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Are Geographical Indications contributing to environmental conservation? The case of *Café de Colombia*

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Abstract. Colombia has a rich history of coffee production spanning over 300 years. As one of the world's leading producers, the country dedicates a significant portion of its land to cultivating this vital crop. In the early 2000s, *Café de Colombia* received Geographical Indication (GI) certification, a milestone aimed at strengthening its reputation and competitiveness both nationally and internationally. This paper examines the impact of that recognition on land-use dynamics (*i.e.*, deforestation). Using the Synthetic Control Method on a country-level panel dataset from 1992 to 2020, it estimates the effect of the GI certification on Colombia's national deforestation rate. The findings reveal That deforestation would have been about 0.2 percentage points lower on average without the acknowledgement. Based on these results, the paper proposes to adopt a territorial-based and community-led policy mix to convert local peculiarities in strategic assets for sustainable development.

Keywords: Geographical Indications, Cafè de Colombia, Deforestation, Synthetic Control Method, local development.

1. INTRODUCTION

Colombia, along with Brazil and Vietnam, is one of the world's top three countries for coffee production, consumption, and export. (FNC, 2011; FAO, 2022a). Although with a decreasing trend over the last decades, more than 800 thousand hectares of national land, mainly managed by artisanal and family farmers, are still dedicated to this crop that remains a cornerstone of the national economy and identity.

After the International Coffee Agreement ended in 1989, Colombia adopted a quality differentiation strategy to strengthen the reputation of its coffee both nationally and internationally. In this effort, coffee's place of origin became a key factor in defining quality (Marescotti and Belletti, 2016), making the protection of the origin name so important to certify the *Café de Colombia* as a Protected Geographical Indication (PGI) in December 2004

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(Quiñones-Ruiz *et al*., 2015). Following the EU scheme, GI is a sign used on agri-food products that have a specific geographical origin and possess qualities and reputation that are essentially or exclusively due to a particular geographical environment, made of natural and human factors (Reg. (EU) 1442/2024).

The positive role of certifying a product within the GI scheme was stressed by economic literature that, among benefits, listed: premium pricing (Duvaleix *et al*., 2021), farmers' income (Hughes, 2009; Vaquero-Piñeiro *et al*., 2025), consumers' choices (Menapace *et al*., 2011), trade (Curzi and Huysmans, 2022; De Filippis *et al*., 2022; Giua *et al*, 2024), and local development (Takayama *et al*., 2021; Crescenzi *et al*., 2022). The presence of GI products in local economies, in fact, generates a set of direct and indirect spill-over effects that become drivers of socio-economic development. Consequently, the GI scheme is no longer an issue affecting only agrifood quality differentiation, but, conversely, has assumed a unique economic significance at the local level. More recently, the scheme has been enriched by a potential key role also in supporting the transaction towards more environmentally sustainable production processes (FAO and oriGIn, 2024). The new EU GI Law (Reg. EU No. 1443/2024) introduces, in fact, the possibility of including in the GIs' Product Specifications sustainable criteria, encompassing environmental, social and economic objectives that go beyond mandatory standards (Art. 7), and reporting on them through sustainable reports (Art. 8). This reform marked a turning point in the GI market shaping its contribution on environmental sustainability: *"the environmental objectives should include [...] the conservation and sustainable use of soil, landscape, water and natural resources, the preservation of biodiversity, [...]* (Reg. EU No. 1443/2024). So far, in fact, the GI scheme does not include highly specific production rules or environmental constraints (Marescotti and Belletti 2016). In this respect, over the last years, the EU has put a lot of effort into financing research projects that will provide evidence-based recommendations to strengthen the contribution of GI to sustainability, while FAO proposed a Sustainability Strategy for GIs with specific intervention themes, topics and indicators (FAO and oriGIn, 2024) (Example of EU projects are: STRENGTH2FOOD and GISMART Horizon projects). Most of the existing studies attempting to evaluate the effects on a set of environmental indicators focused on European products (*e.g.*, water and carbon footprint, food miles (Caragliu *et al*., 2024), but some exceptions exist that also look at extra-EU GIs (Bagal *et al*., 2013; Marescotti and Belletti, 2016; Bellassen *et al*., 2022).

In this context, this paper aims to contribute to the literature on the environmental sustainability of extra-EU GIs by presenting a first reflection on the environmental consequences of the acknowledgement of the *Café de Colombia* on national deforestation patterns. The analysis was conducted on a country-level panel dataset over the 1992-2020 period by employing a Synthetic Control Method approach.

The effect on forest pattern represents a critical issue for sustainable socio-economic analysis, given that forests, from various perspectives, are recognised as a key ecosystem for sustainable development (Blackman *et al*., 2014). In developing countries, such as Latin America, they play an even more crucial role in determining societies' evolution and community well-being as a source of primary and non-primary goods (Ros-Tonen and Wiersum, 2003; Bakkegaard *et al*., 2017) and fighting climate change (Kramer *et al*., 1997; Lugo, 1997; Houghton *et al*., 2000; Cunningham *et al*., 2015; Wisniewski and Marker, 2019).

The acknowledgement of a GI may have a dual consequence, indeed. On the one hand, even if not automatically, but rather based on producers' and institutions' agreements, it may limit the deforestation practice by defining a production area that does not affect forest ecosystems and establishing higher environmental sustainability requirements. On the other hand, however, it could also be true that the economic benefits generated by GI may lead to expansion of agricultural land at the expense of forests, if not well designed and managed.

The empirical setting designed for the study is ideal for several reasons. Firstly, the study focuses on a pioneering case of extra-EU GI. The extension of the scheme to extra-EU products represents a strategic tool to accomplish trade agreements without making use of tariff measures (UNCTAD, 2019). Nowadays, extra-GIs are more than 360, and their role in trade agreements will become even more relevant in the future, given the extension of this scheme to manufacturing and craft products.

Second, the analysis investigates the effects of the GI policy since its inception in Colombia in 2005, rather than looking at a specific time subset, and looks at a strategic environmental outcome not only for climate adaptation, but also for the socio-economic development of local communities. Conversely to the existing studies, which conducted similar research by using qualitative approaches (Ingram *et al*., 2020), this paper estimates the effect by means of causal empirical methodologies, making the approach replicable. In this context, the paper provides a welcome basis for policy debate on the potential impact of such a policy scheme on the preservation of ecosystems and natural habitats (FAO and oriGIn, 2024).

The remainder of this paper is organised as follows. Section 2 details the contextual framework guiding this paper, which includes the history of coffee production in Colombia, its link with forests and the institutional background of GIs. Section 3 introduces the empirical setting, Section 4 presents the results, together with some robustness checks, while Section 5 offers some policy implications and advice. Eventually, Section 6 concludes the manuscript.

2. CONCEPTUAL FRAMEWORK

In the EU, the GI quality scheme was established in 1992 to protect the name of local high-quality agri-food products whose characteristics are linked to the place where they are made, the so-called region of origin (Reg. EU No. 2024/1143). Even if preserving high-quality local productions and reducing information asymmetry between producers and consumers remain the main aims of this scheme, over the years, several socio-economic territorial externalities that literature demonstrated are associated with GIs. Among them, papers stressed the capacity of increasing agricultural added value (Cei *et al*., 2018), supporting local development (Crescenzi *et al*., 2022; De Simone *et al*., 2023; Vaquero-Piñeiro *et al*., 2025) and internationalisation (Giua *et al*., 2024). At the same time, scholars have demonstrated that GIs may support the transition towards more sustainable food systems and diets (Galli *et al*. 2020; Gocci and Luetge, 2020; Vaquero-Piñeiro and Curzi, 2024), with some positive evidence on the contributions to achieving environmental sustainability targets (Arfini *et al*., 2019). However, a contradictory picture about positive-negative implications of GIs remains for different components of environmental protection (Falasco *et al*., 2024).

The GI scheme is, in fact, not necessarily linked to preserving natural resources and several can be the transmission channels through which this scheme may affect, positively, negatively or both, environmental performances. The 2024 FAO Sustainability Strategy for GIs clearly highlighted the fact that GIs can be more sustainable than their conventional counterparts, but not automatically. The sustainability of a GI largely depends on how it is structured and on the extent to which local actors (e.g., producers, institutions, governments) collaborate to invest in sustainable practices. Farmers and producers acting collectively, for example, may have more powers than individual producers and take environmental responsibilities (Gori and Sottini, 2014). Environmental objectives could be introduced in the GI product specifications by limiting the region of origin with respect to pre-existing ecosystems or by making environmental production practices mandatory for all the GI producers. Among the key environmental challenges faced by GI systems, the FAO strategy explicitly highlights forest conservation and regeneration as a specific commitment for GI producers. By increasing the profitability of productions, and consequently the rent for producers and the value of land, the acknowledgement as a GI could constitute a risk for forest preservation. The economic benefits generated by agricultural activities (González-González *et al*., 2021; Armenteras *et al*., 2013) and GI reputation could enhance land-use changes from forest to agricultural land. To increase production without affecting the quality through the shift toward intensive production processes, producers can operate on the extensive margin by extending the production area at the expense of non-agricultural land, such as forest land.

In addition, land use changes may be induced by the free-riding behaviour of producers that offer similar non-certified goods, i.e., Colombian coffee without the GI certification. They indirectly benefit from the origin reputation induced by the GI without having any mandatory requirements to respect (Menapace and Moschini, 2024; Mao and Görg, 2025). For example, they can use the most recent coffee varieties that, conversely to the autochthonous coffee varieties that grew in the shade of natural forests (Beer, 1988), are sun-grown, do not need shade and can be planted instead of forest (FNC, 2008; Jha *et al*., 2011; Somarriba and Lopez-Sampson, 2018; González-González *et al*., 2021).

2.1 The Colombian case study

Coffee arrived in Colombia in the 18^{th} century, introduced by Jesuits and over the decades has become the most widespread agricultural production of the country, accounting for 16% of the national agriculture gross domestic product (GDP) (Ciravegna *et al*., 2024). More than 500,000 people are employed in the coffee production, with a great number of small coffee growers (95% smaller than 5 hectares) and a few international corporations working as roasters, traders and distributors (Barjolle *et al*., 2017). From the 1930s, the Colombian coffee market was regulated by the National Federation of Coffee Growers, which, twenty years later, introduced a common strategy to differentiate its product and preserve its authenticity. Over the years, the claim "*Colombian coffee*" has become a guarantee of quality worldwide, and in the early 1980s, a specific trademark was registered (*i.e*., Juan Valdez). In 2005, Colombia applied for certified *Café de Colombia* as a PGI under the EU GI scheme (Quiñones-Ruiz *et al*., 2015), becoming the first non-EU agri-food product recognised by the EU. With the GI acknowledgement, the reputation of *Café de Colombia* increased even more, becoming, on the one hand, a crucial production for the economic development, while, on the other hand, a potential risk to local ecosystems, such as the forest. The Colombian area is covered, in fact, for more than half (53.3%) of its surface by forest area and hosts 8% of the entire Amazon Rainforest (FAO, 2022a; Hansen *et al*., 2013). The mountain region where coffee plantations are primarily located (Armenteraas *et al*., 2011) was one of the regions that, over the last decades, experienced the largest share of deforestation (63 per cent) (GFW, 2023; González-González et al., 2021). As reported in the product specification: "*growing coffee exists in the Andean Mountain range and its foothills, which run the length of the country*". In this context, it is presumable, therefore, that forests, which are included in the region of origin, are potential targets of expansion for producers seeking to enlarge cultivation areas, generating a negative impact on deforestation, as seen in the case of *Cafè de Colombia*. In Colombia, in fact, the distance between agricultural areas and forest frontiers is mostly immediate, with a relatively small, if not absent, degraded area (Hyde, 2012).

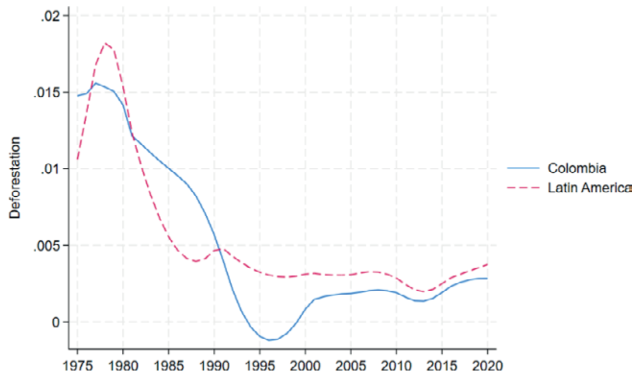

Figure 1. Deforestation trend, Colombia *vs* Latin America. Notes: the group of Latin America is composed by: Argentina, Bolivia, Barbados, Belize, Brazil, Chile, Colombia, Costa Rica, Cuba, Dominica, Dominican Republic, Ecuador, El Salvador, Grenada, Guatemala, Guyana, Haiti, Honduras, Jamaica, Mexico, Nicaragua, Panama, Paraguay, Peru, Uruguay, and Venezuela.

3. DATA AND METHODOLOGY

To investigate what has happened in Colombia after the acknowledgement of the Café de Colombia in 2005, we use a novel dataset at the national level, exploit the Synthetic Control Method over the 1992-2020 period and rely on Stata19 software (Athey and Imbens, 2017).

3.1 Data

Our analysis relies on a dataset arranged by considering different sources of data. Regarding forest cover, we considered as a primary source the FAO's 2020 Forest Resources Assessment (FAO, 2022b) that represents an official source of forest cover data where countries must follow common guidelines (Total Forest cover as the sum of natural and planted forest. Source: FAO, 2018). To have a better cross-country comparison (Hyde, 2012; Puyravaud, 2003), we use as outcome variable the yearly deforestation rate, whose trend for Colombia and the rest of the Latin America is depicted by Figure 1.

The dataset embodies several other variables which identify both socio-economic country characteristics and potential drivers of forest cover change and operate as controls in our model (Table A1). First, we include the share of agricultural area, the index of agricultural trade openness calculated as the ratio between the value of agricultural exports and imports (Hyde, 2012) and cereal yield, generally identified as a proxy to capture agricultural intensification (Barbier and Burgess, 2001). The agricultural land variable includes hectares dedicated to both crop and livestock. This allows us to control for all possible competing agricultural expansions.

Second, we control for population density and the share of people living in rural areas, which are considered by the literature as proxies of pressure on natural resources (Geist and Lambin, 2002; Grau and Aide, 2008; Carr *et al*., 2009). The variable of GDP per capita represents the core index of economic development for a country, widely used within the forest economics literature, especially through the Environmental Kuznets Curve (EKC) hypothesis (Caravaggio, 2020). We retrieved this variable from the World Development Indicators (WDI) of the World Bank (WB, 2022), and it is expressed in constant 2015 US$. Trade openness is another core economic variable of a country which may affect in different ways the use of natural and planted forests both negatively (Angelsen and Kaimowitz, 2001; Libman and Obydenkova, 2013; Lankina *et al*., 2016; Leblois *et al*., 2017) and positively (Meyer *et al*., 2003; Niklitschek, 2007; Hyde, 2012). We proxied this variable by using the sum of import and export as share of total GDP as proposed from the WB (2022) from which data has been retrieved. To identify the role of institutions we relied on data provided by Freedom House (2022) where the two variables of civil liberties and political rights have been merged within a unique proxy variable which identify the quality of institutions.[1] Good institutions are generally associated with better forest management, hence less deforestation (Bhattarai and Hammig, 2001, Murtazashvili *et al*., 2019, Cary and Bekun, 2021). Eventually, to account for the role played by climate change, we considered the variable of temperature change provided by FAO (2022a) which aggregates at country level monthly data of mean temperature anomalies with respect of a baseline climatology corresponding to the period 1951-1980.

