as a central finding, challenging conventional wisdom and adding a layer of complexity to the understanding of CAP's effects on farm productivity.

The consideration of both pillars separately and their subsequent interaction, a distinctive feature of our study, sheds light on the intricate relationship between direct payments and income support (first pillar) and rural and sustainable development through local initiatives (second pillar). Our results emphasize the need for an integrated view, highlighting the crucial role of complementarity in fully grasping the effects of CAP funds on productivity.

Furthermore, our detailed methodological approach, which includes estimating production functions for TFP, using Solow's Residuals Approach, and the dynamic assessment of CAP subsidies over time, strengthens the robustness of our results. The data from the RICA dataset, carefully selected to be representative of Italian agriculture, provide a rich source of insights into the complexities of farm-level dynamics.

As we delve into the results, the intricate interplay of factors such as labor inputs, capital stock, and land utilization becomes apparent, shaping the value-added of farms in diverse ways. This underscores the importance of continuous and in-depth analysis of these dynamics for informed policy decisions and strategic interventions in the agricultural sector.

In conclusion, our findings highlight the nuanced nature of the relationship between CAP subsidies and agricultural productivity, emphasizing the need for carefully crafted policies aligned with broader agricultural and environmental objectives. The results obtained in the Italian context, which indicate an unexpectedly positive interaction between the two pillars, open avenues for further investigation and may prompt further investigation into whether similar patterns exist in other European countries to shape sustainable and resilient growth in the agricultural sector. In summary, while the results of this study provide valuable insights into the Italian experience with CAP incentives, it is essential to recognize the complexity and diversity of European agriculture. Comparative analyses between countries can enrich our understanding of how CAP measures interact with different agricultural landscapes, contributing to more informed and context-specific policy recommendations at the European level.

Chapter 3

A long-term vision for rural areas: A case study of Sicilian farms

3.1 Introduction[9]

In the previous chapters, we delved intof the European Union (EU) agricultural policies, emphasizing the Common Agricultural Policy (CAP)[10] as a pivotal instrument for economic growth and regional cohesion. CAP, comprising direct payments (first pillar) and rural development policies (second pillar), operates independently despite substantial implications for economic, environmental, and social aspects, as highlighted by Esposti (2007).

CAP reforms have emphasized various objectives, including support for organic farming, greening measures, agri-environmental actions, improvement of animal welfare, and working conditions for farmers. Recently, attention has shifted towards promoting a long-term vision for rural areas, where local actors play a strategic role in preserving biodiversity, soil, and cultural heritage (Aronica et al., 2021; Esposti, 2012). In line with this, the latest CAP reform and the

[9] A revised version of this chapter, realized in collaboration with Professor Davide Piacentino, Professor Maria Francesca Cracolici, Dr Martina Aronica and Dr Salvatore Tosi, was published in 2023 in Regional Studies, Regional Science under the title “A long-term vision for rural areas: a case study of Sicilian farms” .

[10] For details, see https://ec.europa.eu/info/food-farming-fisheries/key-policies/common-agricultural-policy/cap-glance_en

Green Deal have set primary goals of strengthening the socio-economic context in rural areas and fostering sustainable development of rural enterprises, highlighting key factors such as digitalization, innovation, and sustainability as fundamental prerequisites for development (EC, 2020a; 2021a; 2021b). However, a frequently overlooked aspect is the crucial role of small farms, particularly significant in the Mediterranean region in terms of numbers and ecosystem services to rural communities (Guiomar et al., 2018). The COVID-19 pandemic has underscored the economic, environmental, and social importance of these enterprises (Laborde et al., 2020). In an attempt to valorize their contribution, the CAP explicitly aims to strengthen rural areas by introducing policies for generational turnover, sustainable growth of rural enterprises, social inclusion, and gender equality.

Italy, with its variety of landscapes and agricultural traditions, plays a crucial role in the European context and faces unique challenges, ranging from small realities in internal areas to broader challenges related to sustainability and innovation. Indeed, the recent emphasis on CAP and the Green Deal reforms targeting small farms indicates a shift in perspective and increased attention to ecological and social transitions. However, despite these developments, small farms still face significant challenges in promoting balanced development in rural areas, especially where family farming predominates, as in the Mediterranean area.

In this section of the thesis, we will focus on a detailed analysis of the internal dynamics of Sicilian farms in the South of Italy. In the post-CAP reform era and in harmony with global challenges such as climate change and the green transition, Sicilian farms are called upon to play a strategic role not only in food production but also in environmental conservation, cultural heritage enhancement, and the promotion of sustainable agricultural practices. In this context, the analysis of farms becomes particularly relevant as a key tool to understand how these entities are adapting and contributing to shaping the future of Sicilian rural areas.

The goal is to explore the responsiveness and adaptability of these farms to the fundamental determinants of a long-term vision for rural areas, with a particular emphasis on digitalization, innovation, and sustainability. These factors are considered fundamental prerequisites for making local communities resilient to potential external shocks (Organisation for Economic Co-operation and Development (OECD), 2020a), especially in light of the COVID-19 pandemic. Despite the macro-spatial policies outlined by CAP and the Green Deal, we acknowledge that the effectiveness of such policies may be limited without support for behavioral changes at the micro-enterprise level (Fazio and Piacentino, 2010; Randelli et al., 2014). For instance, investments in technological infrastructure to reduce the digital divide between urban and rural areas may have limited returns if not accompanied by the spread of digital culture in rural areas (Lythreatis et al., 2021).

In this context, we investigate whether Sicilian farms possess a long-term vision for rural development and how they perceive their role post-pandemic. Our survey into rural areas (here defined by a policy criterion[11]) examines the territorial areas where Local Action Groups (LAGs)[12] implement policies to achieve the goals set out in the regional rural development plan (PSR). We have selected four LAGs out of the 23 in Sicily (Metropoli Est; ISC Madonie; Geoparco della Rocca di Cerere; Sicani), covering a wide range of northern and central Sicily to explore how receptive farms are to a long-term vision.

Our approach is based on collecting data from a random sample of 149 farms through a structured questionnaire[13], addressing general characteristics and key factors of the long-term vision. These factors, including digitalization, innovation, and sustainability, help define farmers' *Vision* of development and their *Attitude to Change*. By combining *Vision* and *Attitude to Change*, we explore whether farms with a short-term *Vision* – namely, those that have so far not invested in digitalisation, innovation and sustainability – have a positive *Attitude to Change*. The empirical analysis emerging from this phase of the research promises to provide an in-depth look at the geographical distribution of Sicilian farms, revealing a prevalence in the central internal areas of Sicily, often lacking a well-defined long-term development vision. However, beyond this predominant scenario, we expect the study to reveal a more nuanced picture. While

[11] Empirical analyses usually adopt an administrative criterion to define the spatial units of investigation (e.g., regions)

[12] European policies have favoured a more direct participation of local actors in rural development strategies adopting a bottom-up approach, called community-led local development (CLLD). In this approach a key role is played by LAGs, public–private partnerships with an understanding of the needs of rural communities financed by the European Agricultural Fund for Rural Development (EAFRD) to implement local policy actions. See https://enrd.ec.europa.eu/leader-clld_en

[13] The questionnaire utilized is accessible in the published paper or can be obtained by reaching out to the authors upon request.

some farms seem anchored to a static perspective, without a clear development vision, other industry actors show a notable positive attitude towards change. These success cases will not only serve as enlightening examples but could also be sources of inspiration for future development strategies. To the best of our knowledge, this is the first attempt at an empirical analysis to assess the receptiveness of local farmers to European strategies of rural development and their awareness of the changes induced by the pandemic shock[14]. Although the empirical results of our case study involve only a small sample of Sicilian farms, it may pave the way for future studies aimed at exploiting the receptiveness of entrepreneurs to the opportunities deriving from specific policies. Furthermore, it is expected that this research will provide a solid foundation for formulating practical and informed recommendations for policy-makers, industry operators, and other key stakeholders, encouraging initiatives that can optimize the potential of Sicilian farms in line with the new directions outlined by CAP and the Green Deal. The second part of the chapter will continue exploring European policies in agriculture and rural development, integrating evidence from scientific literature. Subsequently, key aspects of the survey methodology will be introduced, followed by the discussion of empirical results. We will conclude the chapter by highlighting the importance of our findings and outlining implications for future policies.

[14] There is only one study that looks at the attitude of farms in response to rural development policy challenges, but its approach is mainly psychological (Stojcheska et al., 2016).

3.2 European policy evolution: towards a long-term vision for rural areas

The CAP in its first edition of 1962 had the following main goals: (1) increasing agricultural productivity; (2) supporting farmers' incomes; and (3) stabilising markets and regulating prices[15]. There is no mention of the impact of agricultural production in terms of environmental and social sustainability. Indeed, the policies of those days encouraged process innovation aiming at higher levels of agricultural productivity without any respect for the soil and other natural resources. The implementation of such policies generated overproduction and environmental damage with serious consequences for future generations.

Since the early 1990s, policymakers have recognised the need to reverse this trend and have introduced important reforms such as: (1) The MacSharry reform in 1992; (2) Agenda 2000; and (3) The Fischler reform in 2003. These reforms have led to an evolution of agriculture policies that have moved away from sectoral productivity to rural development. To implement these reforms, specific European funds, for example, the second pillar of CAP[16], have been exclusively reserved for rural development (Dwyer et al., 2007; Mack et al., 2021), and at the same time new mechanisms have been introduced conditioning agricultural subsidies to respect environmental standards, that is, the so-called conditionality (e.g., Bartolini and Viaggi, 2013; Moro and Sckokai, 2013). In this policy framework, the role of local actors is considered pivotal to the adoption of a sustainable approach to rural development (Daugbjerg, 2003; Frascarelli, 2017; Henke, 2002, 2004; Rizov, 2004).

More recently, to increase the competitiveness of rural economies, innovation and sustainability practices at farm level have further been supported by the Europe 2020 reform (European

[15] For more details, see https://ec.europa.eu/info/food-farming-fisheries/key-policies/common-agricultural-policy/cap-glance_en

[16] For more details, see https://ec.europa.eu/info/funding-tenders/find-funding/eu-funding-programmes/european-agricultural-guarantee-fund-eagf_en; and https://ec.europa.eu/info/funding-tenders/find-funding/eu-funding-programmes/european-agricultural-fund-rural-development-eafrd_en

Commission, 2020b)[17] and other European agricultural programmes[18] (Frascarelli, 2017; Mantino, 2015; Pelucha and Kveton, 2017). These policies have not only reserved additional resources for rural development but also increased the flexibility of their use by member states (De Castro et al., 2021).

Finally, the European Green Deal (European Commission, 2019), the Biodiversity Strategy for 2030 (European Commission, 2021a), and the Farm to Fork strategies (European Commission, 2020c) have enriched the policy framework, stressing the role of rural economies in preserving the environment and biodiversity globally, as well as moderating the effects of climate change (Marandola and Vanni, 2019).

In 2021, following the direction indicated by these policies, the European Commission defined a long-term vision for the EU's rural areas (European Commission, 2021b). This vision identifies four complementary actions to make rural areas: (1) stronger, empowering rural communities by increasing access to services, and facilitating innovation and digitalisation; (2) connected, by improving infrastructures; (3) more resilient to environmental, health and economic shocks; and (4) more prosperous, by encouraging the diversification of economic activities (for more details, see European Commission, 2021b).

To achieve this, factors such as digitalisation, innovation and sustainability play a key role. The digitalisation of local communities and farms, for example, should reduce the remoteness of rural areas (Salemink et al., 2017), making these more connected and stronger. Innovation affects the competitiveness of rural economies – increasing the quality of agricultural production and offering new business opportunities (Esposti, 2012) – and makes them stronger and more prosperous. Finally, investments in sustainability, for example, agroecological practices or other greening measures (Capitanio et al., 2016; Coderoni and Esposti, 2018; Cortignani and Dono, 2015; Garini et al., 2017), as well as the diversification of farming activities (Balezentis et al., 2020), are fundamental in making rural areas more resilient.

[17] Europe 2020 is the EU's 10-year strategy for smart, sustainable and inclusive growth. In order to deliver on this objective, five ambitious targets have been set, covering employment, research and development, climate change and energy sustainability, education, and the fight against poverty and social exclusion. See 'Glossary –Regional Policy –European Commission' (europa.eu)

[18] See https://ec.europa.eu/info/food-farming-fisheries/key-policies/common-agricultural-policy/new-cap-2023-27/key-policy-objectives-new-cap_en#nineobjectives

However, there is still a long way to go before such a vision is realised due to the urban–rural cultural and digital divide to be found not only in Europe but also in the rest of the world (OECD, 2018). For instance, in the case of Wales, Bowen and Morris (2019) find that 19% of farmers have no access to broadband connection, with damaging consequences for their ability to innovate and grow, and also that many of them under-use the internet due to their limited digital literacy. This may be also attributed to the elderly population of rural areas and the small size of farms. Indeed, smaller farms with older and less educated farmers seem to be less likely to adopt digital technologies (Marescotti et al., 2021) and innovate (Arzeni et al., 2021; García-Cortijo et al., 2019; Läpple et al., 2015; Mc Fadden and Gorman, 2016).