2.2 Synthetic Control Method

The Synthetic Control Method is a counterfactual approach to estimate the impact of a policy on a single unit in panel data settings (Abadie *et al*., 2010). It creates a synthetic control unit for the treated observation (Colombia in our case) to simulate via a data-driven approach what its outcome path would be if it did not undergo the policy under analysis. The synthetic unit is obtained by combining and weighting the characteristics of a control group (*i.e*., donor pool) to construct an artificial control (not treated) unit that follows similar outcome's pre-trends of the treated one, but that has not experienced the policy. Some studies already exist that used Synthetic Control Method to estimate the effects of different events on forest projections. Sills *et al*. (2015) studied the impacts of local initiatives on the gross deforestation in Brazil (*i.e*., loss of mature forest), Rana and Sills (2018) the effects of forest management certifications on tropical deforestation, while Amador-Jimenez *et al*. (2020) the impact of Covid-19 lockdown on forest fires in Colombia. Furthermore, Cappelli *et al*. (2022) used the Synthetic Control Method to estimate whether the implementation in the national constitution of the *Buen Vivir* principles has proved effective in reducing forest losses in Bolivia. In this paper, the treated unit is Colombia, the policy is the acknowledgment of the GI scheme in 2005, while the pre-period is from 1992 to 2005 and the post-period from 2005 to 2020. The first pre-treatment year is 1992 because it was when the EU food GI quality scheme came into force and extra-EU countries started to replicate and adopt the same scheme nationally.

The control group has been selected based on a set of socio-economic, cultural and environmental factors measured at the country level (Table A1) that literature has identified as forest cover change determinants, and the value of the outcome variable averaged over the pre-trend years to help that the synthetic control unit adequately mirrors the treated unit's deforestation trajectory before treatment (Kaul *et al*., 2015; Ferman *et al*., 2020). We need, in fact, a list of countries that are comparable to Colombia, but that have never implemented a GI certification for coffee.

The treatment variable has been reconstructed from the Product Specification downloadable from the eAmbrosia website and it is a dummy variable that takes the value one for Colombia, and zero otherwise.

To select it, we started from the entire list of 25 Latin American countries and we discard: (i) small islands and tax heaven' countries because in these areas forest cover might have benefitted or lost from their characteristics unrelated to forest issues (*e.g.*, remote locations or economic conditions); (ii) countries for which relevant data are missing; (iii) Dominican Republic since in this country there is a similar policy, the *Cafè of Valdesia*, which has been acknowledged as a GI in 2016. We are conscious that there are other Latin American countries with GIs, but in selecting our control group, we do not discard because: (i) they do not regard coffee industry, and therefore we cannot consider them the same policy; (ii) the GI acknowledgment arrived at the end/after the period of analysis and we do not have enough post period treatment; (iii) the GI refers to wine or spirits and therefore follows a different regulation (see Table S1).

According to the Synthetic Control Method assumptions, to guarantee for the validity of the final control group (16 countries), we checked that the trends of the outcome variable in the treated country and in the donor pool were similar and that the values of pre-treatment predictors in the treated unit was neither the largest or the smallest of the sample (Table S2). From the donor pool, the Synthetic Control Method algorithm weighted all the observables for the synthetic control of Colombia (Table S7).

3. RESULTS

Figure 2 depicts the trajectories of treated and synthetic counterparts (Figure S1 for p-values; Galiani and Quistorff, 2017).

The red line shows the outcome for synthetic Colombia estimated as a counterfactual of what would have been observed for the affected unit in the absence of the intervention. Before the policy began in 2005, the pre-treatment trends in deforestation were similar for the real and the synthetic Colombia. Since 2005, a gap

[1] The two variables of the Freedom House (2022) both span from 1 to 7 where 1 is the highest level (*i.e*., high civil liberties and/or high political rights) while 7 the lowest. The variable used in our analysis is a rescaled sum of these two variables which spans from 1 to 10 (where 1 is the lowest institutional quality level and 10 the highest).

Figure 2. Deforestation trend, Colombia *vs* synthetic Colombia. Note: The Yearly deforestation rate is expressed in hectares. See Table S8 for the weights donated by each country of the donor pool.

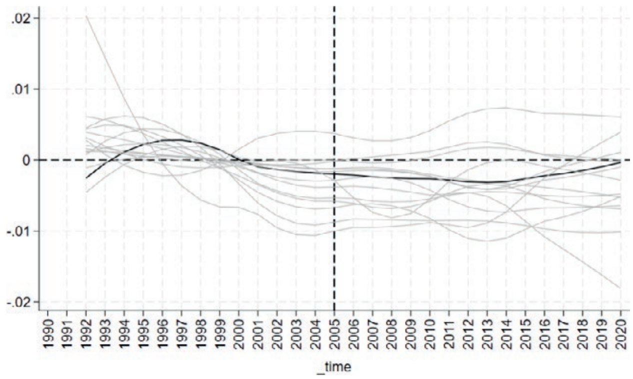

Figure 3. Trends in deforestation in Colombia (treated country) and placebo gaps. Notes: the grey lines represent the difference in deforestation between the respective synthetic control and the state in the donor pool (*synthetic – treated*); the bold black line represents the gap between Colombia and its synthetic country (*synthetic – treated*).

has emerged, with Colombia showing lower deforestation yearly rates. This suggests that, all else being equal, without the acknowledgement of *Café de Colombia* as a GI, the country would have overall experienced a lower deforestation rate. The estimated overall effect is approximately 0.2 percentage points, indicating a higher average deforestation rate over the entire post-treatment period. To quantify the impact of the treatment, we refer to the difference after treatment between the treated and the untreated cohort. It is calculated as the difference between the 2020-2005 difference in Colombia and the 2020-2005 difference of synthetic Colombia.

3.1 Robustness analysis

In order to verify the validity of our results, we conduct several robustness checks.

First of all, we run a placebo test, commonly used in Synthetic Control Method literature, by iteratively replicating the Synthetic Control Method for every other state that did not certify coffee production as a GI during the sample period (Abadie and Gardeazabal, 2003; Bertrand *et al*., 2004; Abadie *et al*., 2010). Figure 3 shows that the synthetic method provides a good fit for the deforestation trend in Colombia before the GI quality scheme. Overall, the gap between deforestation in Colombia and in its synthetic counterpart during the pretreatment period is smaller than for the states in the donor pool, but it becomes relatively higher after the treatment (Figure 3).

Thereafter, we conduct two placebo tests simulating an artificial (placebo) timing of the policy (Abadie et al. 2015, Heckman and Hotz, 1989): (i) we anticipate the treatment year to 2000; (ii) we postpone the treatment year to 2007, when the *Café de Colombia* was included in the EU GI list. The first test confirms the impact of the policy on the forest cover in Colombia, given that there is no significant effect of the artificial 2000 policy (Figure 4 – panel a; Figure S2, Table S9) (Abadie et al., 2021). The second test validates our results highlighting a similar significant trend of the baseline estimations (Figure 4 – panel b; Figure S3, Table S10): what influences the deforestation trend is, therefore, the moment when the *Cafè de Colombia* began to be discussed as a GI and introduced at the policy level, rather than the exact date of its official inclusion in the EU register, since producers already anticipated that recognition would eventually happen.

Thereafter, we replicate the analysis by excluding Brazil from the donor pool, which is the first Latin American agriculture and coffee producer. Neighbour countries, like Colombia, may be affected by Brazilian informal cross-border displacement of agri-food productions and exports (Meyfroidt *et al*., 2010). Results show that our main results are robust (Figure S4, Figure S5, and Table S3 in SM). Findings are mainly coherent and slightly significant, also when we use a different source of data for forest land: Climate Change Initiative land cover (CCI-LC) data (ESA, 2017; FAO, 2022a) (Figure S6, Figure S7, and Table S4 in SM).[2] Even with this different source of forest cover data, the impact of GI has a

[2] According to the land cover reclassification (UN, 2014), we combined tree-covered areas and mangroves. The former category comprises geographical areas dominated by natural tree plants with a coverage of at least 10%, hence both natural and management forests. The latter category includes areas with a woody vegetation with 10% coverage of more but regularly flooded by salt and/or brackish water. Data, aggregated at national level, has been retrieved from FAO (2022a).

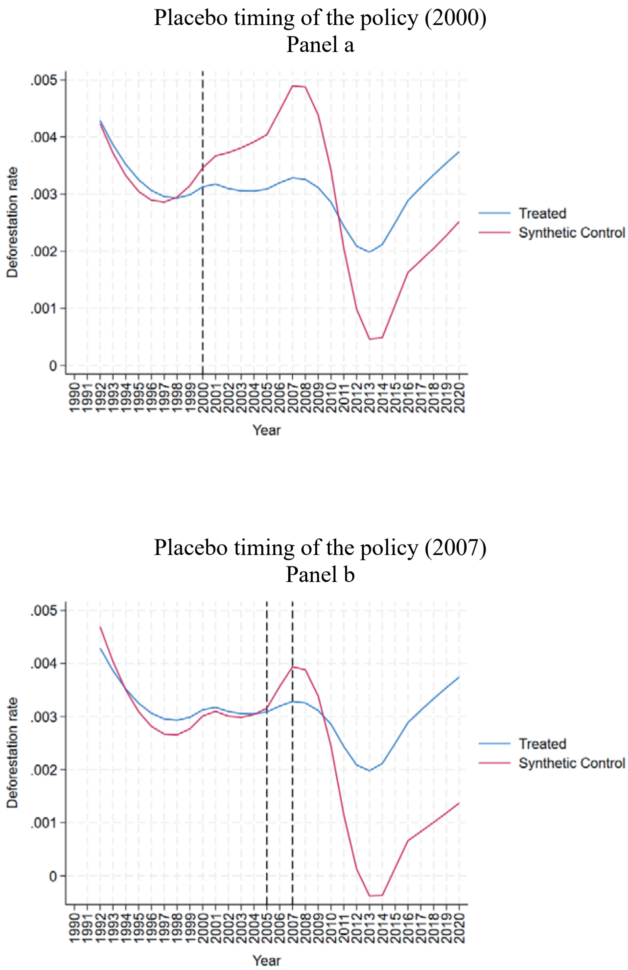

Figure 4 Deforestation trend, Colombia *vs* synthetic Colombia (placebo timing of the policy). Note: Yearly deforestation rate is expressed in hectares. See Table S1 and Table S2 in SM for the weights donated by each country of the donor pool.

detrimental effect on deforestation rates in the first years after the introduction of the policy, while inverts in the long run.

We also conduct two other robustness checks by considering (Kaul *et al.*, 2015): (i) the value of the outcome t - 1 lag averaged over the pre-trend years as a predictor, rather than the outcome at t; (ii) all the lagged values of the outcome, but without other covariates (Ferman *et al.*, 2020). While in the former case, results are in line with the baseline estimations (Figure S8 and S9, Table S5 in SM for weights donated), in the latter case, some differences in terms of significance emerge (Figure S10 and S11, Table S6 in SM for weights donated). In the case under analysis, and in line with Abadie and Gardeazabal (2003) and Abadie *et al.* (2010), covariates are deemed important and should be considered. Excluding them is not a first-best solution to simply optimise the pre-treatment fit by using all pre-treatment values of the outcome as separate economic predictors.

5. DISCUSSION

5.1 Policy implications

We found that the GI scheme might have an overall negative impact on deforestation. These results can help policymakers to design policy interventions capable of addressing the characteristics, in terms of the local production system, that have generated this effect. Overall, policy interventions should aim at preserving forest ecosystems while guaranteeing the higher income generated by GIs (Mourao and Martinho, 2020).

First, our study confirms that more coordinated governance is needed to reduce deforestation (Furumo and Lambin, 2021). In particular, policy interventions that constrain deforestation should be implemented in parallel with those aimed at enhancing economic revenues.

A concrete example for the Colombian government and institutions to consider is the new EU Forest Strategy for 2030 (EC, 2021). It sets concrete actions to improve the quantity and quality of EU forests, while supporting the production of sustainable food through different policy interventions, such as a new approach to finance ecosystems restoration and environmental services (Cantillon et al., 2025).

Second, the paper highlighted the need to set shared norms to guarantee that the GI scheme might contribute to enhancing environmental sustainability, given that it is not one of its primary objectives (EC, 2025). The acknowledgement as a GI, increasing the profitability of productions and, consequently, the rent producers and the value of land, might, in fact, constitute a risk for forest preservation. Common lines of interventions should be set at the national level for the entire supply chain and all the actors involved, regardless of their business form and economic dimensions (Meyfroidt and Lambin, 2011). In the case under analysis, the adoption of sustainability strategies is obstructed by the high fragmentation of the supply chain, which is primarily managed by small-scale rural people and family farms (Gibson *et al.*, 2011; Matricardi *et al.*, 2020). A higher level of power concentration in the upward part of the supply chain may help them to achieve fairer remuneration, increase their market power and avoid the rising costs for marketing and distribution, especially in importing countries, which will decrease the farmers' share in the coffee retail price. Policy makers and practitioners should investigate which production model may be most suitable to strengthen the position of small local producers and promote a reorganisation of local production systems. New entrepreneurial opportunities based on coordination and cooperation among actors along the supply chain (Arias and Fromm, 2019; ICO, 2022; EC, 2024; Belso-Martinez *et al*., 2024; Vaquero-Piñeiro and Pierucci, 2025; Quiñones-Ruiz *et al*., 2016) and public-private partnerships are, in fact, considered as effective policy mechanisms to scale up impacts (Furumo and Lambin, 2020). As declared by the 2025 EU Vision for agriculture and food, "*encouraging* [farmers] *to join cooperatives and/or associations to reduce costs, increase efficiency and improve prices for the market* (EC, 2025: p. 7). In this context, the GI system is, *per se,* a first step toward cooperation, given its peculiar combination of competition and cooperation among geographically close firms (Vaquero-Pineiro et al., 2025). However, a governance regime with greater collaboration between environmental and industry stakeholders achieved better environmental outcomes (Heilmayr and Lambin, 2016). Lastly, it should be appropriate for policy interventions managing the GI scheme in tandem with the increasing diffusion of eco-friendly private certifications, such as the Rainforest Alliance, that pose environmental sustainability as their prime objective (Vanderhaegen *et al*., 2018; Oberlack *et al*., 2023). In this context, the GI might consider the specific standards and requirements established by such certification as a welcome basis and integrate them into the product specification. The information system proposed in the product specification to monitor coffee growers could, for example, record the adoption of private schemes, thereby helping to identify which forest preservation requirements could be most easily incorporated into the specification.

5.2 Limitations

The study proposed has some limitations that should be discussed.

First, the national level could appear too much aggregated and not capable of accounting for regional deforestation patterns. The national level is, however, the only suitable one, given that in the product specification, there are no specific administrative boundaries defining the region of origin. Geo-referenced data on forest and coffee plantations could potentially be downloadable from satellite databases, even with some limitations in terms of time span (Hansen et al., 2013; Sulla-Menashe et al., 2011; Buchhorn et al., 2020) and spatial resolution (Liu et al., 2020). However, it will not be sufficient, given that causal impact estimations necessitate a set of socio-economic and demographic contextual information that does not exist at the gridded level.

Second, the study is limited by the fact that, based on the available data, it is not possible to distinguish between GI and non-GI coffee production. However, given the free-riding effects mentioned before, in this study, we can assume that, at least partially, the effect on land-use change (from forest to coffee plantations) deforestation is, directly and indirectly, driven by the presence of the scheme.

Third, the model does not isolate the potential presence of other simultaneous events that may have impacted the Colombian deforestation patterns in the post-treatment period. An example could be the long-lasting conflict within the Revolutionary Armed Forces of Colombia movement and the Colombian government, which could represent an obstacle to forest preservation. However, given that it has lasted for almost the entire period under analysis (MADR-UPRA, 2014), it can be considered a sort of contextual condition for the whole country (see Sánchez-Cuervo et al., 2012; Murillo-Sandoval et al., 2019; Negret et al., 2019; Clerici et al., 2020).

Fourth, the Synthetic Control Method is sensitive to the donor pool selection, which we tested by changing the donor pool in the robustness checks and the assumption of non-spillover effects. The registration of a GI may incentivise the reallocation of non-GI productions in the neighbouring regions that have not been included in the region of origin, generating a new demand for agricultural area, also in those regions that have not been directly targeted by the intervention. Territorial spill-over effects are, however, more plausible across sub-national areas within the same country than at the national level (Cortinovis and van Oort, 2018; Caragliu and Landoni, 2024).

6. CONCLUSIONS AND TAKEAWAYS

Does the GI scheme pose risks to the diversity of the ecosystem? By looking at the case of coffee production in Colombia, , this paper highlights that for forest ecosystems, such a risk exists. Without Café de Colombia's GI recognition, deforestation would have been about 0.2 percentage points lower on average, indeed. To preserve local ecosystem services (i.e., forest), while enhancing economic performance, a pre-assessment of the effects of policy intervention is, therefore, required. In the case of GIs, in fact, the acknowledgement of a product will enhance product reputation and competitiveness, but it could be at the expense of local ecosystems. Policy strategies belonging to different policy areas of interventions (i.e., agrifood, forest management and economic development) should be evaluated complementarily to obtain a comprehensive framework of the effects and

design a policy mix capable of supporting sustainable development. In the case of Colombia, the socio-economic development of rural and indigenous communities should be promoted through a sustainable forest management approach capable of guaranteeing the preservation of primary and old-growth forests. Territorial-based interventions, such as the GI scheme, should be integrated into a local development strategy that can blend economic performance with natural resources conservation. This synergy may enhance local expertise, converting into a strategic asset for sustainable development.

Our analysis needs, however, to be hedged with some caveats, especially due to data limitations. A better harmonised database at the sub-national level for all the regions of the South American countries could help to improve the level of detail of the analysis. At the same time, more exhaustive outcomes accounting for environmental sustainability (e.g., emissions and water use for coffee production) could help to provide a more comprehensive assessment of the scheme. Despite these limitations, our analysis offers new evidence to properly assess the environmental sustainability of the GI scheme. To our future agenda, we left investigating the linkages explored in this study in the case of other GI Cafès (*i.e.*, *Café de Valdesia* in the Dominican Republic or *Café Antigua* in Guatemala).

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APPENDIX

Table A1. Variables' definitions.

Variable name	Definition	Source
Agricultural area	Share of agricultural (farming and livestock) area over total land area.	FAOSTAT
Population density	Total population over land area.	FAOSTAT
People leaving in rural areas	Share of rural people over total population.	FAOSTAT
Trade openness	Sum of import and export as share of total GDP.	WDI
Cereal yield	Kilograms per hectare of harvested land.	FAOSTAT
Temperature change	Mean monthly temperature anomalies with respect of a baseline climatology corresponding to the period 1951-1980.	FAOSTAT
GDP per capita	Gross domestic product per capita at 2015 constant US$.	WDI
House of freedom index	Sum of the two variables of civil liberties and political rights rescaled from 1 to 10 (where 1 is the lowest institutional quality level and 10 the highest).	Authors' elaboration on Freedom House data
Agricultural trade openness	Ratio between the value of agricultural exports and imports.	Authors' elaboration on FAOSTAT data
Deforestation	Deforestation rate, calculated on total forest (natural and planted forest) for the reconstructed data and on the sum of tree and mangroves cover for CCI-LC data.	Authors' elaboration on FAOSTAT data

Note: FAOSTAT (source: FAO, 2022a); Freedom House (source: Freedom House, 2022); WDI (source: WB, 2022).

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Farmers, experts and students' subjective probability distributions on methane emission reductions in livestock farming: An experimental comparison across elicitation methods

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Abstract. Subjective probabilities are important determinants of economic choice behaviour, and their elicitation is not trivial. Different methods are available in the literature. This paper compares three of them using an economic experiment with farmers, other experts (animal nutrition and production scientists, vets, as well as animal feed, dairy, and meat company representatives), and agricultural students: the frequency method (FM), the interval method (IM), and the quadratic scoring rule method (QSR). These methods vary in the degree of complexity and saliency of the incentive scheme. Elicited subjective probability distributions refer to methane emissions reductions that can be achieved by changing animal diets in livestock farming. The study investigates whether these methods produce consistent results across methods and participant groups. Subjective probability distributions do not significantly differ across methods and participant groups. Overall, these results support that the use of less complex methods such as the FM and IM may be preferable.

Keywords: subjective probability distributions, quadratic scoring rule, frequency method, interval method, methane emission reductions.

INTRODUCTION

Subjective beliefs help in understanding economic agents' behaviour, particularly in contexts characterised by risk and uncertainty (Manski, 2004; 2018), and the agri-food sector is a fitting example (Cerroni and Rippo, 2023). Eliciting stakeholders' beliefs along the agri-food supply chain is essential to disentangle the role these beliefs play in their decision-making processes

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(Hardaker and Lien, 2010). There is a vast literature showing that farmers' beliefs are correlated with farmers' decisions in different contexts: contract farming (e.g., Cerroni, 2020; Cerroni et al., 2023), insurance uptake (e.g., Arata et al., 2023; Čop et al., 2023), risk management (e.g., Meraner and Finger, 2014; van Winsen et al., 2014), technology adoption (e.g., Purvis et al., 1995; Tjernström et al., 2021), and adoption of sustainability practices (e.g., Trujillo-Barrera et al., 2016; Dessart et al., 2019). Therefore, knowing farmers' beliefs can help policymakers designing information-based interventions that create awareness in the farming community and facilitate a shift towards production patterns that maximize societal welfare (Manski, 2018; Cerroni and Rippo, 2023).

However, eliciting beliefs is not a trivial task. A wide array of methods has been used in the literature, and there is no consensus on the methods that provide the most reliable estimates in mainstream economics (e.g., Trautmann and Van de Kuilen, 2015; Charness et al., 2021). The literature eliciting beliefs in agricultural economics, and more specifically farmers' and experts' beliefs, is limited and very few elicitation methods have been employed to retrieve expectations (Cerroni and Rippo, 2023).

This paper contributes to this literature by comparing farmers' and experts' beliefs elicited via three different methods, the frequency method (FM) (Hurley and Shogren, 2005), the interval method (IM) (Dufwenberg and Gneezy, 2000), and the quadratic scoring rule (QSR) (Brier, 1950) using a framed field experiment (Harrison and List, 2004). A similar exercise has been proposed on farmers' risk preferences by Reynaud and Couture (2012).

Most attempts to elicit farmers' beliefs use Likert scales that elicit qualitative judgments regarding the probability and/or the magnitude of an event (e.g., Meraner et al., 2019; Feyisa et al., 2023). Despite the Likert scales requiring a low cognitive effort from participants, qualitative judgments cannot be incorporated into economic models of decision-making under risk and uncertainty like the subjective expected utility model (SEUT, Savage, 1954). More sophisticated methods can be used to retrieve farmers' beliefs expressed in a probabilistic fashion. These methods can be paired with the use of monetary incentives (see Cerroni et al., 2023 for a review), and, if properly designed, they allow eliciting subjective probability distributions that can be incorporated in standard models of decision making under uncertainty (e.g., Manski 2004; Cerroni et al., 2012). The literature on the elicitation of farmers' subjective probability distributions is relatively limited, especially regarding direct comparison of different incentivised methods (Cerroni and Rippo, 2023).

Several incentive-compatible methods can elicit truthful subjective probability distributions. Some studies have explored whether different elicitation methods produce different subjective probability distributions (Trautmann and van de Kuilen, 2015), and we are not aware of any study that has compared farmers' subjective probability distributions elicited via different incentivized and incentive-compatible mechanisms while linking potential differences to complexity and saliency of the incentive scheme. Complexity refers to the cognitive cost of the elicitation mechanism for participants (Charness et al., 2021). Saliency of the incentive scheme refer to the potential influence that experimental payoffs have on subjects' actions in the experiment (Charness et al., 2016; Kleinlercher and Stöckl, 2017). This study aims to fill this methodological gap by specifically comparing the FM (Hurley and Shogren, 2005), IM (Dufwenberg and Gneezy, 2000), and QSR (Brier, 1950). QSR has been already used to elicit farmers' subjective probabilities distributions in the literature (e.g., Cerroni, 2020; Cerroni et al., 2023; Čop et al., 2023). While the FM and IM were used as well (e.g., Menapace et al., 2013; Čop et al., 2023), these methods were never paired with a proper monetary incentive scheme. The FM asks participants to report how frequently different outcomes of a random variable occur. If the reported frequency matches exactly the empirical frequency (known a priori), participants receive a fixed prize x. The IM is equivalent to the FM, except that, in the IM participants are paid a fixed prize x if the reported frequency approximately matches the empirical frequency. This implies that the saliency of pay-off is higher in the IM than in the FM. According to Charness et al. (2021) FM and IM are less complex than QSR.

In particular, our study focuses on farmers and other experts' beliefs about the potential impact of adopting a new agricultural practice to improve the sustainability of food production. Specifically, it elicits dairy farmers and other experts' beliefs about the methane reductions that can be achieved when introducing specific feed additives (i.e., essential oils) to bovine diets. Other experts involved in our study are animal nutrition and production scientists, vets, as well as animal feed, dairy, and meat company representatives. We also included a group of postgraduate agricultural students (i.e. master-level), both as future sector participants and to contribute to the ongoing debate on the use of student proxies in experiments. Including agricultural students provides an additional test of whether farmer and agricultural students behaviour are consistent in economic experiments (e.g., Grüner et al., 2022; Höhler et al., 2024). Some evidence finds that students and farmers can behave similarly in generic risk tasks (e.g., Grüner et al., 2022), whereas other work warns that lack of domain expertise may lead to divergent responses (e.g., Höhler et al., 2024). Students offer practical advantages for experiments due to their accessibility and learning capacity (Grüner, 2022), but their differences from farmers in age, income, and sector-specific experience may limit how well their responses generalize to the farming population (e.g, Belot et al., 2015). Testing whether student-elicited distributions align with those of practitioners therefore provides valuable evidence on the external validity of experimental results in the agricultural context.

The emphasis on zootechnical feed additives, specifically essential oils, and their impact on reducing methane emissions from livestock production stems from the fact that livestock contributes 14.5% of the total greenhouse gas emissions (GHGEs) from anthropogenic activities (FAO, 2017). Most livestock-related methane emissions are due to enteric fermentation, and the use of essential oils in animal diets can help reduce the sector's carbon footprint (Hristov et al., 2013; Honan et al., 2021). This aligns with EU policies, including the EU Green Deal, the Farm-to-Fork strategy, and the planned revision of the Industrial Emission Directive, which are pushing livestock farmers to lower their carbon footprint. Consequently, farmers are encouraged to adopt innovations that support this goal (Block et al., 2024). The introduction of feed additives such as essential oils is a readily available and cost-effective option to reduce GHGEs at the farm level (Belanche et al., 2020).

In our experiment, each participant provides a subjective probability distribution three times, each time facing a different elicitation mechanism. The order of exposure is randomized. Results show that farmers and other experts' subjective probability distributions do not differ across methods, suggesting that it is preferable to implement simpler methods over complex ones. Farmers, other experts, and students' subjective probability distributions are similar.

This paper is structured as follows: we start with a review of the elicitation of beliefs in the agricultural sector and a description of the three methods employed in this study. Next, we present the empirical application, describe our sample, the experimental design, and the main findings. Finally, we discuss the implications of these findings.

1. LITERATURE REVIEW

1.1. Elicitation of farmers' subjective probability distributions

Farmers' probabilistic beliefs can be elicited using many different approaches. Most studies elicit probabilistic qualitative judgments about the occurrence of given events using Likert scales. Among others, events refer to climatic adverse events, loss in production or income, and efficacy of an innovative risk-reducing technology or insurance product in reducing production or income losses (see Meraner et al., 2019; Feyisa et al., 2023; Villacis et al., 2023). A typical question would be asking how likely an x% loss in production due to climatic events is on a five-point scale from 1 (very unlikely) to 5 (very likely). Probabilistic qualitative judgments are relatively easy to elicit as they require a relatively low design effort from a researcher's perspective and a relatively low cognitive effort from a participant's perspective (e.g., Delavande et al., 2011). However, these strengths are counterbalanced by some limitations. Likert scales are not incentive-compatible, meaning that they do not induce respondents to truthfully reveal their beliefs. In addition, probabilistic qualitative judgments do not facilitate inter- and intra-personal comparisons (e.g. Manski, 2004). Finally, they cannot be incorporated into decision making models of decision making under risk and uncertainty (e.g. Cerroni et al., 2012).

A useful way to circumvent some of these disadvantages is the use of direct elicitation methods (or direct introspection). Participants are directly asked to state the probability of an event to occur. If several direct questions are asked about different states of the world, it is possible to map the entire probability distribution of an outcome variable. This approach has been widely used to elicit farmers' subjective probability in the literature in both developing and developed countries (see Hardaker and Lien, 2010; Cerroni, 2020; Cerroni and Rippo, 2023 for reviews). Direct methods are generally paired with the use of visual aids that facilitate farmers' understanding of the elicitation task. An example would be asking farmers to allocate a given number of tokens (generally 100) among different states of the world that may characterize a given outcome variable, suggesting that each token is equivalent to a probability point. Čop et al. (2023) and Fezzi et al. (2021) used this approach to elicit farmers' subjective probability distributions regarding farm income losses in Croatia and regarding loss in production due to extreme climatic events in Italy. Direct methods are widely used to elicit subjective probability distributions in developing countries (Delavande et al., 2011; Cerroni and Rippo, 2023). While direct introspection is relatively straightforward to implement for researchers, it might be cognitively demanding and challenging for respondents who are not always able and willing to express the likelihood of events in a probabilistic way (Manski, 2004). New web interfaces were recently created to facilitate farmers' understanding of direct elicitation methods (see Crosetto and de Haan, 2023). Direct methods are not generally incentive-compatible; hence, they do not overcome the issue of the potential of misreported probabilities (Trautmann and van de Kuilen, 2015; Cerroni, 2020; Charness et al., 2021).

To overcome the latter issue and elicit truthful beliefs, it is possible to use indirect methods. If associated with a proper incentive scheme, these methods are incentive compatible. These methods ask respondents to make choices between lotteries and allow retrieving subjective probabilities distributions based on respondents' gambling behaviour. For a comprehensive review of these methods, we refer to Cerroni and Rippo (2023). To date, only a very few studies have used these methods to elicit farmer's subjective probability distributions. All these studies have used proper scoring rules. Linear scoring rules have been used by Grisley and Kellong (1983) and Smith and Mandac (1995) in developing countries. Quadratic scoring rules have been used by Cerroni (2020) in Scotland, Cerroni et al. (2023) in Zimbabwe, and Čop et al. (2023) in Croatia. These methods are not free from criticism. A recent study by Danz et al. (2022) argued that individuals' actual behaviour in response to incentives may lead respondents to deviate from truth-telling when eliciting beliefs.