Overall, empirical research on developed countries highlights a persistent digital reticence on the part of rural farmers and the need to promote and incorporate the use of information technologies within an integrated approach for rural development (Grimes and Lyons, 1994).

This integrated approach will mean supporting basic competence-building before introducing more advanced technologies, since even elementary digital skills may be new to farms (Norris, 2020). In this context, education and communication will play a crucial role in encouraging a positive attitude to digitalisation and innovation (Räisänen and Tuovinen, 2020). Similarly, a lower level of human capital in rural areas may threaten the adoption of sustainable practices and will call for skills, education and training to favour long-term development (OECD, 2020b).

Although the COVID-19 pandemic dramatically worsened an already vulnerable socio-economic condition (European Commission, 2021b; OECD, 2020a), today there is a great – maybe the greatest – opportunity for development. The pandemic has accelerated the digital transition in rural areas (Morris et al., 2022). Recovery packages, such as Next Generation EU, have been designed to bridge the urban–rural divide by funding investments in digital infrastructures, digital literacy, innovation and sustainable practices (Mikhaylova et al., 2021).

However, as mentioned previously, changes at a macro-level will not happen if they are not supported by changes in behaviour at a micro-level. Hence, in short, a positive attitude to change on the part of local actors is a precondition to making effective investments. Using a case study approach, the empirical part of our study will explore this issue employing primary data on the specific case of Sicilian rural farmers.

3.3 A local survey on Sicilian rural farms

3.3.1 Questionnaire and sampling procedures

Following a case study approach, our research issues have been addressed by collected data on a random sample of Sicilian farms located in rural areas where four LAGs operate[19]. The questionnaire[20], administered with the support of LAGs, after the acceptance of a declaration of informed consent by the respondents[21], was processed ensuring the anonymity and in accordance with the usual provisions of the legislation on data privacy. The questionnaire is subdivided into four sections in order to investigate the following:

- Farm characteristics such as ownership, management, market share, employees, etc.
- Information and communication technologies (ICTs): to explore the readiness to use basic ICT tools such as websites and social media[22].
- Innovative activities such as product, process, marketing and organisational innovations.
- Sustainable practices: to explore whether or not farms take into consideration social, economic and environmental sustainability.

The last three sections explore the attitude of farms to investment in digitalisation, innovation and sustainability (*Vision*); and also whether this has changed as a consequence of COVID-19 (*Attitude to Change*). Using a Likert scale of 1–10, we measure the opinion of farmers on the

[19] Territorial systems that include cohesive aggregations of municipalities defined by the 2014–2020 Sicily Rural Development Program (RDP) and the Operational Program (PO) European Regional Development Fund (ERDF) Sicily 2014–2020. There are 22 LAGs in Sicily; in our study we consider the Metropoli Est, Sicani, ISC Madonie and Rocca di Cerere Geopark LAGs. It should be mentioned that LAGs only have the authority to implement policy actions in rural and marginal areas, that is, those areas classified as C and D in the Sicilian RDP, whereas areas classified A and B include urban and high-intensity agricultural areas.
[20] The questionnaire used is available upon request from the authors.
[21] For the full declaration of informed consent, see the Appendix.
[22] As the farms involved in the case study were small and operating mainly in marginal rural areas where broadband connection has not yet become widespread, we refer to the use of basic ICTs and digital tools and do not consider advanced digital technologies, such as the Internet of Things, 3D modelling, etc.

importance of these factors on their economic activities in the pre-pandemic era and how important they think these factors will be in the post-pandemic era.

Before defining the sampling design, the questionnaire was tested through a pilot analysis on 10 Sicilian farms from different LAGs in order to evaluate its comprehensibility and to receive potential feedback so as to improve the questions. The data were collected by means of direct interviews with the owner/administrator of the company using an online platform between 25 June and 10 July 2020. More than 70% of the interviewees declared they found the questionnaire to be clear, well-organised and relevant to the concerns of farmers and rural economies. This meant that only minor changes were needed to obtain the final version of the questionnaire. The sample was randomly extracted at the end of 2020 from the population of Sicilian farms, that is, business units codified as A01 in the ATECO2007/NACE sectoral classification[23]. Starting from a population of about 78,000 farms, we select the subpopulation of 13,762 farms in the areas where the LAGs under consideration operate (i.e., Metropoli Est, Sicani, ISC Madonie and Rocca di Cerere Geopark).

Finally, we extracted a sample of 388 farms by applying a proportional stratified random sampling technique with LAGs and the legal status of the farms as stratification variables. The sample size was obtained using Slovin's formula[24]. The selected farms were first contacted by email with the help of the LAGs. However, even at this early stage the problem of digital reticence emerged as some farmers did not even have an email address. Therefore, in some cases, interviews were conducted by telephone or in person. The survey was carried out from April to July 2021. The response rate was 38%. Hence, we collected data on 149 farms spatially distributed as follows: Metropoli Est (43), Sicani (36), ISC Madonie (33) and Rocca di Cerere Geopark (37). There is heterogeneity in responses among LAGs, with a higher frequency in the Metropolis East LAG (see Table C).

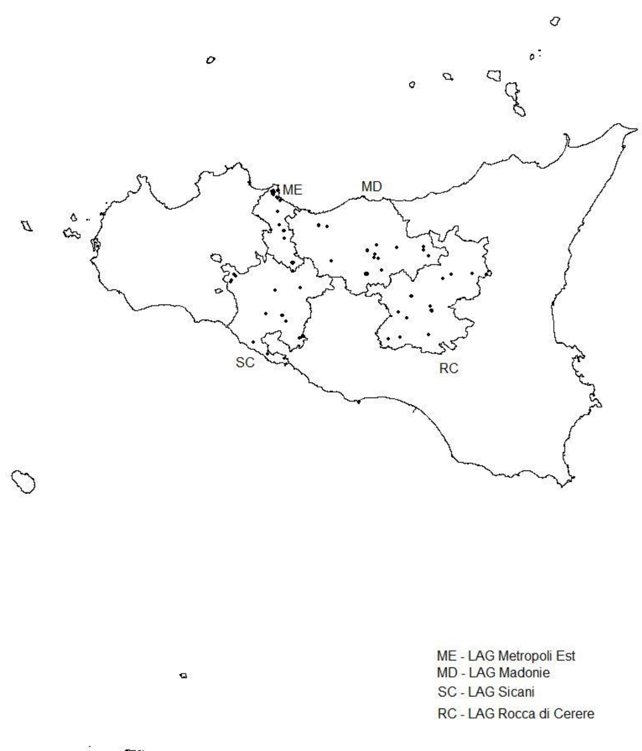
Figure 3.1 shows the rural areas explored and the spatial distribution of the farms selected. This is a large portion of middle Sicily. The Metropoli Est (ME) LAG is the nearest to the

[23] We thank the Palermo Chamber of Commerce for allowing us to use these data.

[24] Slovin's formula $n = N(1 + Ne^2)$ is used to calculate the optimal sample size (n) from a population (N), deciding a certain level of error tolerance (e). In this case, $N = 15{,}000$ and $e = 0.05$ (Altares et al., 2003; Guilford, 1950; Guilford & Frucher, 1973)

metropolitan city of Palermo. Of the areas we studied, this has the easiest access to transport infrastructures and public services (airport, port, highways, broadband connections, etc.). Of course, even within this LAG, there are considerable differences between rural coastal and rural inner areas. The Sicani (SC) LAG area extends from the southern coast to the borders of the Metropoli Est LAG, crossing the Sicani mountains and the historic route of the Magna Via Francigena. The ISC Madonie (MD) LAG area covers a large portion of the northern coast of Sicily, with its famous tourist destinations such as the city of Cefalù, and extends inland through the Madonie mountains characterised by fascinating medieval villages. Finally, the Rocca di Cerere Geopark (RC) LAG includes exclusively inner rural areas and suffers most from the lack of transport infrastructures.

Figure 3.1 Distribution of sampled farms by local action group (LAG)



Even though the sample was obtained with statistically validated sampling procedures, the small number of observations obtained calls for the need to enlarge the targeted sample in future.

3.4 Empirical analysis

3.4.1 Variables

Table 3.1 lists the variables used in the analysis[25]. We record a few missing values with observations that range across variables from 140 to 149. Among the list of variables *Males* highlights a significant gender gap, with 82% of respondents being men, in the *Age* variable the majority (62%) are under 50 years old, only 16% are under 30 and some 20% are over 60. 81% of farms have fewer than 4 employees (non-seasonal), while only 7% have more than 9 employees. Only 30% of farms operate outside their regional market (*Outside Regional Market*), with 99% selling products in their own region, 33% in other Italian regions, 19% in EU countries and only 4% in Extra-EU countries. More than half of farms (56%) are organised as family businesses (*Family Business*) and only 42% of farms have at least one certification among International Organization for Standardization (ISO) 22000, ISO 9001, International Food Standard (IFS), Brand Reputation through Compliance (BRC), global Good Agricultural Practice (GAP) and protected denomination of origin and Protected Geographical Indication (DOP-IGP) (*Certifications*). Specifically, 12% have ISO certification, 2% IFS, 4% GAP, and 36% DOP-IGP. In addition, about 65% use retail channels of trade, while only 12% use large retailers.

[25] For the full list of questions included in the questionnaire.

Table 3.1: *Variables description*

Variables	*Definition*	*Respondents*	*Yes*
Males	Dummy variable equal to 1 if the farmer is male and 0 otherwise.	148	82%
Age	Categorical variable indicating the age of farmer:		
	Under 30	148	16%
	30-40 years	148	22%
	41-50 years	148	24%
	51-60 years	148	18%
	> 60 years	148	20%
Outside Regional Market	Dummy variable equal to 1 if the farm also sells outside the regional market and 0 otherwise.	145	30%
Family Business	Dummy variable equal to 1 if farmer's family members work in the farm and 0 otherwise.	147	56%
Certifications	Dummy variable equal to 1 if the farm has at least one certification (ISO 22000, ISO 9001, IFS and BRC, Global GAP or DOP-IGP) and 0 otherwise.	142	42%
ICTs	Dummy variable equal to 1 if the farm uses websites or social media and 0 otherwise	144	40%
Innovation	Dummy variable equal to 1 if the farm has introduced over the last three years technological or non-technological innovations and 0 otherwise	145	43%
Environmental Sustainability	Dummy equal to 1 if the farm uses renewable energies or ecological products or chooses sustainable suppliers, and 0 otherwise.	145	75%

Social Sustainability	Dummy equal to 1 if the farm provides training courses on and health and safety for employees or collaborates on charitable projects for the local community or discloses its sustainable aims in official documents, and 0 otherwise.	145	62%
Economic Sustainability	Dummy equal to 1 if the farm adopts sustainable practices to attract investors or to improve its economic performance, and 0 otherwise.	140	56%
Commercial channels			
	Retail	137	65%
	Sale	141	56%
	Large	121	12%
Sell			
	Sicily	145	99%
	Italian regions	127	33%
	EU	121	19%
	Extra-EU	118	4%
Number of employees	Categorical variable indicating the number of employees (non-seasonal):		
	1 = employees ≤ 4;	120	81%
	2 = 5 ≤ employees ≤ 8;	18	12%
	3 = employees ≥ 9	9	7%
Detail certifications			
	ISO 22000	131	12%
	ISO 9001	134	12%
	IFS	130	2%
	GAP	130	4%
	DOP-IGP	141	36%
Website	Dummy equal to 1 if the farm has a website, and 0 otherwise.	148	22%
Social media	Facebook	147	34%
	Instagram	139	15%
	Twitter	135	3%
	Youtube	133	9%

Before the Covid-19 pandemic, about 82% of companies did not sell abroad. After Covid-19, this percentage dropped to 73% (see Figure A3.1 in the Appendix C).

Focusing on the variables that are of particular interest for this analysis, we find that only 40% of farms use websites or social media (*ICTs*), reflecting the digital reticence of rural areas. We separately asked farmers whether they have a website and if they use social media (Facebook, Twitter, Instagram, YouTube). Specifically, 22% have a website, 34% use Facebook, 15% Instagram, 3% Twitter, and 9% YouTube. We also asked what purposes people use the website and social media for, for example, 52% use the website for sales, 58% for product promotion, 55% for customer management, and only 7% for recruitment.

In contrast, 85% of farms use social media for marketing, 75% to manage customer relationships, 38% to collaborate with other partners, 13% use social to search for staff, and finally 20% for internal communications with employees (see figure A3.2 in the Appendix C).