1.2. Comparing methods for eliciting subjective probabilities distributions

Reliable subjective probability distributions are often needed in economic modelling to explain or predict human behaviour. Hence, it is essential to have reliable measures of individuals' subjective beliefs. Several methods are available and choosing the right one for eliciting truthful beliefs is a relevant issue (Charness et al., 2021). The reliability of elicited subjective probability distributions is contingent upon the methodology employed and the participants' comprehension of it.

Charness et al. (2021) ranked the methods available to elicit beliefs according to a scale based on complexity, which is the subjective burden a rule places on a decision-maker (Oprea, 2020). In our study, complexity pertains to the extent of the understanding required to generate utility-maximising belief reports. Some methods, such as the FM and the IM, have a low degree of complexity. In contrast, some others, such as QSR, entail a higher degree of complexity and may not be fully understood by participants at the cost of truthful belief reports.

To the best of our knowledge, there is limited research that compares complex methods to simpler ones, and this paper aims to fill the gap. Trautmann and Van de Kuilen (2015) compared subjective probabilities related to whether a participant accepted or rejected an allocation submitted by a proposer in a simple two-player ultimatum game using different elicitation techniques. Specifically, they tested non-incentivised direct method (i.e., direct introspection) against incentivised and incentive compatible methods such as outcome-matching, probability matching, and QSR with or without corrections for deviations from risk neutrality. Internal validity was investigated by testing for additivity and consistency of players' beliefs with their allocation decisions during the game, while external validity was investigated by testing whether elicited beliefs matched objective probability measured at the end of the game (i.e. accuracy). Results suggest that incentivised and incentive-compatible methods predict better respondents' behaviour during the game than non-incentivised introspection without necessarily having better performances in terms of additivity and accuracy. Schlag et al. (2015) and Charness et al. (2021) discuss the strengths and limitations of different elicitation mechanisms and conclude that more research in this direction is needed. For a comprehensive discussion of the most suitable methods to elicit subjective probability distributions for agricultural research, which particularly focuses on developing countries, we suggest reading Cerroni and Rippo (2023). We contribute to this literature by comparing three subjective probability distribution methods that differ in terms of complexity, and saliency of the incentive scheme.

1.3. Frequency method (FM), Interval method (IM), and Quadratic scoring rules (QSR)

The FM is among the least complex methods. Participants are asked to guess the empirical frequency of a random variable, either when the random variable has two possible outcomes (Hurley and Shogren, 2005) or multiple ones (Schlag and Tremewan, 2021). In both cases, participants are rewarded with a fixed prize x if and only if their reported frequencies match exactly the empirical frequencies. This rewarding mechanism can be applied either when empirical frequencies are observable or not yet observable. In the latter case, a few options to match unobservable frequencies would be by asking experts about it, or by using forecasts based on historical data. The main advantage of the method is that it is very easy to implement and easy to understand, in fact, it does not require any mathematical calculations, and natural frequencies are processed better by individuals than other formats (e.g., numbers, percentages) (Schlag and Tremewan, 2021). These characteristics (i.e., better understanding, fast responding, and less likelihood of choosing focal points) make the frequency method FM theoretically robust to deviations from risk neutrality and therefore more likely to be empirically incentive compatible (Schlag and Tremewan, 2021). Nevertheless, when faced with situations where there are many possible outcomes and unfamiliar topics, people may feel that their chances of achieving a reward are low because they must make correct predictions for each potential outcome. As a result, they may tend to misreport their beliefs, as they perceive the likelihood of being rewarded is tied to accurate predictions.

This major disadvantage of the FM can be alleviated by the IM, which is *de facto* a variation of the latter. It is still ranked as a simple method. Yet, it mitigates the low likelihood of being rewarded by allowing participants to guess correctly when their reported frequencies are approximately equal to the underlying ones. The primary challenge is in establishing an appropriate margin of error to not incentivize under- and over-reporting. While this approach significantly reduces complexity by retaining similar characteristics to the previous method, the literature reflects a scarcity of applications utilising the IM (e.g., Dufwenberg and Gneezy, 2000; Charness and Dufwenberg, 2006). A similar approach is eliciting beliefs using most-likely intervals (MLI) (Schlag and van der Weele, 2015). The interval method aims at providing a probability distribution within a certain percentage range of the underlying distribution, while MLI consists of specifying an interval that contains the most likely outcomes. This specification changes how the reward is calculated. While in the IM, participants are rewarded based on how well their entire probability distribution aligns with the underlying probability distribution within a certain margin of error, in the MLI participants are typically rewarded based on the width of the interval they provide, with narrower intervals being rewarded more favourably.

Moving to more complex methods, QSR is a frequently used incentive-compatible method to elicit beliefs, which first appeared in Brier (1950). It is a specification of the family of the proper scoring rules, which assign a numerical score to the individuals' probabilistic predictions regarding future outcomes, rewarding them for the accuracy of their reports, while having severe punishments if they miss the true allocation in that interval (Harrison et al., 2017). The payoff score is defined as

$$S = (2 \times r_k) - \sum_{i=1,..,K} (r_i)^2 \quad \text{(Eq .1)}$$

where K corresponds to the number of intervals, $r_k$are the reports of the likelihood that the event (i.e., methane reduction) falls in the interval $\mathrm{k} = 1, \ldots, \mathrm{K}$. Each $r_k \geq 0, \forall k$ and $\sum_{i=1,..,K} (r_i) = 1$ Matheson and Winkler, 1976). The method is incentive-compatible under the assumption of risk neutrality and expected utility maximisation (Kadane and Wrinkler, 1988; Schlag and van der Weele, 2015; Winkler and Murphy, 1970). Under these assumptions, an individual who is sufficiently risk averse would be drawn to report a probability distribution close to a uniform one, or report probabilities equal to 50% in the case of binary events (Andersen et al., 2014). It is good practice to accompany the task with measurements of individuals' risk attitudes, to control for the initial assumption of risk neutrality (Andersen et al., 2014; Offerman et al., 2009). However, Harrison et al. (2017) demonstrated that having a large enough set of intervals (i.e. states of the world *k*) allows a reliable elicitation of subjective probability distributions without undertaking calibration for risk attitudes. QSR is classified as a complex elicitation method by Charness et al. (2021). Participants may have difficulties in understanding the multiple layering of the QSR, which, accompanied by a substantial aversion to complexity (Oprea, 2020), might impair truthful reports.

2. EMPIRICAL APPLICATION

The Global Methane Pledge at a global level, the EU Green Deal, the Farm to Fork Strategy, and the EU Methane Strategy at a European level, are among the variety of initiatives currently underway to mitigate the significant climate impact of methane (CH_4) from one of its predominant sources, that is the agricultural sector. Mitigating methane emissions would allow for short-term effects on the climate, due to the evidence that CH_4 has about 82 times the climate-changing impact of carbon dioxide (CO_2) over 20 years (Smith et al., 2021). In the agricultural sector, animal production is a significant contributor, particularly through ruminants' enteric fermentation, which alone accounted for 69% of CH_4 emissions within the sector at the European level (EEA, 2020).

There is a vast range of mitigation technologies available in agriculture, such as production intensification, dietary and rumen manipulation, and selection of low-CH_4-producing animals (Beauchemin et al., 2022). Some of these may be available at low cost and bring additional benefits for farms, but barriers such as insufficient knowledge and expertise and lack of financial incentives (Long et al., 2016) need to be addressed since their uptake is uneven across the European Union.

Different methane-reducing technologies have different potential for mitigation (Arndt et al., 2022). In our empirical application, we consider the wide class of CH_4-reducing essential oils that can be categorised as zootechnical feed additives for animal diets. Including essential oils in bovine feed is a practice that is effective in the short term, and studies suggest it is leading to a positive impact on feed efficiency and hence milk production (Wells, 2024). Essential oils, derived through a steam distillation process of various parts of plant species, act as rumen modifiers and can cause an inhibition of the methanogenesis process in ruminants (Glasson, 2022). Many studies show that, even though there is a substantial reduction in enteric CH_4, the results are variable (Honan et al., 2021; Hristov et al., 2013). Arndt et al. (2022) built a database reporting the effects of various mitigation strategies, including 115 studies on additives. Feed additives, such as essential oils, have a mean value of the reduction in daily CH_4 emissions of -8.3%, with a 95% confidence interval (-9.8%, -6.8%). The variation depends on several factors such as the environment, the animal's diet and health, and others.

3. METHODS

3.1 Sample characteristics and data collection

The sample consists of 60 individuals, evenly distributed between two groups: 20 dairy farmers from various Italian regions, 10 livestock experts, and 30 master's students from various agri-food faculties.[1] For simplicity, the group of farmers and experts is going to be called the "dairy sector" throughout the paper. The sample was recruited using a snowball sampling method, a non-probabilistic approach where initial participants were asked to refer others who fit the study criteria. Data was gathered during the summer and the autumn of 2023 primarily through one-to-one with farmers and experts or group experimental sessions with students on the Zoom platform.[2] Participants were asked to report their probability on the web interface generated via the software o-Tree (Chen et al., 2016). Ethical clearance was granted by the Ethical Review Board at the University of Trento (Italy).[3]

3.2 Experimental design

In this study, farmers, experts, and students were asked to report their subjective probability distribution regarding the reduction (in percentage value) of enteric methane emissions which could be achieved using essential oils in bovine diets in a dairy farm across three consecutive tasks. Specifically, each participant completed the same task three times, each time under different elicitation methods: FM, IM, and QSR. The only difference among the three tasks was how the monetary reward was attributed. To control for order effects, the order of the task was randomized. Participants were divided into two groups. Specifically, one group was exposed to tasks in the following order: i) FM, ii) IM, and iii) QSR, and the other group as follows: i) QSR, ii) FM, and iii) IM. The FM was always presented before the IM to facilitate the understanding of the IM, which is a variation of the FM.

Before the elicitation of the subjective probability distributions, participants were provided with the following standardised information: i) a description of policy initiatives aiming at reducing methane emissions from the agricultural sector, ii) a description of strategies to reduce methane emissions in dairy farming with a focus on essential oils, and iii) a description of benefit and opportunities of using essential oils. Experimental instructions are available in the Supplementary materials.

Regardless of the elicitation mechanism, participants were informed that the reduction in methane emissions can fall in any percentage value between -6.6% and -10% given the information retrieved from the literature (Arndt et al., 2022). Using the mean and confidence interval reported in Arndt et al. (2022), we approximated an empirical benchmark distribution by fitting a normal distribution, against which participants' subjective probabilities were compared. The normal distribution can be a good approximation because it provides a continuous, two-parameter reference distribution for comparing participants' subjective probabilities without further assumptions. Participants were instructed to allocate 70 tokens across seven predefined intervals each representing a range of methane emission reduction percentages using the interface depicted in Figure 1. These intervals included the following percentages of reduction: (-10%, -9.6%), (-9.5%, -9.1%), (-9%, -8.6%), (-8.5%, -8.1%), (-8%, -7.6%), (-7.5%, -7.1%), and (-7%, -6.6%). They were informed that the number of tokens allocated to each interval should reflect their perceived likelihood of the corresponding methane emission reduction occurring in the future. A higher allocation of tokens to a particular

[1] The 10 experts consulted are: 3 professionals from a public unit for forage resources and livestock production (including a technologist, a technician, and a department head), 2 veterinarians, 2 experts in animal feed development and commercialization, 1 head of a dairy consortium, 1 food processing technologist, and 1 agronomist.

[2] 10 sessions in total (4 participants in session 1, 3 participants in session 2, 3 participants in session 3, 3 participants in session 4, 1 participant in session 5, 6 participants in session 6, 1 participant in session 7, 4 participants in session 8, 4 participants in session 9, 1 participant in session 10). While the procedures and instructions were identical across settings, we acknowledge different settings might have introduced subtle differences, resulting in a minor limitation of the study design.

[3] We did not collect demographic data, as the primary aim was to compare elicitation methods. This was intended to reduce respondent burden and keep participants focused on the tasks.

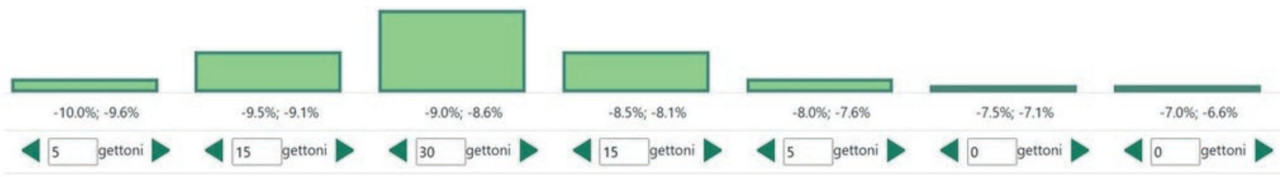

Figure 1. Example of the interface used in the economic experiment.

interval indicates a higher subjective likelihood of that reduction range according to the participant's beliefs.

The experiment was incentivised. Participants did not receive any participation fee, but they could get a reward of up to €25, knowing that, at the end of the session, one of the three tasks would have been randomly extracted and used to determine their final payoff. Each elicitation method has a different incentivisation scheme. The FM pays €25 if and only if the probability distribution matches exactly the empirical distribution, otherwise it pays €0. Matching exactly meant that the number of tokens allocated by the participant perfectly corresponded to the probabilities defined by the empirical distribution. The IM pays €25 if and only if the subjective probability distribution matches the empirical distribution with an error margin equal to 10% in each interval, otherwise it pays €0. The payment scheme of the QSR is completely different as the QSR allows for a more continuous spectrum of payoffs as explained in Eq. 1.

4. RESULTS AND DISCUSSION

4.1 Comparisons across elicitation methods

Figure 2 shows the subjective probability distributions across elicitation methods when the sample is pooled (dairy sector plus students).

We test differences in subjective probability distributions across elicitation methods using the Wilcoxon signed-rank test for paired samples.[4] Results suggest no statistically significant differences across methods when the sample is pooled (dairy sector plus students). Results hold when we estimate a generalized linear model with an underlying binomial distribution for our dependent variable and a logistic link function *a la* Papke and Woolridge (1996) (see Table 1). This modelling approach is particularly well suited when the state space of the dependent variable ranges from 0 to 1 as is the case in our study (e.g. Cerroni et al., 2012). Our dependent variable $p_{i,k}$ is the probability associated with each participant i to each interval k (i.e. state of the world) shown in Figure 2.[5] Our discrete independent variables are associated with the elicitation mechanism: FM_k equals 1 if the probability was elicited using the FM, and IM_k equals 1 if the probability was elicited using the IM. The variable QSR_k is used as a baseline and equals 1 if the probability was elicited using the QSR.[6] Standard errors are clustered at the individual level. The model is specified as follows:

$$P_{i,k} = \alpha + \beta_{FM} FM_{i,k} + \beta_{IM} IM_{i,k} + \varepsilon_{i,k} \qquad \text{(Eq. 2)}$$

These results suggest that different methods elicit equivalent subjective probability distributions. We can conclude that less complex (i.e. cognitively demanding) elicitation methods (FM and IM) are performing equivalently to a complex elicitation method such as the QSR. Subjective probability distributions are stable regardless of the use of completely different incentive schemes (FM and IM vs QSR). In addition, the difference in the saliency of payoffs between FM and IM does not produce any significant effect on the elicited subjective probability distributions. Therefore, we conclude that the use of less cognitively demanding techniques like IM and IF might be a viable approach for the elicitation of subjective probability distributions. We acknowledge that failure to detect differences across methods within subjects may be because subjects tend to confirm their beliefs over time, showing a sort of confirmatory bias (e.g., Rabin and Schrag, 1999; Zappalà, 2023). We evaluated the presence of confirmatory bias by taking advantage of the task randomization. More specifically, we are comparing subjective probability distributions elicited via the FM and the QSR when these were the first methods faced by our participants. This between-subject analysis rules out the presence of confirmatory bias. Results from the Kolmogorov-Smirnov test suggest that there is no difference in subjective probabilities across groups, indicating that subjective probability distributions are similar across methods even when confirmatory bias does

[4] Results from the non-parametric tests are available in Table S4 in the Supplementary materials.

[5] In our study, seven possible states of the world were introduced.

[6] QSR serves as the baseline category, and thus it is not explicitly included as a variable in the equation.

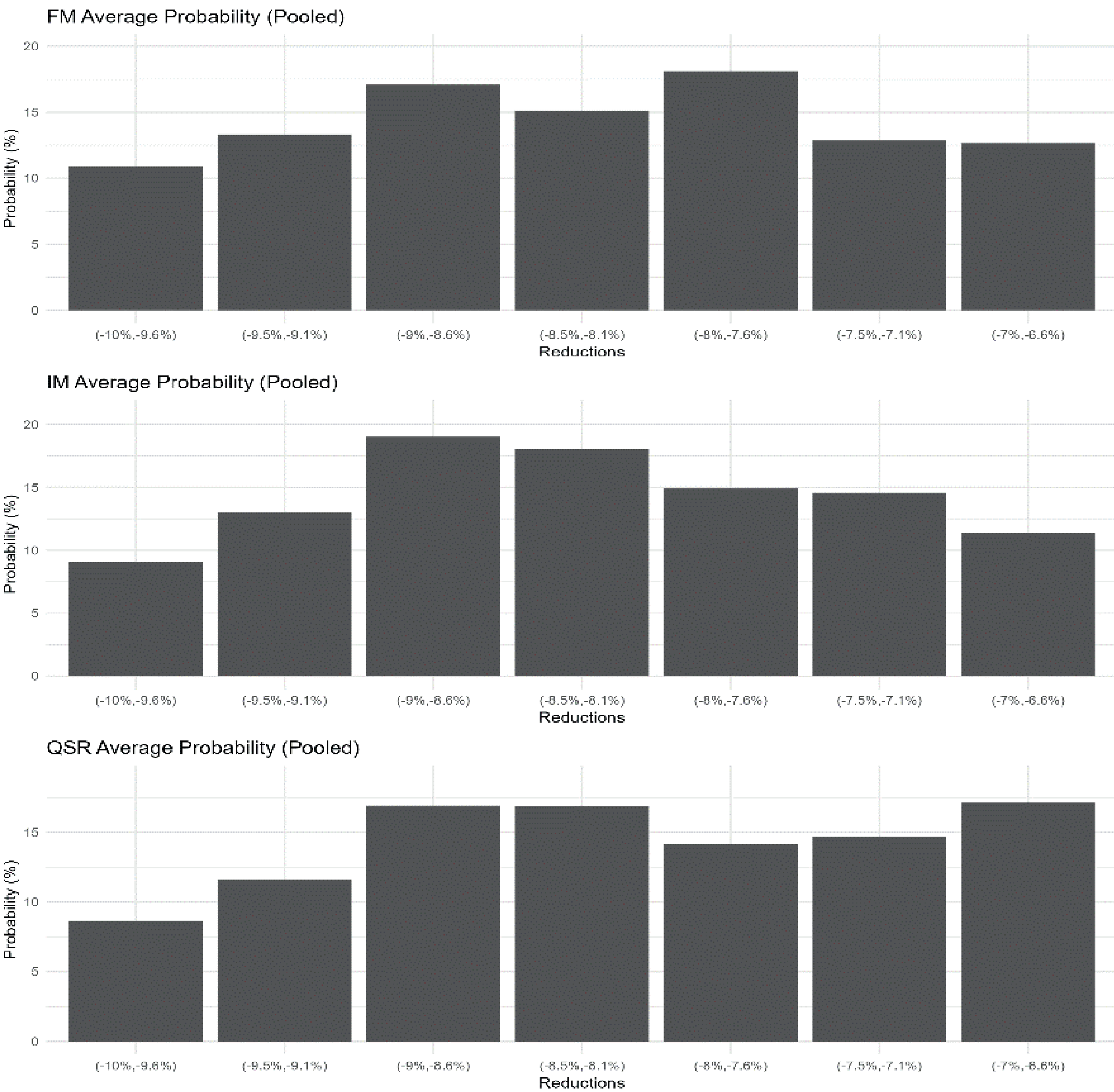

Figure 2. Within-group average subjective probability distributions per task.

not play any role.[7] Results hold when estimating generalised linear models (Eq. 3) (see Table 2), as above. In this case FM_first_k equals 1 if the probability was elicited using the FM as a first task, and QSR_first_k equals 1 if the probability was elicited using the QSR as the first task. The latter is used as a baseline.

$$P_{i,k} = \alpha + \beta_{FM_{first_k}} FM_{first_k} + \varepsilon_{i,k} \quad \text{(Eq. 3)}$$

4.2 Comparisons across groups

Figure 3 and Figure 4 show subjective probability distributions across elicitation methods for the dairy sector (farmers plus experts) and students, respectively. These provide insights into probabilistic beliefs of dairy farmers, experts, and students across different outcomes. It is

[7] Results from the non-parametric tests are available in the Supplementary materials in Table S5.

Table 1. Effect of elicitation methods on subjective probabilities (for each interval).

Dep. Var.: $(P_{i,k})$	1	2	3	4	5	6	7
FM	0.255	0.157	0.012	-0.130	0.294	0.156	-0.355
	(0.619)	(0.554)	(0.486)	(0.499)	(0.500)	(0.531)	(0.518)
IM	0.053	0.130	0.144	0.083	0.061	-0.011	-0.477
	(0.643)	(0.557)	(0.476)	(0.481)	(0.518)	(0.516)	(0.532)
Constant	-2.358***	-2.031***	-1.592***	-1.596***	-1.803***	-1.757***	-1.576***
	(0.459)	(0.403)	(0.344)	(0.345)	(0.370)	(0.364)	(0.343)
Observations	180	180	180	180	180	180	180
LL	-33.676	-28.225	-39.625	-34.450	-37.143	-36.065	-51.568

Note: *p<0.1; **p<0.05; ***p<0.01.
LL stands for Log-Likelihood.
Robust standard error in brackets.

Table 2. Effect of confirmatory bias on subjective probabilities (for each interval).

Dep. Var.: $(P_{i,k})$	1	2	3	4	5	6	7
FM_first	-0.308	-0.589	0.313	0.459	0.112	0.056	-0.286
	(0.509)	(0.451)	(0.406)	(0.423)	(0.418)	(0.437)	(0.435)
Constant	-2.080***	-1.622***	-1.729***	-1.893***	-1.746***	-1.844***	-1.678***
	(0.368)	(0.311)	(0.323)	(0.342)	(0.325)	(0.336)	(0.317)
Observations	180	180	180	180	180	180	180
LL	-33.843	-27.684	-39.304	-34.388	-37.762	-36.414	-51.831

Note: *p<0.1; **p<0.05; ***p<0.01.
LL stand for Log-Likelihood.
Robust standard error in brackets.

noticeable that, overall, the probability mass is concentrated in the three central intervals, suggesting that these groups generally expect moderate to average outcomes of future reduction in methane emissions in dairy farming. This is a typical stance when evidence or confidence in the topic is neither very strong nor very weak. However, it is interesting to note that students assign a moderate probability (around 10%) to the scenario with the lowest reduction in methane emissions. This probability rises to approximately 15% and 20% when assessed by farmers and experts, indicating a degree of scepticism about the efficacy of essential oils in reducing methane emissions, and signalling a need for further research on the topic.

Differences in subjective probability distributions across groups (dairy sector vs students) were assessed using the Kolmogorov-Smirnov test for the between-subjects comparison.[8] Results indicate that there are no significant differences in token allocation across groups. Equivalent results are obtained when we estimate a generalized linear model (binomial distribution and logistic link function as above) where the dependent variable $p_{i,k}$ is the probability associated with each participant i to each interval k (i.e., state of the world) shown in Figure 1 (see Table 3). Our discrete independent variable is $Dairy\_Sector_k$ that equals 1 if the probability was elicited from a farmer or an expert (otherwise = 0), while students were used as a baseline. Standard errors are clustered at the individual level. The model is specified as follows:

$$P_{i,k} = \alpha + \beta_{Dairy\_Sector} Dairy\_Sector_{i,k} + \varepsilon_{i,k} \quad \text{(Eq. 4)}$$

These results may be driven by the fact that agricultural students are very aware of climate change mitigation strategies that can be implemented at the farm level and hence they are as knowledgeable and aware as farmers and experts regarding the specific topic under investigation. On the other hand, it might be possible that, given the novelty of the topic and the high degree

[8] Results from the non-parametric tests are available in Table S6 in the Supplementary materials.

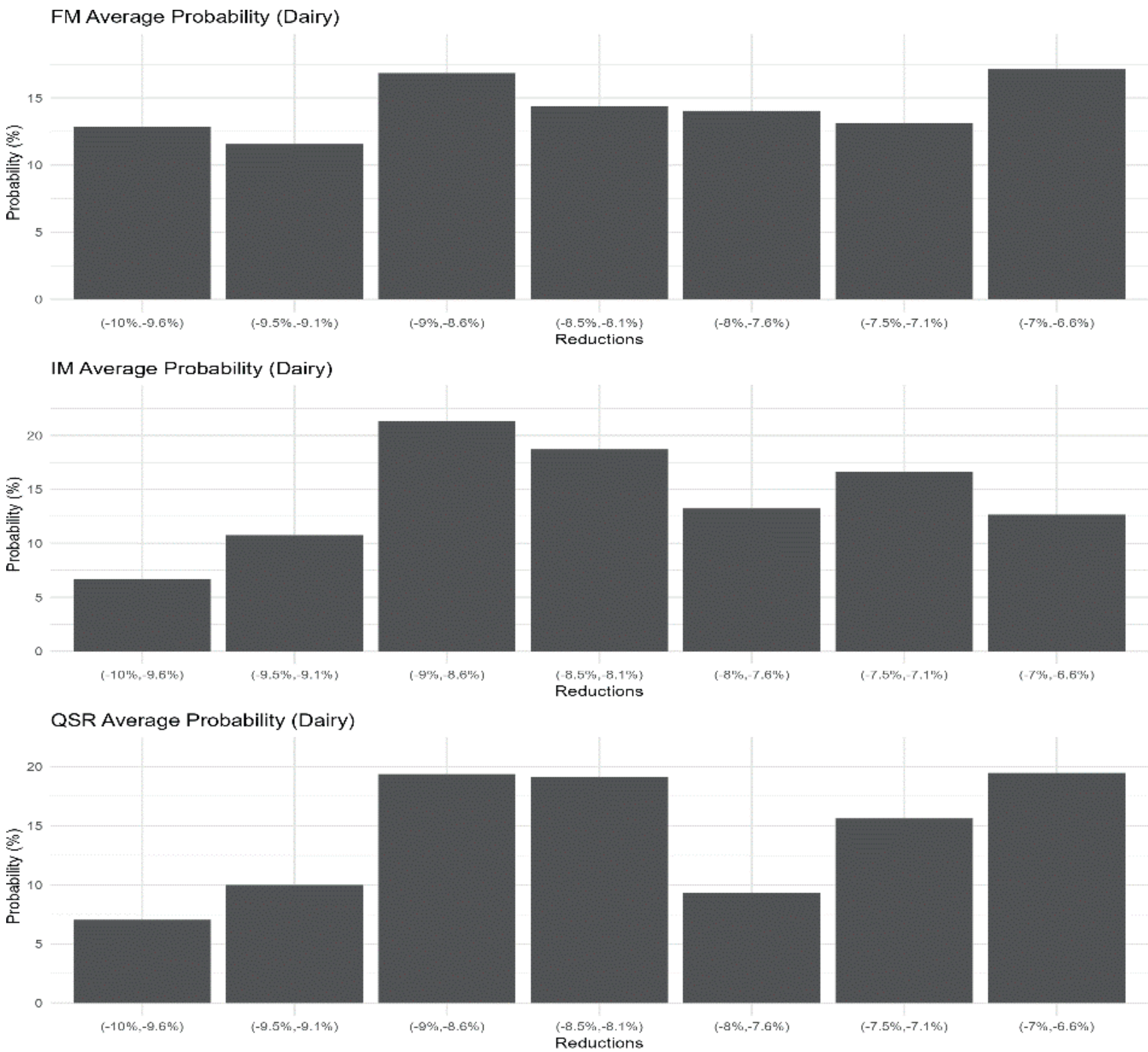

Figure 3. Dairy sector's average subjective probability distributions per task.

of uncertainty related to the efficacy of introducing feed additives to reduce methane emissions from livestock production, both students, farmers and experts have little knowledge and awareness of the problem.

5. CONCLUSION

This study compares three indirect methods – FM, IM, and QSR – to elicit farmers', other experts' and students' subjective probability distributions about a specific agricultural outcome using a framed economic experiment. The outcome variable considered is the methane emission reduction which can be achieved by the introduction of zootechnical feed additives to bovine diets. Feed additives, more specifically essential oils, are readily available and cost-effective solutions to reduce the carbon footprint of animal production (Belanche et al., 2020). As the EU is designing policies that require farmers to reduce their GHGEs (e.g., the Green Deal, the Farm-to-fork Strategy, and the Industrial Emission Directive), understanding farmers' and other stakeholders' beliefs regarding the effectiveness of GHGE-reducing innovations can help anticipate adoption behaviour.