We then constructed a general variable, which we call ICTs, that assumes a value of 1 if the farm has adopted at least one of these digital tools, 0 otherwise. Those farms that had adopted them seemed, from a preliminary analysis, to be using only basic tools such as Facebook, which the literature suggests is not very useful for business purposes (e.g., Aronica et al., 2021b). A total of 43% of farms have introduced innovations over the last three years (*Innovation*). We divided this category into two: technological (product and process) innovations; and non-technological (organisational and marketing) ones. However, for our purpose, we aggregate this information in a variable called *Innovation*, which assumes a value of 1 when a farm has introduced at least one type of innovation, 0 otherwise. Farms seem to be slightly more oriented to innovation (43%) than to adopting ICTs (40%).

There is a greater willingness to adopt sustainable practices: 75% of farms adopted at least one *Environmental Sustainability practice*; 62% at least one Social Sustainability practice; falling to 56% in the *Economic Sustainability* category. We measure these dimensions of sustainability by a set of variables largely suggested by the literature (Arfini et al., 2019; Hosseininia and Ramezani, 2016). Environmental sustainability is initially measured by means of three binary variables that refer to the following practices: (1) using renewable energies; (2) using ecological products; and (3) preferring suppliers that adopt environmentally sustainable practices. We then aggregate this information to obtain a variable that assumes a value of 1 if the farm has adopted at least one of those practices, 0 otherwise (*Environmental Sustainability*). Similarly, we measure *Social Sustainability* by a variable that is 1 if the farm has adopted at least one of these practices: (1) providing health and safety training courses; (2) collaborating with charitable projects in the local community; and (3) disclosing sustainable aims in official documents or other channels. *Economic Sustainability* is measured by aggregating the following binary variables: (1) adopting environmentally sustainable practices to attract investors; and (2) adopting environmentally sustainable practices to improve economic performance. Finally, we construct a variable, called *Sustainability*, that is 1 if the farm has adopted at least one type of sustainable practice, irrespective of its dimensions.

It should be emphasised that our focus is not on specific aspects of ICTs, innovation and sustainability, but is rather from a holistic and multidimensional perspective, as we endeavour to understand whether an agricultural enterprise is adopting a long-term vision of development or remains short-sightedly short-term in its outlook. To this end, we construct a categorical variable called Vision and labelled as follows:

- 0 if ICTs, *Innovation* and *Sustainability* assume values = 0. We call this category *"Short-Term Vision"*.
- 1 if one of the above variables is = 1. We call this *"Long-Term Vision – low intensity"*.
- 2 if two of the above variables are = 1. We call this *"Long-Term Vision – medium intensity"*.
- 3 if all three variables are = 1. We call this *"Long-Term Vision – high intensity"*.

This categorical variable will enable us to address our first research issue, that is, whether farms are prone to a long-term vision for rural areas. Specifically, we will observe the association between the Vision and the main characteristics of a farm in order to find some regularities.

To address our second research issue, that is, how aware farms are of the changes induced by the pandemic crisis, we define another variable that aims to capture farmers' Attitude to Change in response to the pandemic. To this end, we use information from the following questions:

- ***BEFORE*** the Covid-19 pandemic, how important do you think the following were to your business:
    - *adopting ICTs.*
    - *introducing innovations.*
    - *using renewable energies.*
    - *other ...*
- ***AFTER*** the Covid-19 pandemic, how important do you think the following will be to your business:
    - *adopting ICTs.*
    - *introducing innovations.*
    - *using renewable energies.*
    - *other ...*

We measure each item by means of a Likert scale 1–10[26]. We take the average score of the different sustainable practices to obtain the aggregate measures described above (Environmental Sustainability; Social Sustainability; Economic Sustainability). Therefore, we define a measure of Attitude to Change as follows:

$$Attitude\ to\ Change = \boldsymbol{AFTER}\ pandemic - \boldsymbol{BEFORE}\ pandemic \tag{3.1}$$

and classify farms as follows:

- 0 if Attitude to Change is negative. We call this category “*Negative”*.
- 1 if Attitude to Change is null. We call this “*Neutral”*.
- 2 if Attitude to Change is positive. We call this “*Positive”*.

In the next section, we will cross-reference the two variables Vision and Attitude to Change. Our findings could be particularly useful to policymakers at different levels of governance as they face the challenges of the upcoming period of recovery and resilience[27].

[26] To test the consistency of responses related to multiple-items measurements of attitudes, Cronbach’s Alpha was used. It assumes acceptable values ranging from 0.86 to 0.90.
[27] For details on European and Italian Recovery and Resilience Plans, see ttps://ec.europa.eu/info/strategy/recovery-plan-europe_en#nextgenerationeu

3.5 Empirical results

3.5.1 Vision

Table A1 in the Appendix B gives an overview of *Vision* and the main demographic and business characteristics of the rural farms involved in the analysed case study. We note that while *Vision* is not significantly associated with gender (*Males*), it is connected to all the other characteristics. Younger farmers ($Age \leq 50\ years$), farms that also operate outside their regional markets, farms organised as a family business and farms with at least one certification are less likely to have a *Short-Term Vision*. For example, while only 2% of farms that commercialised their products outside the regional market were classified as having a *Short-Term Vision*, 62% of them were termed as having a *Long-Term Vision* of high intensity. And only 4% of farms with quality certifications have a *Short-Term Vision* in comparison with 39% of them with a *Long-Term Vision* of high intensity.

Table A2 in the Appendix B shows the frequency distribution of *Vision* by LAG. Farms with a *Short-Term Vision* are particularly concentrated in the ISC *Madonie* and *Rocca di Cerere Geopark* LAGs (50% and 26%, respectively), which probably suffer more than most from inadequate transport infrastructure and poor essential services. Just to mention a few of them, the section of the Palermo–Catania highway that crosses these areas has serious structural problems that affect traffic flow, broadband connection is still a mirage, and hospital services have been drastically reduced over recent years. The *Metropoli Est* and *Sicani* LAGs, however, have the highest percentages of farms with a *Long-Term Vision* of high intensity (34% and 39%, respectively). Almost half of the farms interviewed (46%) in the *Sicani* LAG have a *Long-Term Vision* of high intensity. This evidence is even clearer from a visual inspection of Figure 3.2 and Table C. In our sample, on the one hand, there are 26 farms with a *Short-Term Vision* – marked by crosses on the map – that are almost exclusively located in the innermost zone of Sicily where the ISC *Madonie* and *Rocca di Cerene Geopark* LAGs operate. On the other hand, the 38 farms with a *Long-Term Vision* of high intensity – marked by black triangles on the map – seem to be less spatially concentrated, except for a cluster in the coastal area of the *Metropoli Est* LAG which is close to the metropolitan city of Palermo.

Figure 3.2 Farmers' vision by local action group (LAG)

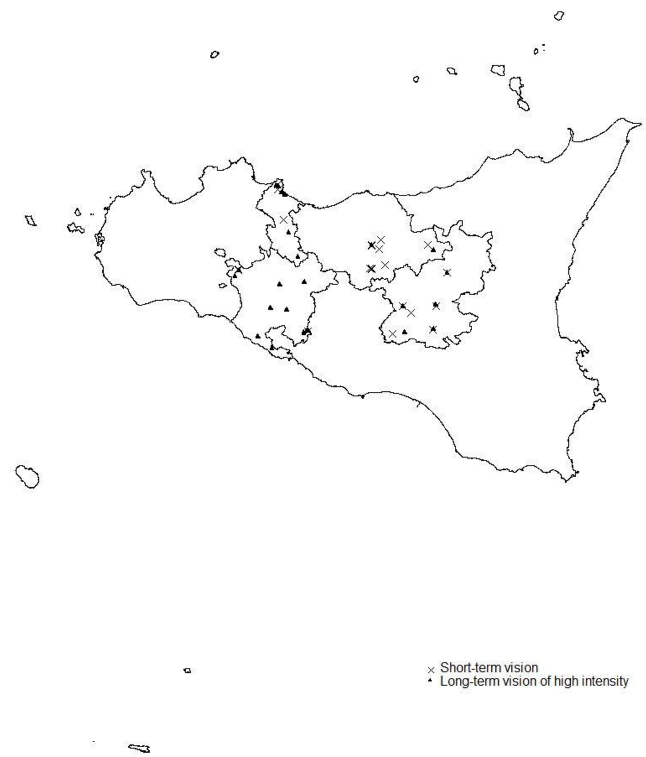


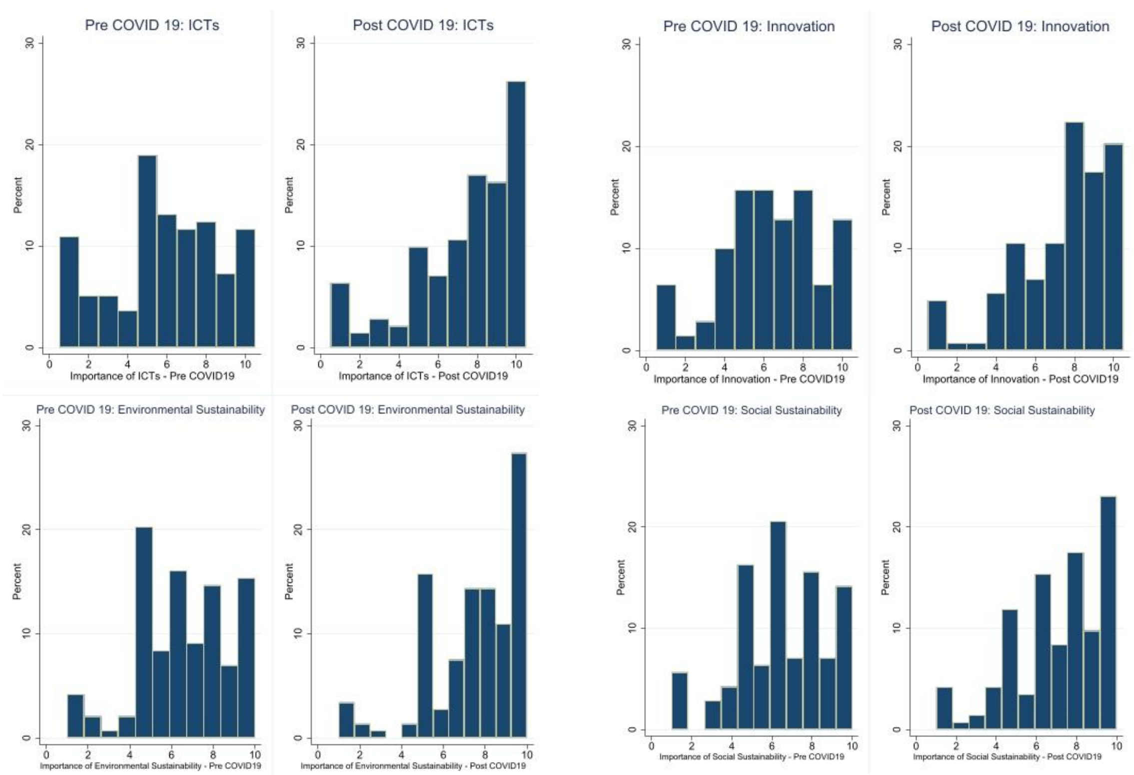
Table C: Local Action Group (LAGs)

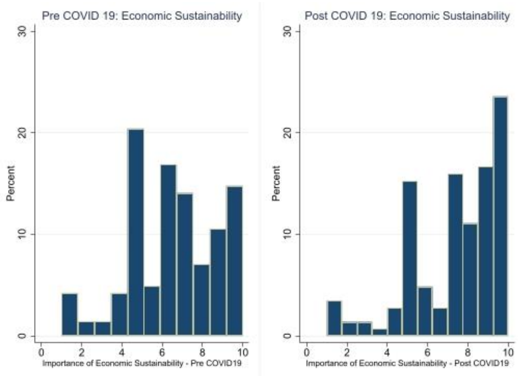
LAGs	*Freq.*	*Percent*	*Cum.*
Metropoli Est	43	28.86	28.86
ISC Madonie	33	22.15	51.01
Rocca di Cerere Geopark	37	24.83	75.84
Sicani	36	24.16	100.00
Tot.	149	100.00	

3.5.2 Attitude to Change

Figure 3.3 compares the answers of farms on the importance of ICTs, Innovation and the three dimensions of Sustainability before and after the pandemic. As a consequence of the pandemic, there has been an increased awareness of the role of digital tools, innovation and sustainability. Indeed, all histograms on the right-hand side show a greater concentration of respondents with the highest scores.

Figure 3.3 Farmers' attitude to change





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Tables A3–A7 in the Appendix B focus on the distribution of *Attitude to Change* by LAG. As regards ICTs, we observe that 59% of farms have a *Positive Attitude*, 39% are *Neutral* and the remaining 1.48% are *Negative* (see Table A3 in the Appendix B). In general, farmers seem to be aware of the increasing importance of information and communication technologies in the post-COVID19 era. We do not find important differences across LAGs: the share of *Positive* ranges from 68% of Sicani to 45% of ISC Madonie.

Farmers seem less interested in the role of innovation post-COVID (see Table A4 in the Appendix B). Only 44% have a *Positive Attitude*, while 52% are *Neutral* to change. There is a spatial heterogeneity across LAGs with a higher concentration of *Positive* in the Metropoli Est and Rocca di Cerere Geopark LAGs (the row percentages being 32% and 39%, respectively) and of *Neutral* in the other two LAGs (the row percentages being 32% in ISC Madonie and 30% in Sicani).

As far as sustainability is concerned, the farmers are more *Neutral* than *Positive*, independently of the type of sustainability (see Tables A5–A7 in the Appendix B). The percentages of *Positive* are 46%, 31% and 44% for environmental, social and economic sustainability, respectively. However, looking at each LAG we observe some differences, especially between the ISC Madonia and the Rocca di Cerere Geopark. Although the two LAGs are similar enough in terms of *Vision*, there are significant differences in terms of *Attitude to Change*. Indeed, the ISC Madonie has the lowest concentration of *Positive* of all the LAGs (16%, 13% and 20% for environmental, social and economic sustainability, respectively), while the Rocca di Cerere

Geopark has the highest (62%, 39% and 61%, respectively).

Overall, rural farmers seem to be more concerned about environmental and economic sustainability than social sustainability. However, this evidence has to be carefully interpreted as it emerges from a case study involving mainly small size farms. Indeed, smaller farms might have less motivation to invest in social sustainability, especially charitable projects in comparison to larger farms with more economic resources and a greater reputation to maintain.

3.5.3 Vision *versus* Attitude to Change

Looking at the association between *Vision* and *Attitude to Change*, as concerns ICTs, Table A8 in the Appendix B shows that about 46% of farms with a *Short-Term Vision* have a *Positive Attitude*. This evidence is encouraging since it means that a large percentage of rural farms which do not have a *Long-Term Vision*, still recognise the increasing role played by digital technologies. As expected, the share of farms with *Positive Attitude* increases significantly in the case of *Long-Term Visions* (55%, 72% and 68% for *low*, *medium* and *high*, respectively).

The results are less exciting for innovation. Table A9 in the Appendix B shows that only 38% of farms with *a Short-Term Vision* have a *Positive Attitude*. We need to reach *a Long-Term Vision* of high intensity before we find 50% of farms with *Positive Attitude*. Looking at the full sample, we find that most farms are *Neutral* to change (52%) in terms of innovation. Tables A10–A12 in the Appendix B show that 40% of farms with a *Short-Term Vision* have a *Positive Attitude* in the case of environmental and economic sustainability, while only 24% do so when we consider social sustainability. Only farms with *a Long-Term Vision* of high intensity exceed 50% of *Positive Attitude*, reaching 60% in the case of environmental and economic sustainability.

Overall, even those farms with a *Short-Term Vision* are aware of the role that information and communication technologies may play in the post-pandemic era. However, it is mostly those with a Long-Term Vision of high intensity who have a *Positive Attitude to Change* when it comes to innovation and sustainability. Finally, even those farms with *Long-Term Visions* seem to have only a limited interest in social sustainability.

3.6 Empirical strategy

3.6.1 A regression analysis

To examine the previous empirical evidence in greater depth, a regression analysis has been performed. First, we estimate an ordered probit model to explore the effects of farm characteristics and location on the probability of being in the upper levels of *Vision* (Table 3.2). To this end, the variable *Vision*, i.e. whether farms are inclined towards a *Long-TermVision* for rural areas, is divided into four categories:

1.	0 if *ICT, Innovation and Sustainability* assume values = 0	*“Short-term vision”*
		“Long-term vision”:
2.	if one of the above variables is = 1	“low intensity”
3.	if two of the above variables are = 1	“medium intensity”
4.	if all three variables are = 1	“high intensity"

This classification is then used as the dependent variable in the following ordered probit model:

$$y_i^* = x_i' + \beta + \varepsilon_i$$
$$y_i = j \quad \text{if} \quad \mu_{j-1} < y_i^* \leq \mu_j \quad \text{with} \quad j = 1, \dots, 4 \tag{3.3}$$

where, as usual y_i^* is unobserved and what is observed is y_i[28].

[28] See Greene (2012)

The μ's and the β's are the unknown parameters to be estimated, while x is a vector of covariates that includes, among the others, age, male, Outside Regional Market, family business, certifications and the 4 LAGs (Metropoli Est, ISC Madonei, Rocca di Cerere Geo park and Sicani)[29].

As you can see in table 3.2, in the first column for "*Vision",* the *Short-Term Vision* represents the reference category. The estimations show that those in the younger (*Age*) group are much more likely to be found in an upper level of *Vision* as are farms that operate *Outside Regional Market* and have at least one *Certification*. We also found that farms located in the ISC Madonie LAG have lower probabilities of being in the upper levels of *Vision*. From estimates, we have computed marginal effects to interpret the magnitude of impacts (columns 2–5 in Table 3.2). We found that younger farmers are 13.6% less likely to have a *Short-Term Vision* and 15.5% more likely to have a *Long-Term Vision* of high intensity. Farms operating outside the regional market are 16% less likely to have a *Short-Term Vision*, and 29.4% more likely to have a *Long-Term Vision* of high intensity. Finally, farms with at least one certification are 8.6% less likely to have a *Short-Term Vision*, and 11.1% more likely to have a *Long-Term Vision* of high intensity.

Table 3.2. *Farms: Vision – Ordered Probit Model*

		Marginal Effects			
Variables	*Vision*	*Short-Term Vision*	*Long-Term Vision (low)*	*Long-Term Vision (medium)*	*Long-Term Vision (high)*
Age	0.668***	-0.136***	-0.0523**	0.0341**	0.155***
	(0.216)	(0.0465)	(0.0227)	(0.0159)	(0.0487)
Male	0.190	-0.0378	-0.0138	0.00772	0.0439
	(0.284)	(0.0580)	(0.0191)	(0.0127)	(0.0642)
Outside Regional Market	1.036***	-0.160***	-0.161***	0.0264	0.294***
	(0.256)	(0.0362)	(0.0543)	(0.0172)	(0.0777)
Family Business	0.371	-0.0728	-0.0324	0.0172	0.0879
	(0.230)	(0.0456)	(0.0233)	(0.0131)	(0.0547)
Certifications	0.458**	-0.0866**	-0.0448	0.0203*	0.111**
	(0.219)	(0.0404)	(0.0273)	(0.0118)	(0.0549)

[29] To check the parallel lines assumption a Brant test has been run after the ordered probit model. However, it rejects the null hypothesis indicating that the assumption was not violated, thus, it was sufficient to rely on the ordered probit model.

Metropoli Est	*Reference*	*Reference*	*Reference*	*Reference*	*Reference*
ISC Madonie	-0.844***	0.191***	0.0596*	-0.0647**	-0.186***
	(0.307)	(0.0721)	(0.0352)	(0.0309)	(0.0677)
Rocca di Cerere Geopark	-0.316	0.0591	0.0393	-0.0178	-0.0806
	(0.278)	(0.0525)	(0.0369)	(0.0169)	(0.0714)
Sicani	0.378	-0.0507	-0.0652	0.00595	0.110
	(0.304)	(0.0405)	(0.0548)	(0.00880)	(0.0891)
Observations	129	129	129	129	129

Notes: The first column reports the estimates, while the other four columns the marginal effects. Standard errors in parentheses

In Table 3.3, we estimate a set of probit models to look at the probability of having a *Positive Attitude to Change* for each of the factors used to define *Vision*[30], as follows:

$$\begin{gathered}
\Pr(Positive\ Attitude_ICTs = 1) = G(\beta_0 + \beta_1 Vision) \\
\Pr(Positive\ Attitude_Innovation = 1) = G(\beta_0 + \beta_1 Vision) \\
\Pr(Positive\ Attitude_Environmental\ Sust. = 1) = G(\beta_0 + \beta_1 Vision) \qquad (3.4) \\
\Pr(Positive\ Attitude_Social\ Sust. = 1) = G(\beta_0 + \beta_1 Vision) \\
\Pr(Positive\ Attitude_Economic\ Sust. = 1) = G(\beta_0 + \beta_1 Vision)
\end{gathered}$$

where *Positive Attitude to Change for ICTs*, *Positive Attitude to Change for Innovation*, *Positive Attitude to Change for Environmental Sustainability*, *Positive Attitude to Change for Social Sustainability*, *Positive Attitude to Change for Economic Sustainability* are dummy variables that equal to 1 if there is a positive attitude to change in farms towards digital tools, towards innovation, towards sustainability and 0 otherwise i.e. if the attitude to change is null or negative. Our results show that having a *Long-Term Vision* of medium and high intensity impacts only on the *Positive Attitude of Change* in the case of *ICTs* and *Social Sustainability*. In all the other cases, there are no significant differences. What the evidence indicates is that

[30] To avoid potential multicollinearity with Vision, we do not add other covariates into the specification.

there is a large percentage of farms with a *Short-Term Vision* which still have a *Positive Attitude*. Therefore, the regression analysis reveals that even some of the "less virtuous" farms have not yet abandoned the idea of change, and recognise the increasing role of digitalisation, innovation, and sustainability in their businesses, especially in the post-pandemic era. This evidence should be carefully read by policymakers so as to identify the *most fertile* ground in which to plant the seeds of recovery.

Table 3.3. *Attitude to Change – Probit Models*

Variables	*ICTs*	*Innovation*	*Environmental Sustainability*	*Social Sustainability*	*Economic Sustainability*
Short-Term Vision	*Reference*	*Reference*	*Reference*	*Reference*	*Reference*
Long Term Vision (low)	0.224	0.231	-0.117	0.0500	-0.157
	(0.321)	(0.323)	(0.318)	(0.344)	(0.320)
Long Term Vision (medium)	0.687*	0.0468	0.253	0.140	-0.0185
	(0.370)	(0.354)	(0.347)	(0.372)	(0.349)
Long Term Vision (high)	0.584*	0.319	0.520	0.772**	0.520
	(0.333)	(0.331)	(0.327)	(0.342)	(0.327)
Constant	-0.105	-0.319	-0.253	-0.706**	-0.253
	(0.256)	(0.261)	(0.254)	(0.275)	(0.254)
Observations	129	133	136	134	135

Notes: Models estimate the probability of *Attitude to Change* is *Positive*. Standard errors in parentheses

3.7 Conclusions

The social and economic changes of recent decades have made rural areas very vulnerable due to depopulation and ageing of the population, and lack of infrastructures and services. To combat this, the latest European policy is based on strategies with a long-term vision of rural development in the areas of digitalisation, innovation and sustainability. Moreover, in response to challenges related to the COVID-19 pandemic, the European Commission has also allocated extraordinary resources to support investment in these areas.

These initiatives provide opportunities to promote the green and digital transition in these places which will, in turn, ease the diversification of economic activities, preserve biodiversity and rural landscape, and attract younger people, avoiding land abandonment (European Commission, 2021b). However, for these policies to be effective they should be supported by changes in behaviour at a micro-firm level, that is, rural farmers should be aware of the opportunities and recognise the social and economic implications.

Even though these issues are highly important, empirical research is still limited and existing studies have mostly focused on individual aspects of the problem, such as digital and innovative backwardness or the lack of sustainable development. In contrast, using a case study approach on Sicilian farms, we adopt a holistic perspective considering all three issues (i.e., digitalisation, innovation and sustainability) in a single framework of analysis. To this end, we devised a questionnaire and conducted a survey on Sicilian farms located in the rural areas where the Metropoli Est, Sicani, ISC Madonie, and Rocca di Cerere Geopark LAGs operate.

Empirical results highlight the digital reticence of rural farms, especially in the more inland areas, farther away from the metropolitan city of Palermo. Overall, rural farms seem to have oriented their strategies more towards environmental and economic sustainability than towards digitalisation and innovation. We find that farmers under 50 are more likely to have a Long-Term Vision as are farms with at least one certification and those which also operate outside the regional market. Farms which are family businesses also seem to be more likely to have a Long-Term Vision, although this is not confirmed by regression analysis.

We find that farms with a Long-Term Vision are more likely to have a Positive Attitude to Change only in the case of information and communication technologies and social sustainability. In the other cases, we find that there are a number of farms with a Short-Term Vision but with a Positive Attitude to Change.

In conclusion, the empirical results may provide policymakers interesting insights into the farmers' attitude to long-term development. We observe that rural companies generally lack a long-term vision, meaning that they are not able to invest in digitalisation, innovation and sustainability simultaneously, even though they recognise their importance. This is probably due to a lack of economic resources as well as digital literacy. This suggests that rural farmers are aware of the opportunities offered by recent European policies and if adequately supported, both in terms of additional economic resources and digital culture, they could bridge the rural–urban divide.

Although our empirical results emerge from a case study based on a small random sample, we have been able to highlight, some important features of farmers behaviour and their long-term vision of rural development using innovative activities, digital tools and sustainable practices even in the face of the challenges of COVID-19. Our questionnaire explored the key factors of rural development in a holistic way and we believe its use could be extended to other regions and repeated over a longer period to make findings more generalisable. This could help policymakers to identify local areas and 'less virtuous' farms which would benefit from their support in building a long-term vision of rural development.