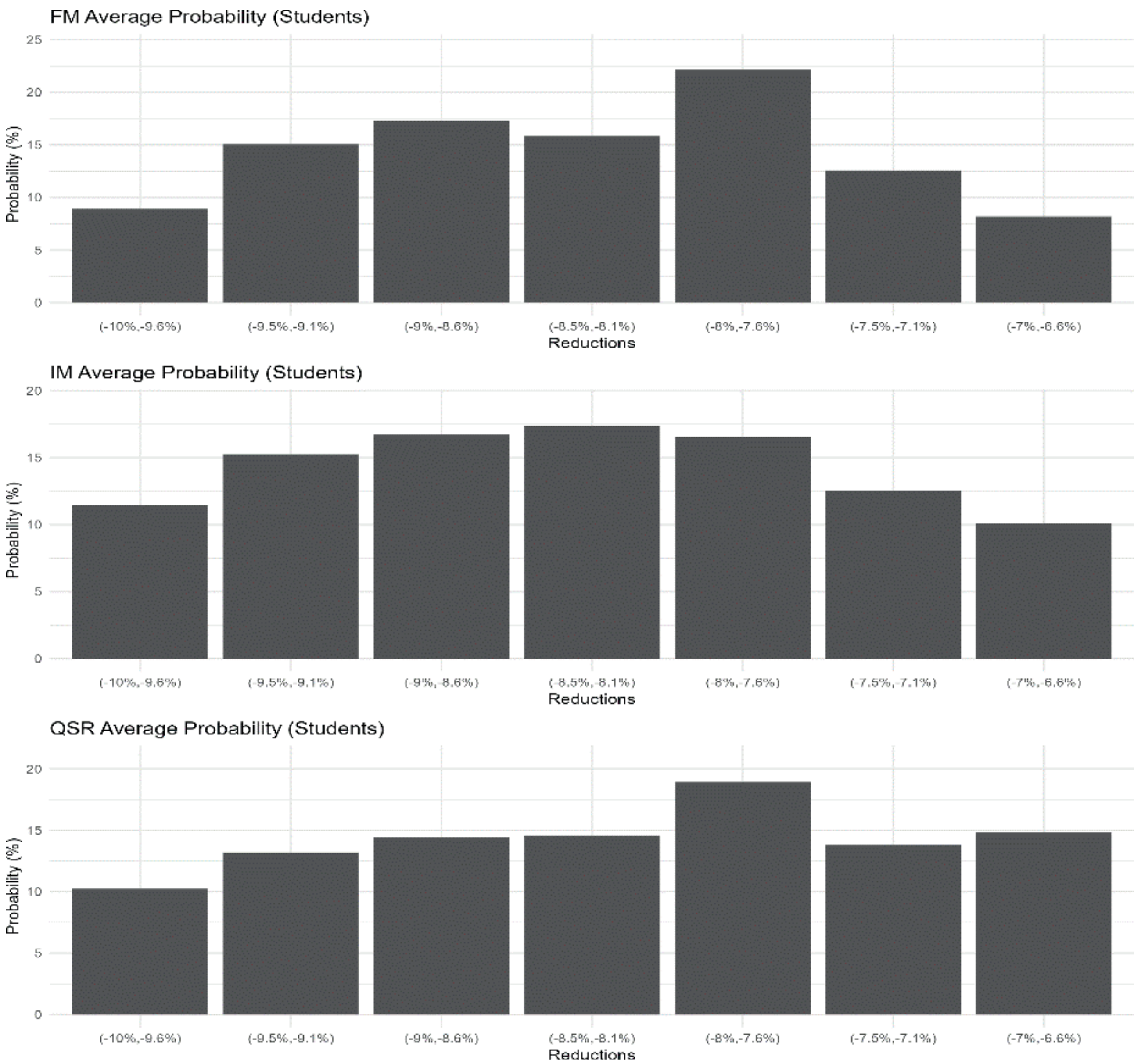

Figure 4. Students' average subjective probability distributions per task.

The three elicitation methods differ in two main features: the level of complexity (i.e., the cognitive cost of the elicitation mechanism for participants) and the saliency of the incentive scheme (i.e., the ability of the incentive scheme to alter behavior). Following Charness et al. (2021), we classify the QSR as complex, and the FM and IM as simple. Similarly, the IM and the QSR have more salient incentive schemes than the FM. The QSR has been recently used to elicit farmers' subjective probability distributions using proper incentive schemes (Cerroni et al., 2020; Cerroni et al., 2023; Čop et al., 2023), while the FM and IM have been applied without incentivization in earlier studies (e.g., Menapace et al., 2013; Čop et al., 2023).

In our study, each participant was asked to provide a subjective probability distribution when exposed to these three different methods. The order of the tasks was randomized to mitigate order effects. Our sample consists of farmers, other experts (i.e., animal nutrition and production scientists, veterinaries as well as feed, dairy, and meat company representatives), and postgraduate agricultural students. Our results indicate that, on aver-

Table 3. Effect of being a farmer or expert (dairy sector) on subjective probabilities (for each interval).

Dep. Var.: ($P_{i,k}$)	1	2	3	4	5	6	7
Dairy Sector	-0.157	-0.339	0.210	0.106	-0.537	0.179	0.461
	(0.509)	(0.453)	(0.392)	(0.400)	(0.419)	(0.430)	(0.441)
Constant	-2.175***	-1.775***	-1.648***	-1.663***	-1.436***	-1.904***	-2.088***
	(0.348)	(0.299)	(0.286)	(0.288)	(0.268)	(0.314)	(0.336)
Observations	180	180	180	180	180	180	180
LL	-33.884	-27.904	-39.335	-34.399	-37.208	-36.064	-51.289

Note: *p<0.1; **p<0.05; ***p<0.01.
LL stands for Log-Likelihood.
Robust standard error in brackets.

age, the subjective probability distributions elicited using the three methods do not differ significantly, implying a consistent elicitation through tasks. This leads us to suggest that less complex elicitation methods (FM and IM) may be preferable when feasible in experimental studies. No difference has been highlighted between groups. In fact, subjective probability distributions were elicited consistently across the dairy sector (i.e., farmers and experts), and agricultural students. Dairy farmers, experts, and students generally expect moderate to average reductions in methane emissions from essential oils. However, while students see a moderate chance of achieving the lowest methane reduction possible, dairy farmers and experts are more sceptical, highlighting the need for further research on the efficacy of essential oils.

Little variation across groups may suggest that agricultural students are as knowledgeable as experts and farmers about reductions in methane emission that can be achieved using essential oils. Nevertheless, an alternative explanation is that, given the high degree of uncertainty surrounding the outcome variable, both the dairy sector (farmers and experts) and students form similar uncertain beliefs.

In this regard, as the exercise focused on a highly uncertain outcome, that is methane reductions achievable through the use of essential oils, about which even experts hold wide-ranging opinions, it remains an open question whether method performance would remain equivalent when eliciting beliefs about more familiar or less ambiguous outcomes (for example, crop yields or weather events).

Although our primary objective was methodological (comparing FM, IM, and QSR) rather than producing broadly representative estimates, the modest sample size may still cast doubt on external validity. To reinforce and extend these findings, future research should replicate the experiment with larger, stratified samples spanning different regions, crop systems, and farm structures.

In practical terms, our results offer clear guidance for researchers in agricultural and environmental economics: simpler, low-burden elicitation methods can be as effective as complex scoring rules, easing implementation without compromising data quality. To build on this work, future research should (1) replicate the comparison across different domains of uncertainty, (2) employ larger, stratified samples to bolster statistical power, and (3) explore alternative interfaces or incentive schemes. Such extensions will help sharpen our understanding of how methodological choices shape the elicitation of subjective probabilities in decision-making under uncertainty.

While this study is primarily methodological, understanding how farmers and other stakeholders form beliefs may indirectly support the design of information-based interventions. For instance, clearer communication (e.g., informational workshops, webinars or farmer-friendly explanatory materials) or demonstration activities (such as on-farm trials where farmers can directly observe outcomes) could help reduce scepticism toward innovations such as feed additives. Nevertheless, such applications fall beyond the scope of this study and would require further targeted research.

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Addressing needs for the diffusion of digital greenhouse farming. Insights from Living Labs in the Mediterranean basin

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Abstract. Agriculture 4.0 represents a huge opportunity for the transformation of agrifood sectors. However, its adoption (and diffusion) in real-world farming contexts faces multiple challenges. This study focuses on greenhouse farming within the Mediterranean basin. It aims to assess the needs of actors involved in the uptake of Agriculture 4.0 and define enabling conditions to support achieving these needs, focusing on the introduction of an innovative decision support system in real-world greenhouses for tomato production. A qualitative and comparative approach is implemented, using participatory data collection methods with cross-disciplinary experts from four case studies across the Mediterranean Basin. Data are collected through one-to-one open discussions, supported using context and SWOT analyses to stimulate reflection and recall. The findings highlight the need to improve digital literacy among farmers and advisors, build trust through tailored education conditions and mentorship, and support young farmers with financial incentives and training. Market dynamics are relevant as well, pinpointing the need for stronger product images and increasing consumer awareness through certification and labelling. Great interest and technology potential emerges from the possibility to enable (partial) remote work thereby benefiting a work-life balance. Simplifying bureaucratic processes and enhancing policy support for cooperation and farmer unions are also essential for encouraging farmers to adopt digital technology.

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1. INTRODUCTION

Agriculture 4.0, or digital agriculture, is widely recognised as a promising pathway to enhance the sustainability and competitiveness of agri-food systems through data-driven technologies such as the Internet of Things, data analytics and artificial intelligence (Wolfert et al., 2017; Mondejar et al., 2021; Maffezzoli et al., 2022). These technologies are particularly relevant for intensive production systems such as greenhouse farming, where input optimisation and monitoring can generate significant efficiency gains (Maffezzoli et al., 2022). However, a growing body of literature cautions that digital solutions risk limited effectiveness if they are not developed and implemented according to the actual needs of actors directly involved in adoption and diffusion processes (Rose et al., 2021; Klerkx et al., 2019).

Empirical research highlights multiple and interrelated needs shaping the uptake of Agriculture 4.0, ranging from usability and affordability to digital skills, advisory support and enabling policy frameworks (Klerkx et al., 2019; McFadden et al., 2022; Yuan and Sun, 2024). Addressing these needs requires the creation of enabling conditions, understood as the institutional, social and economic settings that allow innovations and policies to operate effectively in practice (Huber-Stearns et al., 2017). From a policy perspective, enabling conditions are increasingly framed in terms of coherence between productivity, environmental sustainability and social objectives, especially within European Union's (EU) agricultural policy debates (Coderoni, 2023; Matthews, 2021).

Despite growing investments in digitalisation, evidence on the impacts of Agriculture 4.0, particularly its social implications, remains contested. While several studies emphasise benefits related to efficiency, working conditions and rural wellbeing (MacPherson et al., 2022; Xu et al., 2024), others highlight risks linked to inequality, uneven access and governance challenges (Carolan, 2024; Klerkx et al., 2019). These contrasting findings indicate that there is a need to understand how and under which conditions digital technologies contribute to sustainability, rather than assuming positive outcomes (Ingram et al., 2022; McGrath et al., 2023).

Recent contributions therefore stress the importance of participatory, territorially embedded approaches to bridge the persistent research–practice gap in agricultural digitalisation (McFadden et al., 2022; Matthews, 2021). However, research explicitly centred on actor[1] needs remains limited, particularly when operationalised through Living Labs (LLs) or comparable real-world innovation settings (Mgendi, 2024; Ogunyiola et al., 2024). Moreover, there is a lack of comparative qualitative studies able to generate analytically generalisable insights across diverse socio-economic and institutional contexts beyond single case studies (Klerkx and Rose, 2020; Maffezzoli et al., 2022).

Against this background, this study aims to assess actor needs and identify enabling conditions for fostering the diffusion of Agriculture 4.0 in Mediterranean greenhouse farming through qualitative, actor-centred research. The analysis focuses on the real-world introduction of an innovative decision support system (DSS) and is framed within a Responsible Research and Innovation (RRI) perspective (Owen et al., 2012; Stilgoe et al., 2013). RRI is operationalised through LLs, which are increasingly recognised as suitable environments for inclusive and context-sensitive innovation processes in agriculture (Eastwood et al., 2019; Campos and Marín-González, 2023).

Empirically, the study draws on cross-disciplinary experts participating in LLs across four Mediterranean case studies, i.e. Almería (Spain), Antalya (Turkey), Monastir (Tunisia) and Tuscany (Italy), selected to reflect both the relevance of greenhouse production and substantial diversity in socio-economic and institutional conditions (Sturiale et al., 2024). The research follows a stepwise approach combining: (i) identification of priority socio-economic issues shaping adoption and diffusion; (ii) elicitation of corresponding priority actor needs; and (iii) definition of enabling conditions to support the fulfilment of these needs.

The article advances the literature in three main ways. First, it contributes to actor-oriented research on Agriculture 4.0 by translating locally prioritised needs into analytically structured enabling conditions, strengthening transferability beyond individual cases (Soriano et al., 2023). Second, it bridges digital agriculture debates with RRI and LLs approaches, showing how participatory processes can reveal social and institutional dimensions often overlooked in technology-centred analyses (Lajoie-O'Malley et al., 2020; MacPherson et al., 2022). Third, by providing a cross-country Medi-

[1] The term actor is used consistently throughout this study (instead of stakeholder) o better reflect the actor-centred nature of this research.

terranean perspective, the study clarifies which challenges are recurrent across contexts and which are territorially specific, thereby supporting more targeted and context-sensitive policy strategies for sustainable digital transitions in agriculture (Bocean, 2024).

2. METHODOLOGY AND DATA

2.1 Analytical framework

Actor needs are the requirements, expectations, and preferences of those who have an interest or stake in a particular project, process, or system, including a wide range of operational, economic, social, and environmental aspects that are deemed critical for ensuring the successful adoption and implementation of innovations. Identifying and addressing key actor needs is essential for aligning project outcomes with the interests and priorities of all involved parties, thereby enhancing the overall effectiveness and sustainability of the initiative (Feng et al., 2024; Littau et al., 2010). These needs respond to issues experienced not only by farmers but also by other actors, such as e.g., advisors, which are generally context-specific and can negatively affect the uptake and widespread use of digital agriculture in rural areas (Dibbern et al., 2024). Research indicates that real-world issues are barriers to Agriculture 4.0 and can create lock-in situations that hinder the achievement of sustainability goals through digital transformation. Especially, these issues can prevent the full adoption and integration of digital technologies in agriculture, thereby limiting the potential benefits in terms of productivity, profitability, and sustainability (da Silveira et al., 2023a, 2023b).

The literature identifies drivers and barriers of Agriculture 4.0 (da Silveira et al., 2021; Dibbern et al., 2024). Drivers include, e.g., the potential for increased productivity, profitability, and viability of farming through the optimisation of resource use, cost reduction, and enhancement of crop yields (Fragomeli et al., 2024). Other drivers encompass education, age, and farm size; for instance, younger and more educated farmers managing larger, capital-intensive enterprises are more likely to adopt Agriculture 4.0 technologies (Kroupová et al., 2024). Barriers include economic constraints, such as the high initial costs and limited access to capital, which can deter adoption, particularly among small and medium-sized farms (Dibbern et al., 2024). Other examples of barriers are the lack of technical literacy and insufficient information about the benefits and profitability of digital agriculture that hinder farmers' willingness to invest in new technologies (Kroupová et al., 2024). Identifying enabling conditions to support the realisation of actors' needs is of particular relevance to improve the sustainability of farming through digital tools, by removing the barriers and then overcoming lock-in situations (da Silveira et al., 2023b).

Enabling conditions include financial support, technological infrastructure, policy frameworks, and capacity-building initiatives that collectively create a conducive environment to harness the potential of digital tools for enhancing farmers' productivity, resource efficiency, and decision-making capabilities. For instance, financial support through subsidies and incentives can reduce the initial cost burden, making these technologies more accessible to smaller farms (Fragomeli et al., 2024). Public or private support to investment in physical assets in rural areas can address inadequate infrastructure, facilitating the effective and widespread use of Agriculture 4.0 technologies (Derakhti et al., 2023). Implementing training programs to enhance technical expertise among farmers can bridge the knowledge gap and ease the integration of digital tools on farm (Wang et al., 2020). Additionally, creating knowledge-sharing initiatives and fostering a culture of innovation can help overcome resistance to change and build social trust in Agriculture 4.0 (Ganeshkumar et al., 2023).

2.2 Research methods and data

This study adopts a qualitative and comparative case study design (Yin, 2014) to identify priority socio-economic issues affecting the diffusion of Agriculture 4.0 in Mediterranean greenhouse farming and to derive corresponding actor needs and enabling conditions. The methodological approach builds on the RRI framework operationalised through LLs, following project-level procedures developed and applied consistently across all case studies (Owen et al., 2012; Campos and Marín-González, 2023; Ehlers et al., 2025).