Conclusion

The final conclusions of this thesis represent a convergence point of the three distinct chapters, providing a comprehensive overview of the dynamics of the Common Agricultural Policy (CAP) of the European Union (EU), its impacts on Italian agricultural productivity, and the attitudes of Sicilian farms in the face of emerging challenges, pre and post the COVID-19 pandemic.

The first chapter outlined a comprehensive history of the CAP, emphasizing the evolution of its two pillars and the introduction of the LEADER approach through Local Action Groups (LAGs). This analysis provided the necessary context to understand the significance of the CAP in the European context, highlighting significant transformations and challenges faced over time.

The second chapter, through a decade-long analysis of Total Factor Productivity (TFP) of Italian farms, expanded the understanding of the role of the CAP in the Italian national context. The discovery of a positive interaction between the two pillars of the CAP represented an innovative contribution to existing literature, underscoring the importance of complementarity between direct payments to producers and sustainable rural development.

The third chapter addressed the specific dynamics of Sicilian farms, examining their long-term visions and attitudes towards emerging challenges, including the COVID-19 pandemic. This section of the thesis emphasized the need to promote a long-term vision and encourage a mindset shift among farms, especially in the face of new opportunities and challenges.

Our overall goal was to trace and understand the trajectory of the CAP, evaluating its impact on agricultural productivity and analyzing the attitudes of farms in a specific context, such as Sicily. The detailed analysis of TFP highlighted the need to consider both pillars of the CAP in an integrated manner to maximize overall benefits.

In conclusion, this thesis has made a significant contribution to the understanding of agricultural dynamics in Europe and Italy, providing important insights to enhance the effectiveness of agricultural policies and promote sustainable development in the sector. The long-term perspective of Sicilian agricultural enterprises and their response to emerging challenges represent fertile ground for further investigations and offer valuable guidance for shaping future agricultural policies.

Limitations and directions for further research

The literature review primarily focused on the Common Agricultural Policy (CAP) of the European Union (EU), limiting the analysis to a specific context. Potential future research could delve into the impacts of national agricultural policies and examine how CAP policies directly affect local communities, actively involving local actors and agricultural organizations.
Certain specific aspects of the CAP, such as national-level implementation and the responses of local actors, may not have been fully explored. Further research could investigate how European policies adapt at the national level. Additionally, expanding the research to include comparisons between European countries could provide a more comprehensive view of the diverse implementations of the CAP.

In the second chapter, the analysis concentrated on Total Factor Productivity (TFP) using data from the "Rete d'Informazione Contabile Agricola" (RICA), which might affect the sample's representativeness. Moreover, the analysis covers the period 2009-2019, excluding developments beyond that timeframe. Significant events post-study period could have influenced agricultural dynamics. Future research could examine more recent impacts.
The results obtained from our analysis of the CAP may not be fully generalizable to all European agricultural realities. The diversity of local conditions, farm sizes, and implementation policies could significantly influence the results. Therefore, extending the sample internationally could offer a broader view of the CAP's impacts on TFP.

In the analysis of TFP, some factors may not have been fully considered, such as climate change, variability in commodity prices, and market fluctuations. Further investigations could contribute to a more comprehensive understanding of these variables.

In the third chapter, the focus on Sicilian farms might limit the generalization of results at the national or European level and not cover sector-specific specificities. Future research could examine specific sectors and consider the evolution of agricultural dynamics post-COVID-19. Expanding the research to other Italian or European regions could provide a more comprehensive overview of agricultural dynamics post-COVID-19. Examining key agricultural sectors in Sicily to better understand sectoral challenges and opportunities represents an additional perspective.

Considering unforeseen events like the COVID-19 pandemic, further research could explore how farms adapt and respond to such circumstances. Integrating and overcoming these limitations could further enrich the overall understanding of the impacts of the CAP, TFP, and agricultural dynamics, contributing to more effective guidance for future policies in the agricultural sector.

Appendix A1

Chapter 2

Table 2.1: Literature on the effect of CAP funds

Authors	Period	Farm-Level	Effect CAP on TFP
Serra et al. (2008)	1998-2007	Yes	Negative
Latruffe et al. (2008)	2010	Yes	Positive
Lambarraa et al. (2009)	1995-2003	Yes	Negative
Lakner (2009)	1994-2006	Yes	Negative
Kazukauskas et al. (2010)	2001-2007	Yes	Negative
Zhu & Lansink (2010)	1995-2004	Yes	Negative
Latruffe et al. (2012)	1990-2007	Yes	Negative
Weber & Key (2012)	2002-2007	Yes	Negative
Mary (2013)	1996-2003	Yes	Negative
Kazukauskas et al. (2013)	2001-2007	Yes	Positive
Rizov et al. (2013)	1990-2007	Yes	Negative
Latruffe & Desjeux, (2016)	1990-2006	Yes	Positive
Dudu & Kristkova, (2017)	2007-2013	Yes	Positive
Latruffe et al. (2017)	1990-2007	Yes	Negative
Minviel & Latruffe (2017)			Positive
Garrone et al., 2019	2004-2014	Yes	Neutral
Bonfiglio et al. (2020)	2014-2020	Yes	Negative
Khafagy & Vigani, (2022)	2004-2015	Yes	Negative

Table 2.2 : Year by Macro Regions with means of **Pillar 1**

Year	Macro Regions				
	North-West	*North-East*	*Centre*	*South & Islands*	Tot.
2009	18232.937	17102.454	19659.879	9726.5646	15257.525
2010	21633.864	18232.193	16494.335	10145.846	15637.856
2011	20499.726	17002.507	15675.129	10059.078	14897.847
2012	21682.681	16898.67	15390.224	10561.956	15253.251
2013	22865.414	18221.305	16286.56	10691.448	15929.563
2014	23130.396	18407.034	15153.87	10701.254	15781.49
2015	22819.835	15290.721	15506.273	11505.599	15373.445
2016	21674.395	15549.383	15215.17	11229.449	15066.087
2017	21050.751	14704.074	14683.848	10816.736	14362.026
2018	18105.157	12641.857	13899.075	10594.683	12946.446
2019	19339.555	12698.834	13122.224	10496.266	13040.153
Tot.	21120.176	16000.417	15482.566	10632.859	14861.451

Table 2.3: Year by Macro Regions with means of **Pillar 2**

Year	Macro Regions				
	North-West	*North-East*	*Centre*	*South & Islands*	Tot.
2009	8192.5256	12877.443	9580.611	8305.8	8917.5867
2010	8118.257	13995.002	10614.136	13373.093	11116.586
2011	8682.6823	11997.435	13703.093	11472.965	11118.824
2012	7562.7389	12180.419	12349.802	10648.314	10107.782
2013	7015.7612	12110.315	10316.776	10025.719	9451.7291
2014	7867.1093	11542.123	11700.812	8910.5479	9434.9527
2015	12118.199	11364.803	11237.112	9118.5976	10592.508
2016	9255.2659	9815.1024	11090.105	6841.1914	8684.0414

2017	9684.4426	8622.3173	9239.7765	7603.8284	8508.8579
2018	10947.811	9211.4535	11973.363	8058.7383	9486.7656
2019	11229.871	9563.2911	11680.17	7749.3619	9457.5765
Tot.	9043.377	10782.344	11312.158	8878.9845	9651.326

Table 2.4: OTE by Macro Regions with means of **Pillar 1**

OTE	**Macro Regions**				
	North-West	*North-East*	*Centre*	*South & Islands*	Tot.
OTE 1	21543.829	24020.783	14413.475	10643.126	17061.226
OTE 2	21549.912	12215.523	16526.843	10892.678	14255.552
OTE 3	15086.001	13599.029	12446.481	9010.0658	7895.6491
Tot.	21120.176	16000.417	15482.566	10632.859	14861.451

Table 2.5: OTE by Macro Regions with means of **Pillar 2**

OTE	**Macro Regions**				
	North-West	*North-East*	*Centre*	*South & Islands*	Tot.
OTE 1	13150.523	11515.287	13364.747	8751.7477	11128.257
OTE 2	6479.3023	10749.937	10714.763	9235.501	8916.5804
OTE 3	6358.4968	7298.9643	10009.343	7468.4336	7895.6491
Tot.	9043.377	10782.344	11312.158	8878.9845	9651.326

Table 2.6: Economic Size by Macro Regions with means of **Pillar 1**

Economic Size	**Macro Regions**				
	North-West	*North-East*	*Centre*	*South & Islands*	Tot.
Medium	7877.7962	5848.2157	9720.3778	8578.2192	8066.0279
Small	2554.8568	2722.9915	3895.3317	4017.6754	3556.61
Large	39963.435	30696.19	30805.878	21068.621	30311.264
Tot.	21120.176	16000.417	15482.566	10632.859	14861.451

Table 2.7: OTE by Macro Regions with means of **Pillar 2**

Economic Size	Macro Regions				
	North-West	*North-East*	*Centre*	*South & Islands*	Tot.
Medium	6911.0313	6582.4003	7638.1944	6936.4893	6980.7334
Small	2545.6776	3337.0645	3397.2324	3388.0932	3148.3262
Large	14486.111	17216.07	19576.418	15568.07	16269.504
Tot.	9043.377	10782.344	11312.158	8878.9845	9651.326

Table 2.8: Family Farm

Family Farm	Macro Regions				
	North-West	*North-East*	*Centre*	*South & Islands*	Tot.
Not family members	1,570	1,984	2,320	7,894	13,768 (14.05%)
Family members	21,166	20,031	14,172	28,823	84,192 (85.05%)
Tot.	22,736	22,015	16,492	36,717	97,960

Table 2.9: Family Farm by Macro Regions with means of **Pillar 1**

Family Farm	Macro Regions				
	North-West	*North-East*	*Centre*	*South & Islands*	Tot.
Not family members	78421.179	73091.222	34896.88	19605.117	35840.199
Family members	16809.558	10302.879	12375.41	8258.4901	11402.908
Tot.	21120.176	16000.417	15482.566	10632.859	14861.451

Table 2.10: Family Farm by Macro Regions with means of **Pillar 2**

Family Farm	Macro Regions				
	North-West	*North-East*	*Centre*	*South & Islands*	Tot.
Not family members	21444.188	29717.071	18887.93	14079.455	17754.477

Family members	8188.4666	8781.7845	9582.8371	7498.6719	8270.399
Tot.	9043.377	10782.344	11312.158	8878.9845	9651.326

Table 2.11: One-man farm

One-man farm	**Macro Regions**				
	North-West	*North-East*	*Centre*	*South & Islands*	Tot.
Not One-man	3,430	4,320	3,152	2,385	13,287 (13.56%)
One-man	19,306	17,695	13,340	34,332	84,673 (86.44%)
Tot.	22,736	22,015	16,492	36,717	97,960

Table 2.12: One-man farm by Macro Regions with means of **Pillar 1**

One-man farm	**Macro Regions**				
	North-West	*North-East*	*Centre*	*South & Islands*	Tot.
Not One-man	51535.063	42009.601	29614.091	25174.462	38551.145
One-man	14554.725	8833.7541	12114.542	9632.6101	10876.534
Tot.	21120.176	16000.417	15482.566	10632.859	14861.451

Table 2.13: One-man farm by Macro Regions with means of **Pillar 2**

One-man farm	**Macro Regions**				
	North-West	*North-East*	*Centre*	*South & Islands*	Tot.
Not One-man	15904.428	21650.992	18252.069	20576.722	19110.441
One-man	8152.0413	7840.8811	9147.6541	7849.3095	8125.8107
Tot.	9043.377	10782.344	11312.158	8878.9845	9651.326

Table 2.14: Young by Macro Regions with means of **Pillar 1**

Young	Macro Regions				
	North-West	*North-East*	*Centre*	*South & Islands*	Tot.
Not	21198.485	15972.382	15688.42	10727.698	15002.41
Yes	20562.994	16286.541	13987.291	10088.206	13877.222
Tot.	21120.176	16000.417	15482.566	10632.859	14861.451

Table 2.15: Young by Macro Regions with means of **Pillar 2**

Young	Macro Regions				
	North-West	*North-East*	*Centre*	*South & Islands*	Tot.
Not	8725.9343	10529.399	10853.966	8527.0379	9332.8674
Yes	10616.127	12692.414	13997.742	10455.099	11308.303
Tot.	9043.377	10782.344	11312.158	8878.9845	9651.326

Table 2.16: Gender by Macro Regions with means of **Pillar 1**

Gender	Macro Regions				
	North-West	*North-East*	*Centre*	*South & Islands*	Tot.
Male	20997.197	15102.993	16905.268	11073.212	15002.41
Female	21737.105	21625.487	10397.464	9424.6831	13877.222
Tot.	21120.176	16000.417	15482.566	10632.859	14861.451