The case studies are four Mediterranean regions, i.e. Almería (Spain), Antalya (Turkey), Monastir (Tunisia), and Tuscany (Italy), selected to combine sectoral relevance (greenhouse vegetable production) with diversity in socio-economic and institutional conditions (Gong and Tan, 2021; Sovacool, 2011). In each case study, a commercial greenhouse hosted a pilot implementation of a DSS for tomato production, which constituted the concrete innovation context anchoring discussions and activities within LLs. A description of the DSS architecture, functionalities and case-specific implementation features is available in related research and project documentation (Sturiale et al., 2024; Sturiale et al., 2025a, 2025b; Gava et al., 2025).

Data were collected from cross-disciplinary experts involved in the LLs, including representatives of agribusiness (38 in total), knowledge creation and transfer (47), and policy (14). Participants were selected through purposive sampling based on their capacity to provide informed insights into barriers, drivers and enabling factors shaping the adoption and diffusion of digital tools in their territorial context (Patton, 2023; Potters et al., 2022). The composition and governance of LLs, as well as their alignment with the four RRI dimensions (anticipation, reflexivity, inclusion and responsiveness) (Ehlers et al., 2025; Stilgoe et al., 2013) are described in detail in Gava et al. (2025).

Actor engagement was facilitated through one-to-one open discussions aimed at prioritising context-specific issues and identifying corresponding needs and enabling conditions. These interviews were conducted via video call, allowing participants to interact with visual materials and texts as they were developed during the conversation.

The discussions were informed by in-depth context analyses conducted at the case study level as part of related research activities. These analyses framed the unique circumstances of each agricultural setting and helped identify the factors influencing the adoption and effectiveness of digital technologies (Rijswijk et al., 2021). They included a broad range of information: physical and technological attributes of greenhouse farming (Klerkx et al., 2019); economic aspects such as financial performance, cost structures, and incentives (Metta et al., 2022); social dimensions including workforce demographics, labour conditions, and public perceptions (Eastwood et al., 2019); and environmental considerations related to sustainability practices and impacts (Rose et al., 2021). Before the interviews, respondents received the context analysis along with a clear explanation of the exercise's aims and procedures. The sessions employed SWOT analysis (see Supplementary materials) as a boundary object, leveraging its accessibility and familiarity to facilitate structured dialogue (Spee and Jarzabkowski, 2009). This approach enabled experts with diverse perspectives to collaboratively identify barriers and drivers of digital technology uptake and to prioritise issues relevant to local contexts (Helms and Nixon, 2010; Pagot and Andrighetto, 2024). Respondents were explicitly invited to elaborate through recall and brainstorming with research team members, following a three-step process:

1) Reflect on priority issues that should be addressed in the greenhouse farming sector at the territorial level to foster agricultural digitalisation, based on their experience in the LL and knowledge of the DSS, but not limited to it;
2) Identify barriers and drivers to solving these issues, derived from SWOT items—specifically, barriers from weaknesses and threats, and drivers from strengths and opportunities (Pagot and Andrighetto, 2024);
3) Highlight priority needs that could help overcome barriers or leverage drivers to address the identified issues.

Enabling conditions for these priority needs were defined through discussion during the final project workshop, which included all scientific partners and LL actors. These conditions were informed by the presentation of project outcomes and refined through collective input.

4. RESULTS AND DISCUSSION

Table 3 provides an overview of the observed priority actor needs and associated enabling conditions, highlighting recurring patterns across all case studies and pointing to common enabling conditions, while also revealing context-specific needs across different territorial settings (detailed qualitative evidence, including illustrative examples for each case study are reported in Supplementary Materials).

4.1 Recurring patterns: skills, trust, market dynamics, and remote farming

Across all case studies, insufficient digital literacy and practical skills emerges as a central barrier to the diffusion of Agriculture 4.0 tools. This limitation affects both farmers and advisory actors and constrains effective uptake even where technologies are technically available, limiting the capacity to translate digital potential into operational change. The consistency of this finding across diverse territorial contexts reinforces the role of enabling conditions centred on training, education reform and strengthened knowledge-transfer mechanisms, which are widely recognised in the literature as prerequisites for responsible, effective and sustainable digitalisation (Dibbern et al., 2024; Fragomeli et al., 2024; Rose et al., 2021). While the need for skills development is common across all case studies, the underlying mechanisms, institutional arrangements and organisational responsibilities through which skills are built vary substantially across territories (Supplementary Materials).

Particularly among older farmers, perceived risks, limited familiarity with digital tools and resistance to change reduce willingness to adopt new technologies. However, trust does not appear as a purely individual

Table 3. Prioritised needs and enabling conditions related to priority issues and SWOT items in the case studies.

Case studies	Priority issues	SWOT items	Priority needs	Enabling conditions
Almería	Knowledge and practical skills	Unskilled labour	Improving technical skills of farmers and advisors	Create and/or improve education and foster knowledge transfer about digital tools
Tuscany		Unskilled labour		
Antalya		Low level of knowledge		
Monastir		Low level of specialisation		
Tuscany	Reluctance to change	Propensity to innovate; Aging farmers	Building acceptability and trust	Create and/or improve education and foster knowledge transfer about digital tools
Almería		Aging farmers		
Antalya		Aging agricultural population		Support for young farmers' entrepreneurship
Monastir		Low profitability		
Monastir	Abandonment of farming activities	Farm exit; Low profitability	Reducing farm exits	Create and/or improve education and knowledge, and foster knowledge transfer about digital tools; Support for young farmers' entrepreneurship
Tuscany		Farm exit; Economic viability		
Almería	High market competition and low consumer awareness	Market competition	Creating product identity	Product branding
Antalya		Market conditions		
Monastir	Too low margin of product sale	Market competitiveness	Increasing farmer margins	Certification and labelling schemes; Policy support for sustainable products
Almería	Unfair distribution of value added along the value chain	Weak bargaining power; Many middlemen	Increasing farmer bargaining	Promote collective approaches (e.g., cooperatives, unions); Organising demand-driven production
Antalya		Many middlemen		
Monastir		Lack of collective organisation		
Tuscany		Low bargaining power; Level of cooperation		
Tuscany	Slow and complex bureaucracy for public incentives	Burdensome bureaucracy	Simplifying bureaucracy	Simplified paperwork for public incentives
Antalya	Insufficient supply of greenhouse-grown food	Low profitability	Developing land and crop production planning	Production-support policy
Monastir		Water shortages		
Antalya	High production costs	Rising energy costs; High input costs	Increasing liquidity for new technology uptake	Support for investment in digital technology
Monastir		High production costs		
Tuscany	Heavya workload and difficult work-life balance	Work-life balance; Climate change	Facilitating remote farming operations	Education and knowledge transfer; Public/private investment in broadband infrastructure
Almería		Workload; Work-life balance		
Antalya		Many working hours		
Monastir		Difficult management of personal life		

disposition. Rather, it emerges as a socially embedded condition shaped by past experiences with innovation, opportunities for experimentation, access to peer learning, and the presence of credible intermediaries such as advisors, cooperatives or researchers. Enabling conditions therefore extend beyond generic information provision and include tailored training pathways, mentorship schemes and support for young farmers' entrepreneurship as potential change agents. These findings align with the literature on barriers to Agriculture 4.0 implementation and on the importance of targeted, context-sensitive support in overcoming adoption lock-ins (da Silveira et al., 2023a, 2023b; Ganeshkumar et al., 2023; Klerkx and Rose, 2020).

Actors across all case studies also emphasise the role of market dynamics and value distribution in shaping incentives for digital technology uptake. The need for stronger product identity, increased consumer awareness and mechanisms capable of improving farmers' margins and bargaining power is consistently highlighted. Enabling conditions in this domain include branding strategies, certification and labelling schemes and, crucially, collective approaches such as cooperatives and unions. These collective arrangements can reduce fragmentation and strengthen negotiation capacity along the value chain, addressing long-standing imbalances in value distribution that limit farmers' incentives to invest in digital innovations, even when such technologies promise efficiency or sustainability gains (Giagnocavo et al., 2014; Eastwood et al., 2017; Rose et al., 2021).

The potential for remote farming operations emerges as a socially relevant opportunity across all case studies. Actors associate remote management with workload reduction, greater flexibility and improved work–life balance, with particular relevance for women and young parents. Importantly, remote farming does not emerge as an isolated technological feature, but as a cross-cutting outcome closely intertwined with observed needs for skills development, trust in digital systems and adequate infrastructural conditions. Enabling conditions include investments in broadband connectivity and collaborative learning platforms, as echoed in the literature on digital divides and the social dimensions of digital innovation in agriculture (Finger, 2023; Gabriel and Gandorfer, 2023; Rose et al., 2021).

4.2 Context specific needs: structural constraints and enabling environments

Several observed needs and enabling conditions for digitalisation mirror territorial diversity, depending on how structural constraints, institutional arrangements and market conditions interact locally.

In Monastir and Tuscany, actors highlight risks of farm exits linked to low profitability and limited generational turnover. These dynamics point to enabling conditions that combine targeted training with financial incentives and broader support for new entrants, reflecting evidence that long-term farm viability and digital innovation uptake depend on complementary socio-economic conditions (Eastwood et al., 2019; MacPherson et al., 2022; Petraki et al., 2025).

In Antalya and Monastir, actors stress constraints related to production planning and liquidity for new technology uptake, particularly under conditions of high input costs and limited financing capacity. In these contexts, digital technologies are perceived as potentially beneficial but financially risky in the absence of adequate support. Enabling conditions include production-support policies and public–private investment schemes that reduce upfront costs, improve access to capital and mitigate financial uncertainty, supporting the central role of economic and financial barriers in shaping Agriculture 4.0 adoption pathways (Dibbern et al., 2024; Derakhti et al., 2023; Klerkx and Rose, 2020).

The Tuscany case study complements this picture by highlighting bureaucratic complexity in accessing public incentives as a particularly salient constraint affecting digital technology uptake. Lengthy and burdensome administrative procedures required to benefit from available support measures are perceived as discouraging farmers from investing in digital tools and sustainable production upgrades. Then, enabling conditions include not only the availability of financial support, but also streamlined administrative processes and targeted technical assistance throughout application phases. These findings align with broader governance debates on how policy design and institutional capacity can either enable or hinder digital transitions in agriculture (McFadden et al., 2022; Martens and Zscheischler, 2022).

5. IMPLICATIONS FOR RESEARCH, PRACTICE AND POLICY

5.1 Critical assessment and recommendations for further research

The research is geographically limited to four case studies in the Mediterranean basin. Although these regions represent significant players in the global greenhouse vegetable market, the findings may not be fully generalisable to other regions worldwide. LL actor selection aimed to ensure representation across the agricultural value chain, however the number of participants per category varied by case study. For instance, in Antalya, only one policy representative was involved, which may have constrained the diversity of policy perspectives relevant to both the local territorial context and Turkey more broadly. The study relies on qualitative data collected through participatory methods involving a diverse group of actors with interdisciplinary expertise. The sample size and composition of engaged actors may not capture the full diversity of views within each region, and the findings might be influenced by the perspectives and biases of the participants. Data collection and reporting is based on internally developed procedures and protocols, tailored to the LL approach and the relatively small sample size. In contexts where such internal management is not feasible (e.g., studies involving randomised sampling, large sample sizes, saturation-based sampling) widely recognised tools for reporting qualitative research should be considered. For example, the COREQ checklist (Tong et al., 2007) offers a structured framework for ensuring transparency and rigour in qualitative research. Findings emphasise the importance of technical skills, trust, market dynamics, and policy frameworks in fostering the adoption of digital technologies. However, other potential factors that may also play an important role in technology adoption were not extensively explored, e.g., cultural attitudes, social networks, economic incentives.

5.2 Recommendations for the science-policy-society interface

Findings highlight how technical skills, trust, market dynamics, and policy frameworks interact to shape the adoption of Agriculture 4.0 technologies across Mediterranean regions. These dimensions do not operate in isolation but reinforce each other, influencing both the willingness and the capacity of actors to engage with digital innovations. Focusing on greenhouse farming, where remote management is relatively more feasible, this study suggests that successful implementations may offer scalable models for broader agricultural applications, while remaining dependent on context-specific enabling conditions (Bocean, 2024; Yuan and Sun, 2024). These findings support the generation of recommendations for the science-policy-society interface, emphasising the need for integrated approaches to unlock the full potential of digital tools in agriculture.

There is a critical need for wider and enhanced collaboration among scientists, policymakers, and agricultural practitioners to foster the successful adoption of Agriculture 4.0 technologies (Matthews, 2021). Encouraging interdisciplinary research that integrates insights from agricultural science, social sciences, and technology studies can address the disconnect between research, advisory services and farm practices that emerged across case studies, by providing a holistic understanding of the challenges and opportunities associated with digital agriculture (Finger, 2023; Rotz et al., 2019). Developing policy frameworks that are informed by empirical research and actor input can ensure that interventions are relevant and effective.

The results also indicate that trust and acceptability are socially embedded and closely linked to institutional and market arrangements. From a science-policy perspective, this implies that digitalisation strategies should move beyond technology promotion and instead support participatory, goal-based governance models that integrate environmental, economic and social objectives. Such coherence is essential to align digitalisation with sustainability and food security goals, as emphasised in EU agricultural policy debates (Coderoni, 2023). Engaging farmers and agricultural advisors in the co-creation of policies and support measures emerges as a key enabling condition for enhancing policy legitimacy and effectiveness (Derakhti et al., 2023; Gabriel and Gandorfer, 2023).

The reported evidence on market dynamics and value distribution highlights the importance of addressing demand-side and value-chain dimensions. Strengthening product identity, improving consumer awareness and supporting collective arrangements can enhance farmers' margins and bargaining power, thereby improving incentives for investment in digital tools. These findings point to the relevance of science–policy–society interactions that also encompass consumers and market actors, particularly through awareness-raising initiatives on sustainability attributes of agricultural products (Gouroubera et al., 2025; Rose et al., 2021).

The successful adoption of digital technologies extends beyond individual farms; it empowers communities and enhances their economic resilience. As these technologies become more widespread, rural areas may experience significant transformations that address long-standing rural-urban disparities. Establishing mechanisms for monitoring and evaluating the impact of digital agriculture initiatives can provide valuable insights into their effectiveness and inform future policy decisions. Continuous feedback loops between research, policy, and practice can enhance the adaptability and responsiveness of agricultural interventions towards digitalisation (Fragomeli et al., 2024; Yang et al., 2024).

As the agricultural landscape evolves, significant potential emerges from the adoption of remote farming technologies. The findings on remote farming underscore that the implications of digitalisation extend beyond productivity and efficiency. Remote management is associated with reduced workload and improved work–life balance, with particular relevance for women and young parents, provided that adequate infrastructural and organisational conditions are in place. These technologies can also foster community support and create new job opportunities, although strategic investment in digital infrastructure is still needed. This appeal can enhance workforce diversity, ensuring that agriculture remains competitive and relevant in the rapidly changing job market. Agricultural digitalisation serves not only ecological sustainability but also uplifts rural communities by fostering a more equitable and diverse agricultural community (Rose et al., 2021; Wolfert et al., 2017).

6. CONCLUSIONS

This study identifies key enabling conditions for the effective implementation of Agriculture 4.0 technologies in Mediterranean greenhouse farming. By following a RRI approach, findings from participatory research across LLs case studies suggest that efforts should focus on improving digital literacy, building trust in technology, leveraging market dynamics, and facilitating remote farming operations. These strategies can support the digital transformation of agriculture while promoting social inclusion, equity, and improved workforce conditions, particularly for women and youth.