Table 2.17: Gender by Macro Regions with means of **Pillar 2**

Gender	Macro Regions				
	North-West	*North-East*	*Centre*	*South & Islands*	Tot.
Male	9370.9904	10771.429	12079.382	9241.943	10035.802
Female	7785.241	10872.904	8696.4123	7852.2872	8239.8588
Tot.	9043.377	10782.344	11312.158	8878.9845	9651.326

Table 2.18: Diversified by Macro Regions with means of **Pillar 1**

Diversified	**Macro Regions**				
	North-West	*North-East*	*Centre*	*South & Islands*	Tot.
Not	20576.159	15317.655	14618.776	10457.917	14239.081
Yes	24884.769	20300.153	19882.075	13985.022	20159.619
Tot.	21120.176	16000.417	15482.566	10632.859	14861.451

Table 2.19: Diversified by Macro Regions with means of **Pillar 2**

Diversified	**Macro Regions**				
	North-West	*North-East*	*Centre*	*South & Islands*	Tot.
Not	8271.2576	10186.524	10680.229	8724.4061	9127.0744
Yes	13106.253	13342.087	13666.294	11790.323	13119.478
Tot.	9043.377	10782.344	11312.158	8878.9845	9651.326

Table 2.20: OTE Summary Statistics

OTE 1 (Animal)	
REGION	OBS. NUTS 1
North-West	7,227
Piemonte, Valle d'Aosta, Liguria, Lombardia	
North-East	5,941
Trentino, Alto Adige, Emilia Romagna, Friuli-Venezia Giulia, Veneto	
Centre	3,531
Toscana, Marche, Umbria, Lazio	
South and Islands	9,903
Abruzzo, Basilicata, Calabria, Campania, Molise, Puglia, Sardegna, Sicilia	
Tot.	26,602
OTE 2 (Plant)	
REGION	OBS. NUTS 1
North-West	14,109
Piemonte, Valle d'Aosta, Liguria, Lombardia	
North-East	14,154
Trentino, Alto Adige, Emilia Romagna, Friuli-Venezia Giulia, Veneto	
Centre	10,911
Toscana, Marche, Umbria, Lazio	
South and Islands	23,385
Abruzzo, Basilicata, Calabria, Campania, Molise, Puglia, Sardegna, Sicilia	
Tot.	62,559
OTE 3 (Mixed)	
REGION	OBS. NUTS 1
North-West	1,400
Piemonte, Valle d'Aosta, Liguria, Lombardia	
North-East	1,920
Trentino, Alto Adige, Emilia Romagna, Friuli-Venezia Giulia, Veneto	
Centre	2,050
Toscana, Marche, Umbria, Lazio	
South and Islands	3,429
Abruzzo, Basilicata, Calabria, Campania, Molise, Puglia, Sardegna, Sicilia	
Tot.	8,799

Table 2.21: Regional Division of Italy for OTE

REGION	OTE 1 (Animal)	OTE 2 (Plant)	OTE 3 (Mixed)	Tot.
Piemonte	2,936	6,046	838	9,820
Valle d'Aosta	1,441	739	142	2,322
Liguria	701	3,817	175	4,693
Lombardia	2,149	3,507	245	5,901
Alto Adige	1,307	1,365	194	2,866
Trentino	359	2,129	112	2,600
Emilia Romagna	1,319	4,118	591	6,028
Friuli-Venezia Giulia	900	2,816	424	4,140
Veneto	2,056	3,726	599	6,381
Toscana	851	3,335	589	4,775
Marche	735	2,916	489	4,140
Umbria	717	2,803	735	4,255
Lazio	1,228	1,857	237	3,322
Abruzzo	805	3,357	620	4,782
Basilicata	1,285	2,210	414	3,909
Calabria	154	3,861	274	4,289
Campania	1,574	3,424	592	5,590
Molise	1,133	1,343	445	2,921
Puglia	619	4,388	399	5,406
Sardegna	2,830	1,342	225	4,397
Sicilia	1,503	3,460	460	5,425
Tot.	26,602	62,559	8,799	97,960

Appendix A2

Chapter 2: Robustness Checks

Table 6: ACF Model - OTE Sample Italian farms

VARIABLES	Value-Added OTE 1	Value-Added OTE 2	Value-Added OTE 3
Capital	0.160***	0.0716***	0.0692***
	(0.00713)	(0.00786)	(0.00901)
Labour	0.802***	0.781***	0.633***
	(0.0107)	(0.0110)	(0.0110)
Land (T)	0.0504***	0.108***	0.167***
	(0.0132)	(0.00881)	(0.00873)
Young			
No	*reference*	*reference*	*reference*
Yes	0.0220*	0.0466***	0.100***
	(0.0127)	(0.0102)	(0.00706)
Gender			
Male	*reference*	*reference*	*reference*
Famale	-0.0547***	-0.0844***	-0.0641***
	(0.0112)	(0.00722)	(0.0108)
Economic Size			
Medium	*reference*	*reference*	*reference*
Small	0.555***	0.532***	0.486***
	(0.00670)	(0.0128)	(0.0145)
Large	1.251***	1.062***	1.113***
	(0.0245)	(0.0176)	(0.00837)
Altitude			
Hill	*reference*	*reference*	*reference*
Mountain	-0.0890***	0.260***	0.130***
	(0.00763)	(0.0106)	(0.00888)
Plain	0.353***	0.0721***	0.195***
	(0.00679)	(0.00879)	(0.0106)
Extra-Agri Diversification	0.103***	0.167***	0.296***
	(0.00920)	(0.00628)	(0.0122)
Dummy year	*yes*	*yes*	*yes*
Observations	25,562	60,427	8,599
Number of id	4,870	11,608	2,918

Notes: Table presents estimates in our baseline sample from proxy-variable methods of Ackerberg, Caves and Frazer (2015) (ACF) (using materials as the proxy). ACF estimate generated by Stata command prodest (Rovigatti and Mollisi, 2018).
Robust standard errors in parentheses from bootstraps with 50 replications *10% level, **5% level, ***1% level.

Table 7 - OTE 1 Sample Italian farms

	Table *a*: Pooled Model			Table *b*: Random Effect Model		
VARIABLES	(1) Lag 1	(2) Lag 2	(3) Lag 1 & 2	(1) Lag 1	(2) Lag 2	(3) Lag 1 & 2
L.pillar II	-0.164***		-0.134***	-0.0928***		-0.0951***
	(0.0184)		(0.0317)	(0.0191)		(0.0271)
L.pillar I	-0.102***		-0.122***	-0.0557***		-0.0754***
	(0.0171)		(0.0321)	(0.0179)		(0.0274)
L.pillar II#L.pillar I	0.0169***		0.0132***	0.00988***		0.00909***
	(0.00201)		(0.00344)	(0.00208)		(0.00295)
L2.pillar II		-0.152***	-0.0853***		-0.0851***	-0.0513*
		(0.0205)	(0.0321)		(0.0209)	(0.0280)
L2.pillar I		-0.0815***	-0.0187		-0.0406**	-0.00871
		(0.0191)	(0.0330)		(0.0196)	(0.0287)
L2.pillar II#L2.pillar I		0.0150***	0.00839**		0.00881***	0.00512*
		(0.00225)	(0.00355)		(0.00228)	(0.00311)
Macro regions						
North-West	*reference*	*reference*	*reference*	*reference*	*reference*	*reference*
North-East	0.0958***	0.112***	0.129***	0.0526**	0.0524**	0.0728***
	(0.0145)	(0.0167)	(0.0188)	(0.0223)	(0.0247)	(0.0276)
Centre	-0.0477***	-0.0331**	-0.0194	-0.0745***	-0.0730***	-0.0630**
	(0.0143)	(0.0164)	(0.0178)	(0.0225)	(0.0243)	(0.0263)
South & Islands	0.0420***	0.0489***	0.0688***	0.0107	0.0179	0.0395*
	(0.0117)	(0.0132)	(0.0144)	(0.0189)	(0.0203)	(0.0217)
Dummy years	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Constant	3.369***	3.219***	3.807***	2.918***	2.796***	3.278***
	(0.153)	(0.170)	(0.225)	(0.160)	(0.176)	(0.256)
Observations	24,756	19,054	15,452	24,756	19,054	15,452
R-squared	0.010	0.012	0.013			
Number of id				7,641	6,710	5,469
Wald chi2				79.76***	75.21***	78.59***
Rho				0.481	0.473	0.471

Robust standard errors in parentheses, clustered at the farm level.
*** p<0.01, ** p<0.05, * p<0.1

Table 8 - OTE 2 Sample Italian farms

	Table *a*: Pooled Model			Table *b*: Random Effect Model		
VARIABLES	(1) Lag 1	(2) Lag 2	(3) Lag 1 & 2	(1) Lag 1	(2) Lag 2	(3) Lag 1 & 2
L.pillar II	-0.216***		-0.176***	-0.0919***		-0.107***
	(0.0185)		(0.0318)	(0.0190)		(0.0268)
L.pillar I	-0.0635***		-0.127***	-0.00294		-0.0566**
	(0.0172)		(0.0322)	(0.0178)		(0.0271)
L.pillar II#L.pillar I	0.0204***		0.0161***	0.00911***		0.00966***
	(0.00202)		(0.00345)	(0.00207)		(0.00292)
L2.pillar II		-0.205***	-0.133***		-0.0883***	-0.0625**
		(0.0206)	(0.0322)		(0.0207)	(0.0277)
L2.pillar I		-0.0419**	0.000979		0.0132	0.0185
		(0.0191)	(0.0331)		(0.0195)	(0.0284)
L2.pillar II#L2.pillar I		0.0186***	0.0124***		0.00837***	0.00570*
		(0.00226)	(0.00356)		(0.00227)	(0.00308)
Macro regions						
North-West	*reference*	*reference*	*reference*	*reference*	*reference*	*reference*
North-East	0.112***	0.112***	0.0901***	0.117***	0.103***	0.0851***
	(0.0146)	(0.0168)	(0.0189)	(0.0224)	(0.0247)	(0.0278)
Centre	-0.103***	-0.0911***	-0.0807***	-0.123***	-0.118***	-0.109***
	(0.0144)	(0.0164)	(0.0179)	(0.0227)	(0.0244)	(0.0264)
South & Islands	-0.0520***	-0.0467***	-0.0266*	-0.0810***	-0.0674***	-0.0417*
	(0.0118)	(0.0133)	(0.0144)	(0.0190)	(0.0204)	(0.0218)
Dummy years	yes	yes	yes	yes	yes	yes
Constant	3.513***	3.353***	4.211***	2.823***	2.689***	3.272***
	(0.154)	(0.171)	(0.225)	(0.160)	(0.175)	(0.255)
Observations	24,756	19,054	15,452	24,756	19,054	15,452
R-squared	0.042	0.046	0.042			
Number of id				7,641	6,710	5,469
Wald chi2				370.84***	334.75***	264.56***
Rho				0.495	0.485	0.484

Robust standard errors in parentheses, clustered at the farm level.
*** p<0.01, ** p<0.05, * p<0.1

Table 9 - OTE 3 Sample Italian farms

	Table *a*: Pooled Model			Table *b*: Random Effect Model		
VARIABLES	(1) Lag 1	(2) Lag 2	(3) Lag 1 & 2	(1) Lag 1	(2) Lag 2	(3) Lag 1 & 2
L.pillar II	-0.215***		-0.175***	-0.0915***		-0.107***
	(0.0184)		(0.0316)	(0.0189)		(0.0267)
L.pillar I	-0.104***		-0.153***	-0.0335*		-0.0746***
	(0.0171)		(0.0321)	(0.0177)		(0.0270)
L.pillar II#L.pillar I	0.0207***		0.0164***	0.00908***		0.00969***
	(0.00202)		(0.00344)	(0.00206)		(0.00291)
L2.pillar II		-0.206***	-0.129***		-0.0899***	-0.0595**
		(0.0205)	(0.0321)		(0.0207)	(0.0276)
L2.pillar I		-0.0844***	-0.0148		-0.0202	0.00441
		(0.0190)	(0.0330)		(0.0194)	(0.0283)
L2.pillar II#L2.pillar I		0.0191***	0.0122***		0.00861***	0.00545*
		(0.00224)	(0.00354)		(0.00226)	(0.00307)
Macro regions						
North-West	*reference*	*reference*	*reference*	*reference*	*reference*	*reference*
North-East	0.133***	0.142***	0.129***	0.120***	0.113***	0.105***
	(0.0145)	(0.0167)	(0.0188)	(0.0225)	(0.0248)	(0.0279)
Centre	-0.106***	-0.0943***	-0.0846***	-0.128***	-0.129***	-0.120***
	(0.0143)	(0.0164)	(0.0178)	(0.0228)	(0.0245)	(0.0265)
South & Islands	-0.0435***	-0.0421***	-0.0239*	-0.0696***	-0.0637***	-0.0390*
	(0.0117)	(0.0132)	(0.0144)	(0.0191)	(0.0204)	(0.0219)
Dummy years	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Constant	4.939***	4.800***	5.630***	4.188***	4.082***	4.651***
	(0.153)	(0.170)	(0.224)	(0.159)	(0.174)	(0.255)
Observations	24,756	19,054	15,452	24,756	19,054	15,452
R-squared	0.026	0.029	0.028			
Number of id				7,641	6,710	5,469
Wald chi2				221.55***	201.26***	166.43***
Rho				0.502	0.493	0.491

Robust standard errors in parentheses, clustered at the farm level.
*** p<0.01, ** p<0.05, * p<0.1

Table 10: ACF and LP Model - Robustness checks (2.10)

VARIABLES		ACF MODEL Value-Added	LP MODEL Value-Added
Capital		0.121***	0.158***
		(0.00682)	(0.0411)
Labour		0.802***	0.484***
		(0.00949)	(0.00800)
Land (T)		0.0737***	0.0184***
		(0.00927)	(0.00437)
Young			
	No	*reference*	*reference*
	Yes	0.0387***	0.0446
		(0.00718)	(0.0454)
Gender			
	Male	*reference*	*reference*
	Famale	-0.0865***	-0.0614
		(0.00851)	(0.0602)
Economic Size			
	Medium	*reference*	*reference*
	Small	0.497***	0.566***
		(0.00902)	(0.0292)
	Large	1.139***	0.938***
		(0.0184)	(0.0592)
Altitude			
	Hill	*reference*	*reference*
	Mountain	0.0654***	0.0552
		(0.00611)	(0.0585)
	Plain	0.159***	0.137***
		(0.0112)	(0.0350)
Extra-Agri Diversification		0.152***	0.153***
		(0.00956)	(0.0370)
Agricolture Diversification		-0.166***	-0.144***
		(0.0126)	(0.0255)
Dummy year		*Yes*	*Yes*
Observations		94,588	94,588
Number of id		16,443	16,443

Notes: Table presents estimates in our baseline sample from proxy-variable methods of Ackerberg, Caves and Frazer (2015) (ACF) and Levinsohn and Petrin (2003) (LP) (using materials as the proxy). ACF and LP estimate generated by Stata command prodest (Rovigatti and Mollisi, 2018).
Robust standard errors in parentheses from bootstraps with 50 replications *10% level, **5% level, ***1% level.

Table 11 - Robustness checks ACF Model

	Table *a*: Pooled Model			Table *b*: Random Effect Model		
VARIABLES	(1) Lag 1	(2) Lag 2	(3) Lag 1 & 2	(1) Lag 1	(2) Lag 2	(3) Lag 1 & 2
L.pillar II	-0.178***		-0.133***	-0.0621***		-0.0587***
	(0.0166)		(0.0284)	(0.0162)		(0.0222)
L.pillar I	-0.0688***		-0.0995***	-0.00905		-0.0250
	(0.0154)		(0.0288)	(0.0153)		(0.0224)
L.pillar II#L.pillar I	0.0170***		0.0120***	0.00623***		0.00484**
	(0.00182)		(0.00308)	(0.00177)		(0.00242)
L2.pillar II		-0.170***	-0.111***		-0.0637***	-0.0471**
		(0.0184)	(0.0288)		(0.0176)	(0.0231)
L2.pillar I		-0.0515***	-0.0122		-0.00168	0.00203
		(0.0171)	(0.0296)		(0.0166)	(0.0236)
L2.pillar II#L2.pillar I		0.0157***	0.0105***		0.00632***	0.00457*
		(0.00201)	(0.00318)		(0.00192)	(0.00257)
Macro regions						
North-West	*reference*	*reference*	*reference*	*reference*	*reference*	*reference*
North-East	0.0985***	0.102***	0.0960***	0.0792***	0.0647***	0.0594**
	(0.0131)	(0.0150)	(0.0169)	(0.0213)	(0.0235)	(0.0265)
Centre	-0.0843***	-0.0724***	-0.0585***	-0.115***	-0.116***	-0.103***
	(0.0129)	(0.0147)	(0.0160)	(0.0216)	(0.0233)	(0.0252)
South & Islands	-0.00799	-0.00296	0.0152	-0.0425**	-0.0344*	-0.0117
	(0.0106)	(0.0119)	(0.0129)	(0.0181)	(0.0195)	(0.0209)
Dummy years	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Constant	3.280***	3.156***	3.782***	2.626***	2.560***	2.850***
	(0.138)	(0.153)	(0.201)	(0.138)	(0.149)	(0.223)
Observations	24,756	19,054	15,452	24,756	19,054	15,452
R-squared	0.028	0.031	0.028			
Number of id				7,641	6,710	5,469
Wald chi2				183.52***	172.24***	138.59***
Rho				0.593	0.598	0.601

Robust standard errors in parentheses, clustered at the farm level.
*** p<0.01, ** p<0.05, * p<0.1

Table 12 - Robustness checks LP Model

	Table *a*: Pooled Model			Table *b*: Random Effect Model		
VARIABLES	(1) Lag 1	(2) Lag 2	(3) Lag 1 & 2	(1) Lag 1	(2) Lag 2	(3) Lag 1 & 2
L.pillar II	-0.171***		-0.135***	-0.0270*		-0.0340
	(0.0167)		(0.0282)	(0.0156)		(0.0210)
L.pillar I	-0.00539		-0.0503*	0.0798***		0.0333
	(0.0155)		(0.0286)	(0.0148)		(0.0212)
L.pillar II#L.pillar I	0.0209***		0.0156***	0.00445***		0.00406*
	(0.00183)		(0.00306)	(0.00170)		(0.00229)
L2.pillar II		-0.157***	-0.132***		-0.0305*	-0.0357
		(0.0184)	(0.0285)		(0.0169)	(0.0219)
L2.pillar I		0.0168	-0.0445		0.0873***	0.0315
		(0.0171)	(0.0294)		(0.0160)	(0.0224)
L2.pillar II#L2.pillar I		0.0187***	0.0160***		0.00459**	0.00506**
		(0.00202)	(0.00315)		(0.00184)	(0.00244)
Macro regions						
North-West	*reference*	*reference*	*reference*	*reference*	*reference*	*reference*
North-East	0.0982***	0.1000***	0.0820***	0.0972***	0.0866***	0.0677**
	(0.0132)	(0.0150)	(0.0167)	(0.0224)	(0.0246)	(0.0273)
Centre	-0.181***	-0.171***	-0.164***	-0.181***	-0.184***	-0.188***
	(0.0130)	(0.0147)	(0.0159)	(0.0227)	(0.0243)	(0.0260)
South & Islands	-0.0935***	-0.0911***	-0.0697***	-0.118***	-0.111***	-0.0907***
	(0.0106)	(0.0119)	(0.0128)	(0.0191)	(0.0204)	(0.0216)
Dummy years	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Constant	5.058***	4.902***	5.830***	4.357***	4.301***	4.473***
	(0.138)	(0.153)	(0.200)	(0.133)	(0.144)	(0.217)
Observations	24,756	19,054	15,452	24,756	19,054	15,452
R-squared	0.128	0.129	0.125			
Number of id				7,641	6,710	5,469
Wald chi2				953.73***	853.00***	743.41***
Rho				0.663	0.668	0.663

Robust standard errors in parentheses, clustered at the farm level.
*** p<0.01, ** p<0.05, * p<0.1

Appendix B

Chapter 3

Table A1. *Farms: Vision and Characteristics*

Farms' Vision	*Males*		*Age ≤ 50 years*		*Outside regional market*		*Family Business*		*Certifications*	
	yes	*no*	*yes*	*no*	*yes*	*no*	*yes*	*no*	*yes*	*no*
Short-Term Vision	20 18%	5 21%	11 13%	14 28%	1 2%	23 24%	7 9%	17 29%	2 4%	24 31%
Long-Term Vision (low)	38 34%	7 29%	27 31%	18 35%	7 18%	38 40%	22 29%	23 39%	19 34%	26 34%
Long-Term Vision (medium)	23 20%	6 25%	16 19%	13 25%	7 18%	22 23%	22 29%	7 12%	13 23%	12 16%
Long-Term Vision (high)	32 28%	6 25%	32 37%	6 12%	24 62%	13 13%	26 33%	12 20%	22 39%	15 19%
Chi-square test	0.51		9.05*		34.66*		14.99*		18.21*	

Notes: Column percentages in the second row; *significant at 1% level.

Table A2. *Farmers' Vision by LAG*

Farms' Vision	*Metropoli Est*	*ISC Madonie*	*Rocca di Cerere Geopark*	*Sicani*	Total
Short-Term Vision	3 11.54% 7.69%	13 50.00% 41.94%	7 26.92% 19.44%	3 11.54% 9.38%	26 100% 18.84%
Long-Term Vision (low)	12 26.67% 30.77%	11 24.44% 35.48%	15 33.33% 41.67%	7 15.56% 21.88%	45 100% 32.61%
Long-Term Vision (medium)	11 37.93% 28.21%	5 17.24% 16.13%	6 20.69% 16.67%	7 24.14% 21.88%	29 100% 21.01%

Long-Term Vision (high)	13 34.21% 33.33%	2 5.26% 6.45%	8 21.05% 22.22%	15 39.47% 46.88%	38 100% 27.54%
Total	39 28.26% 100%	31 22.46% 100%	36 26.09% 100%	32 23.19% 100%	138 100% 100%

Notes: Row percentages in the second row; Column percentages in the third row

Table A3. *Attitude to Change by LAG – ICTs*

ICTs	*Metropoli Est*	*ISC Madonie*	*Rocca di Cerere Geopark*	*Sicani*	Total
Negative	1 50% 2.63%	1 50% 3.23%	0 - -	0 - -	2 100% 1.48%
Neutral	13 24.53% 34.21%	16 30.19% 51.61%	11 20.75% 31.43%	13 24.53% 41.94%	53 100% 39.26%
Positive	24 30% 63.16%	14 17.50% 45.16%	24 30.00% 68.57%	18 22.50% 58.06%	80 100% 59.26%
Total	38 28.15% 100%	31 22.96% 100%	35 25.93% 100%	31 22.96% 100%	135 100% 100%

Notes: Row percentages in the second row; Column percentages in the third row

Table A4. *Attitude to Change by LAG – Innovation*

Innovation	*Metropoli Est*	*ISC Madonie*	*Rocca di Cerere Geopark*	*Sicani*	Total
Negative	1 25% 2.50%	0 - -	3 75% 8.33%	0 - -	4 100% 2.86%
Neutral	19 25.68% 47.50%	24 32.43% 80%	9 12.16% 25%	22 29.73% 64.71%	74 100% 52.86%
Positive	20 32.26% 50%	6 9.68% 20%	24 38.71% 66.67%	12 19.35% 35.29%	62 100% 44.29%

Total	40 28.57% 100%	30 21.43% 100%	36 25.71% 100%	34 24.29% 100%	140 100% 100%

Notes: Row percentages in the second row; Column percentages in the third row

Table A5. *Attitude to Change by LAG - Environmental Sustainability*

Environmental Sustainability	*Metropoli Est*	*ISC Madonie*	*Rocca di Cerere Geopark*	*Sicani*	Total
Negative	1 25% 2.44%	2 50% 6.45%	0 - -	1 25% 2.94%	4 100% 2.80%
Neutral	21 28.77% 51.22%	24 32.88% 77.42%	14 19.18% 37.84%	14 19.18% 41.18%	73 100% 51.05%
Positive	19 28.79% 46.34%	5 7.58% 16.13%	23 34.85% 62.16%	19 28.79% 55.88%	66 100% 46.15%
Total	41 28.67% 100%	31 21.68% 100%	37 25.87% 100%	34 23.78% 100%	143 100% 100%

Notes: Row percentages in the second row; Column percentages in the third row

Table A6. *Attitude to Change by LAG - Social Sustainability*

Social Sustainability	*Metropoli Est*	*ISC Madonie*	*Rocca di Cerere Geopark*	*Sicani*	Total
Negative	6 46.15% 14.63%	0 - -	5 38.46% 13.89%	2 15.38% 5.88%	13 100% 9.22%
Neutral	21 25.30% 51.22%	26 31.33% 86.67%	17 20.48% 47.22%	19 22.89% 55.88%	83 100% 58.87%
Positive	14 31.11% 34.15%	4 8.89% 13.33%	14 31.11% 38.89%	13 28.89% 38.24%	45 100% 31.91%

Total	41 29.08% 100%	30 21.28% 100%	36 25.53% 100%	34 24.11% 100%	141 100% 100%

Notes: Row percentages in the second row; Column percentages in the third row

Table A7. *Attitude to Change by LAG - Economic Sustainability*

Economic Sustainability	*Metropoli Est*	*ISC Madonie*	*Rocca di Cerere Geopark*	*Sicani*	Total
Negative	0 - -	1 11.11% 3.33%	5 55.56% 13.89%	3 33.33% 8.82%	9 100% 6.34%
Neutral	20 28.17% 47.62%	23 32.39% 76.67%	9 12.68% 25%	19 26.76% 55.88%	71 100% 50%
Positive	22 35.48% 52.38%	6 9.68% 20%	22 35.48% 61.11%	12 19.35% 35.29%	62 100% 43.66%
Total	42 29.58% 100%	30 21.13% 100%	36 25.35% 100%	34 23.94% 100%	142 100% 100%

Notes: Row percentages in the second row; Column percentages in the third row

Table A8. *Farmers' Vision and Attitude to Change – ICTs*

Farmer's Vision	Attitude to Change			
	Negative	*Neutral*	*Positive*	Total
Short-Term Vision	0 - -	13 54.17% 26.53%	11 45.83% 14.10%	24 100% 18.60%
Long-Term Vision (low)	0 - -	19 45.24% 38.78%	23 54.76% 29.49%	42 100.00% 32.56%
Long-Term Vision (medium)	2 8% 100%	5 20% 10.20%	18 72.00% 23.08%	25 100% 19.38%
Long-Term Vision (high)	0 - -	12 31.58% 24.49%	26 68.42% 33.33%	38 100% 29.46%

Total	2 1.55% 100%	49 37.98% 100%	78 60.47% 100%	129 100% 100%

Notes: Row percentages in the second row; Column percentages in the third row

Table A9. *Farmers' Vision and Attitude to Change – Innovation*

Farmer's Vision	Attitude to Change			
	Negative	*Neutral*	*Positive*	Total
Short-Term Vision	1 4.17% 25%	14 58.33% 20%	9 37.50% 15.25%	24 100% 18.05%
Long-Term Vision (low)	0 - -	23 53.49% 32.86%	20 46.51% 33.90%	43 100% 32.33%
Long-Term Vision (medium)	2 7.14% 50%	15 53.57% 21.43%	11 39.29% 18.64%	28 100% 21.05%
Long-Term Vision (high)	1 2.63% 25%	18 47.37% 25.71%	19 50% 32.20%	38 100% 28.57%
Total	4 3.01% 100%	70 52.63% 100%	59 44.36 100%	133 100% 100%

Notes: Row percentages in the second row; Column percentages in the third row

Table A10. *Farmers' Vision and Attitude to Change – Environmental Sustainability*

Farmer's Vision	Attitude to Change			
	Negative	*Neutral*	*Positive*	Total
Short-Term Vision	0 - -	15 60% 21.74%	10 40% 15.87%	25 100% 18.38%
Long-Term Vision (low)	1 2.22% 25%	28 62.22% 40.58%	16 35.56% 25.40%	45 100% 33.09%
Long-Term Vision (medium)	2 7.14% 50%	12 42.86% 17.39%	14 50% 22.22%	28 100% 20.59%

Long-Term Vision (high)	1	14	23	38
	2.63%	36.84%	60.53%	100%
	25%	20.29%	36.51%	27.94%
Total	4	69	63	136
	2.94%	50.74%	46.32%	100%
	100%	100%	100%	100%

Notes: Row percentages in the second row; Column percentages in the third row

Table A11. *Farmers' Vision and Attitude to Change – Social Sustainability*

Farmer's Vision	Attitude to Change			
	Negative	*Neutral*	*Positive*	Total
Short-Term Vision	1	18	6	25
	4%	72%	24%	100%
	8.33%	23.38%	13.33%	18.66%
Long-Term Vision (low)	6	26	11	43
	13.95%	60.47%	25.58%	100%
	50%	33.77%	24.44%	32.09%
Long-Term Vision (medium)	4	16	8	28
	14.29%	57.14%	28.57%	100%
	33.33%	20.78%	17.78%	20.90%
Long-Term Vision (high)	1	17	20	38
	2.63%	44.74%	52.63%	100%
	8.33%	22.08%	44.44%	28.36%
Total	12	77	45	134
	8.96%	57.46%	33.58%	100%
	100%	100%	100%	100%

Notes: Row percentages in the second row; Column percentages in the third row

Table A12. *Farmers' Vision and Attitude to Change – Economic Sustainability*

Farmer's Vision	Attitude to Change			
	Negative	*Neutral*	*Positive*	Total
Short-Term Vision	1	14	10	25
	4%	56%	40%	100%
	12.50%	20.59%	16.95%	18.52%

Long-Term Vision (low)	3	26	15	44
	6.82%	59.09%	34.09%	100%
	37.50%	38.24%	25.42%	32.59%
Long-Term Vision (medium)	2	15	11	28
	7.14%	53.57%	39.29%	100%
	25%	22.06%	18.64%	20.74%
Long-Term Vision (high)	2	13	23	38
	5.26%	34.21%	60.53%	100%
	25%	19.12%	38.98%	28.15%
Total	8	68	59	135
	5.93%	50.37%	43.70%	100%
	100%	100%	100%	100%

Notes: Row percentages in the second row; Column percentages in the third row

Appendix C: Figures

Chapter 1

Figure A1.1

Evolutions

Food security and productivity

Competitiveness

Objective: Rural development

Economic, environmental and social development

1960s	1970s-80s	1992	1999	2003	2008	2013-2014	2018
Early CAP* years	The crisis years	MacSharry reform	Agenda 2000	CAP mid-term review	CAP Health Check	CAP Reform	CAP post-2020
Income support Price support Market Stabilisation Productivity improvement	**Over production** Exploding expenditure Structural measures Not respect for the land	Reduced surpluses Environment Income stabilisation **Market support to producer support** **Direct** **payments**	Deepening the reform process Competitiveness **Rural development**	Market orientation **Decoupling** Environment Simplification 1st to 2nd pillar by reducing direct payments	Reinforcing 2003 reform New challenges Risk management Dairy quotas	Research and innovation **Greening** Goal orientation Redistribution End of production restrictions Value creation chain food	New delivery model National CAP strategic plan Result orientation Green architecture

Figure A1.2

Long-term vision			
Climate and biodiversity			
	Sustainability, food and health		
		Local development in rural areas	
			Integration
2019	**2020**	**2021**	**2023 and future**
Green Deal	Farm to fork	CAP 2023-2027	Agenda 2030
Europe will become the first climate-carbon emission neutral continent by 2050 Sustainable and inclusive growth strategies to stimulate the economy	New sustainable food systems with the **environment**, climate and biodiversity protection objectives	New model: **diversification**, to promote employment, growth, social inclusion and local development in rural areas, including bio-economy and forestry. Focus on young farmers	Integration of strategies and policies

Chapter 3

Figure A3.1

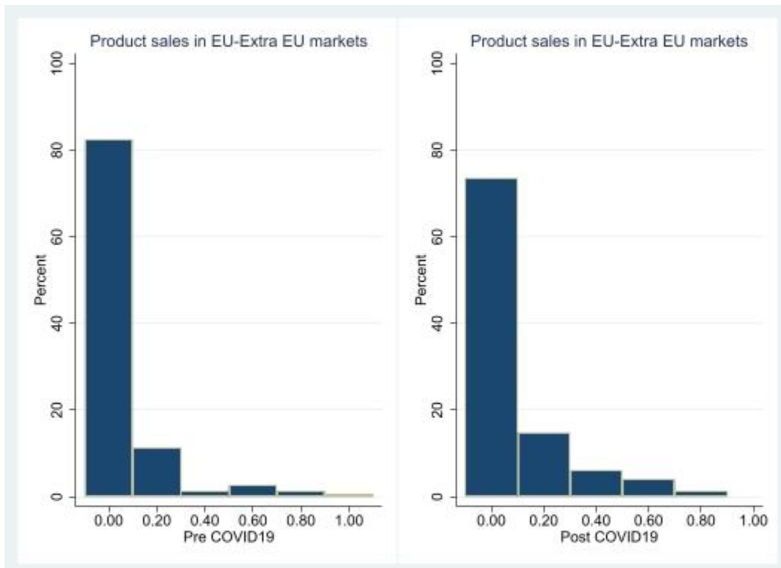
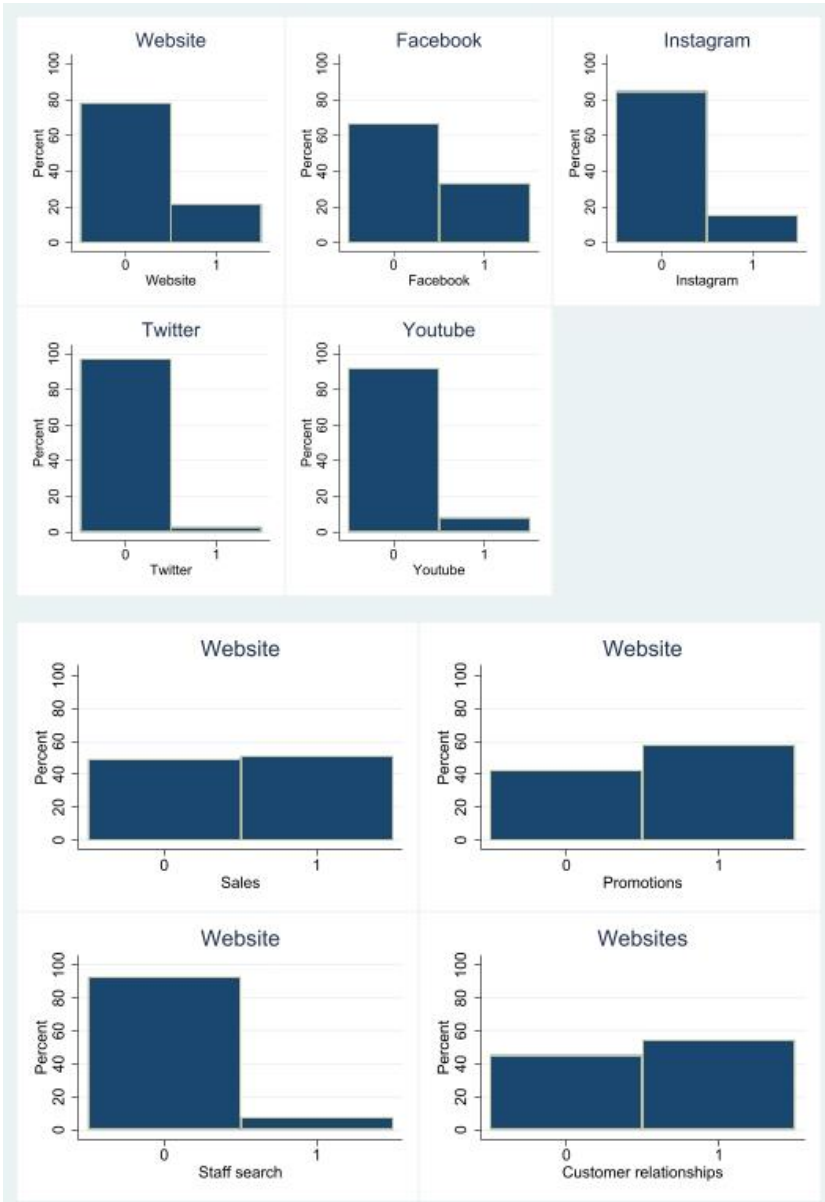


Figure A3.2


Website
Percent
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40
60
80
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1
Website
Facebook
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Sales
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1
Promotions
Website
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Staff search
Websites
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100
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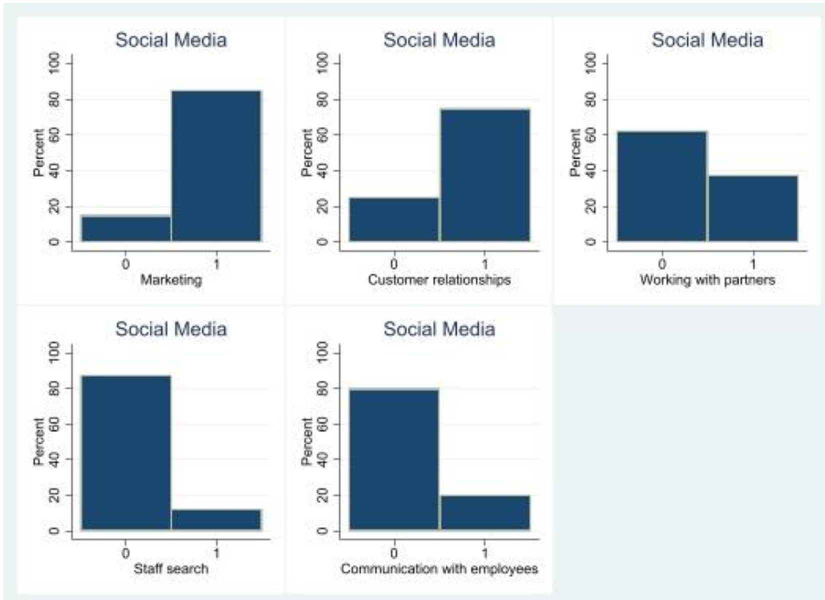
1
Customer relationships

APPENDIX C


Social Media
Percent
Marketing
Social Media
Percent
Customer relationships
Social Media
Percent
Working with partners
Social Media
Percent
Staff search
Social Media
Percent
Communication with employees

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