To support evidence-based decision-making, the following policy recommendations are proposed:

- Invest in digital literacy and training: Tailored educational programs and knowledge transfer mechanisms are essential to bridge the gap between research and farm-level application;
- Support inclusive technology adoption: Initiatives should consider generational and socio-economic differences to avoid inadvertently excluding older or less digitally literate farmers;
- Strengthen market incentives: Certification schemes, consumer awareness campaigns, and simplified bureaucratic processes can enhance product value and encourage investment in digital tools;
- Promote social equity and cooperation: Policies should reinforce farmer unions and collaborative initiatives to improve bargaining power and ensure fair value distribution;
- Enable remote farming solutions: Digital tools that improve work-life balance and operational efficiency can foster sustainability and attract new entrants to the sector.

Key limitations of this study include its context-specific nature and reliance on the socio-institutional dynamics of each territorial LL, which should be carefully considered when interpreting the findings and assessing their broader applicability. Future research should expand the geographical coverage, integrate quantitative methods, and explore additional factors, such as cultural attitudes and social networks, that influence technology adoption. Also, in the context of LLs, integrating Participatory Action Research principles could offer additional value, particularly in enhancing actor agency and long-term impact, given the strong emphasis placed on collective action and transformation led by participants.

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Inequality and concentration in farmland production and size: A regional analysis for the European Union from 2010 to 2020

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Abstract. This article investigates the phenomenon of market concentration in the European agricultural sector from 2010 to 2020 at the regional level. To this end, we exploit the spatiotemporal dynamics of the Gini concentration index for farmland and production. First, we examine the variability within and between countries to assess whether the industry has suffered from increasing concentration during the study period. The next objective is to identify the empirical relationship between the two indicators and determine whether spatial spill-overs occur in terms of market concentration across regions. Our findings confirm the fragmented picture of the European agricultural sector, which is characterized by a high degree of heterogeneity within and across countries as concerns both land concentration and production concentration. In addition, we confirm the existence of a positive association between the two concentration measures. Lastly, the remarkable spatial autocorrelation we observe supports the hypothesis that adjacent regions tend to register similar levels of concentration, generating clusters of regions with either high or low values.

Keywords: agricultural market concentration, Farmland inequality, Gini index, Spatial autocorrelation, European Union regions.

1. INTRODUCTION

Understanding the dynamics of industry concentration in the agricultural sector is crucial for policymakers to determine where and how policies aimed at supporting small-scale farms might be most effective. As a matter of fact, the agricultural sector is a key sector that may help withstand and recover from the impact of economic downturns, especially in rural areas (e.g., see Giannakis & Bruggeman, 2018).

At worldwide level, the picture is very fragmented and, consequently, still opaque. Lowder et al. (2021) provide an overview of the number of farms by

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size at global scale, pointing out that small farms (less than 5 hectares) represent the vast majority of firms, but have less than 20% of the overall farmland. Giller et al. (2021) provide a similar picture, although they recognize that, since production costs and selling prices are determined by large-scale markets, the danger in the next decades is the increase in the marginalization of smallholder farmers, and additional and excessive dependence on very large farms. As of today, the picture of the market is the same as at the beginning of the millennium: the distance described in Von Braun (2005) between the "marginal" farm (small, with low level of sustainability and disconnected to science) and the "dominant" farm (large, more sustainable and users of advanced science) has not closed.

In the European agricultural sector, two large bodies of evidence have emerged. First, research has shown that farm and company structures vary considerably across and within regions and countries (Guarín et al., 2020). A comprehensive review of the scholarship reveals that numerous historical, cultural, geographical, economic, and political factors influence these disparities (Zimmermann et al., 2009). Second, the European Union's (EU) agricultural sector has undergone a significant transformation over the last decades, marked by a steady concentration of agricultural holdings. Because larger farms have the potential to achieve economies of scale, which can reduce production costs and, thus, increase overall production, this concentration may, in theory, increase efficiency. Nonetheless, the intensive agricultural practices associated with larger farms can give rise to issues of soil degradation, water pollution, and biodiversity loss (Fassò et al., 2023). Moreover, the decline of small farms can have adverse effects on rural communities through job losses and the deterioration of social cohesion.

Between 2010 and 2020, the number of EU farms fell from 12 to 9 million, while output rose from €304 to €360 billion (Eurostat, 2024a), indicating growing concentration and structural change.

Figure 1 visually represents the concentration of agricultural sectors within the EU. From 1990 to 2020, the aggregate number of farms fell substantially in most EU countries. Importantly, the average area per farm expanded significantly.

Several factors contribute to this trend. Global competition and volatile market prices push smaller farms

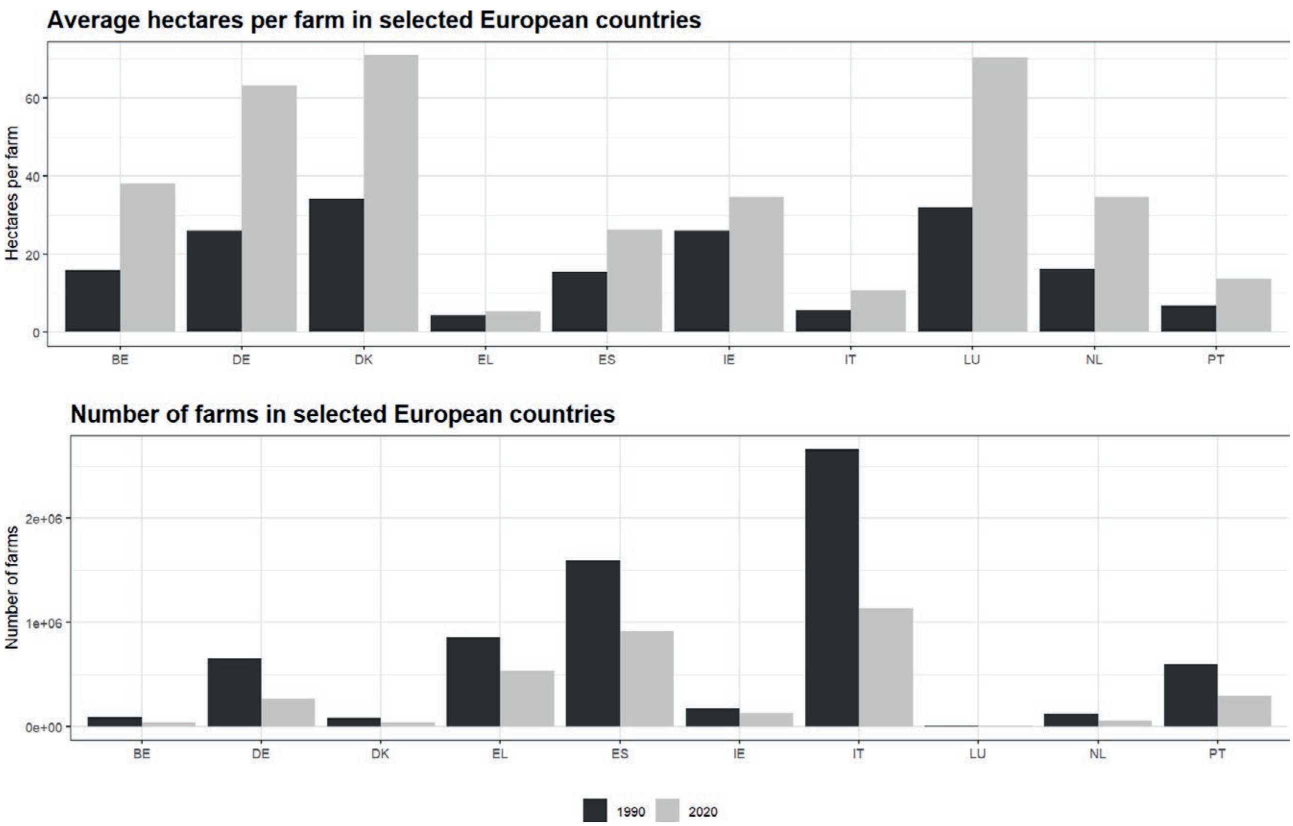

Figure 1. Land concentration of farms within the European Union. Note. Figure 1 shows values referring only to countries for which data is available for both 1990 and 2020.

towards consolidation or closure. Meanwhile, larger farms can often afford advanced machinery and automation, leading to increased efficiency and productivity. In parallel, younger generations are less likely to pursue careers in agriculture, leading to a decline in the available workforce for smaller farms. Lastly, EU policies, while not directly aimed at concentration, affect land distribution and might inadvertently favor larger farms or smaller ones. This raises questions about how the structure (e.g., the type of farming and average size) of farms has changed and whether this change has been uniform or heterogeneous in Europe.

In this paper, we investigate the phenomenon of market concentration in the EU agricultural and livestock farming industry between 2010 and 2020. To this end, we use regional (Nomenclature of territorial units for statistics classification [NUTS-2]) and national (NUTS-0) level data from Eurostat (Eurostat, 2024a) to examine the spatiotemporal dynamics of concentration measures for agricultural standard output (as a proxy for economic size) and farmland (as a proxy for physical size) of European farms. Our research focuses on the evolution of the Gini index (Giorgi & Gigliarano, 2017) within and between countries to assess whether the European agricultural market has seen increased concentration of power in fewer but larger farm holdings during the past decade. The overarching aim of the study can be declined into two research questions:

1) What temporal and spatial patterns characterize the levels of concentration of farmland and agricultural production? Specifically, is there a common trajectory between (i.e., at the national level) and within (i.e., at the regional level) European countries in terms of concentration measures between 2010 and 2020?
2) What empirical relationship exists between the concentration of agricultural farmland and the concentration of standard output? Specifically, are the two concentration measures positively correlated, such that an increase in the physical concentration of agricultural businesses is associated with an increase in their economic concentration, and vice versa?

To the best of our knowledge, the literature on territorial disparity in the European Agricultural sector is still developing. One early notable paper relevant to our analysis was authored by Vollrath (2007) and showed that land inequality is inversely related to productivity. In other words, a decrease in the Gini index of land distribution substantially increases land productivity. This is because farms that operate with family labor benefit from productivity advantages, and more equal land distribution equalizes the marginal product of labor across farms. In this regard, the existence of a sizeable effect of land inequality on output is a symptom of economic inefficiencies in the agricultural sector.

The present paper contributes to the literature in several important ways. First, whereas prior studies have examined land and output concentration at the national or coarse regional levels, our analysis exploits regional data for the EU27 countries over a decade (2010–2020) to offer a finer-grained and more spatially detailed picture of market concentration trends. Second, unlike most of the existing research, we examine both farmland and output (production) concentration jointly, which allows us to explore the relationship between physical and economic size concentration. Third, we incorporate exploratory spatial data analysis techniques to assess the presence of spatial dependence and clustering in concentration patterns, an approach largely overlooked in the current literature. Finally, we provide a temporal and spatial mapping of concentration trends, enabling a dynamic assessment of how concentration evolved over the post–financial crisis decade and in the context of ongoing Common Agricultural Policy (CAP) reforms.

The remainder of this paper is organized as follows. In Section 2, we briefly synthesize relevant issues raised in the agricultural economics literature and directly related to market concentration. In particular, we focus on territorial heterogeneities and the unequal distribution of production, profits, and resources among farms, as well as their economic consequences. In Section 3, we discuss the role of the Gini index in quantifying market concentration and the statistical tools we used to analyze spatial patterns of concentration. We also describe the regionalized Eurostat database on agricultural indicators we drew from to compute the Gini index for production (as a proxy for the economic size) and farmland (as a proxy for physical size) of EU farm holdings. In Section 4, we discuss the empirical findings derived from the data analysis of available data on European regions from 2010 to 2020. Concluding remarks are provided in Section 5.

2. BACKGROUND ON DISTRIBUTIONAL ISSUES IN THE EUROPEAN AGRICULTURAL SECTOR

Disparities in the agricultural sector, particularly in land ownership and productivity, have long been recognized as a major factor shaping economic and social outcomes in rural areas. Unequal access to productive land contributes to broader divisions in income, opportunity, and regional development (Wegerif & Guereña, 2020). In recent decades, the growing consolidation of farmland has renewed concerns about equity, efficiency, and sustainability in European agriculture (van der Ploeg et al., 2015).

The structure of agricultural holdings in the EU reflects a complex mix of historical, geographical, economic, and institutional factors. Post-war land reforms in Eastern Europe (e.g., Poland, East Germany, and Czechoslovakia) broke up large estates, while countries like Italy implemented milder redistributive measures in their southern regions (Bonanno, 1988; Mathijs, 2018; van der Ploeg et al., 2009). These legacies continue to shape farm size and ownership patterns today. In many Western European countries, family-owned farms dominate, while parts of Eastern and Southern Europe show more dualistic or fragmented structures. Natural conditions also contribute to heterogeneous land concentration. Soil quality, terrain, and climatic suitability influence not only the types of crops or livestock but also the potential for economies of scale (Lobley & Winter, 2009). Demographic pressures, such as rural depopulation and aging farmer populations, further affect the viability of smaller holdings (Eurostat, 2022).

Economic and institutional drivers also play a key role. Technological change, globalization, and EU policies, though not directly aimed at consolidation, may have disproportionately benefited larger farms. Notably, investments in capital-intensive machinery and access to financial markets tend to favor actors with greater scale and bargaining power, and policy instruments such as area-based subsidies may inadvertently accelerate concentration processes (Nolte & Ostermeier, 2017).

Several studies have linked land inequality to productivity gaps. Vollrath (2007) found that more equal land distribution tends to increase land productivity, particularly in systems that rely on family labor. In his cross-country analysis, a 0.16 reduction in the farmland Gini coefficient was associated with an 8.5% increase in productivity. This relationship reflects the inefficiency of highly unequal land distribution, which often fails to allocate resources to their most productive use.

Other research has explored spatial patterns of productivity. Ezcurra et al. (2008) documented significant spatial dependence in agricultural performance across European NUTS-2 regions, finding that neighboring regions tend to exhibit similar productivity levels. Giannakis and Bruggeman (2018) added a classification of agricultural systems (e.g., field crops, permanent crops, livestock) and revealed considerable heterogeneity within and between these systems, providing evidence that specialization and geography play intertwined roles.

Recently, Tóth (2023) insisted on the importance of territorial capital in shaping land use outcomes, while Guarín et al. (2020) proposed new typologies of small farms to better understand the diversity and challenges facing this segment of the sector. These works converge on the idea that agricultural disparity is a multi-scalar issue, visible both between countries and within regions, and requires nuanced measurement and analysis. In this context, our study adds to the literature by jointly analyzing the spatiotemporal dynamics of land and output concentration, using disaggregated NUTS-2 level data from across the EU. While much of the existing research focuses either on productivity or land-use patterns, we emphasize distributional concentration and its spatial interdependence, which have been underexplored in empirical assessments of European agriculture.

3. EXPLORING AGRICULTURAL MARKET CONCENTRATION PATTERNS IN EUROPEAN REGIONS USING THE GINI INDEX AND EXPLORATORY SPATIAL DATA ANALYSIS

We considered regionalized data about the agricultural market in Europe provided by Eurostat (2024b) according to the 2010 NUTS. In particular, we examined the regional (NUTS-2) and national (NUTS-0) level information on EU farms contained in the "Main farm indicators by NUTS 2 regions" open database (Eurostat, 2024a). The database features indicators on the agricultural industry in Europe for 2010, 2013, 2016, and 2020.[1] Among the full set of available data, we extracted a subsample concerning the following regional quantities:

- Overall number of agricultural holdings or farms (measured as headcount)
- Utilized agricultural land (in hectares)
- Standard output of agricultural production (in euros)

Given the exploratory nature of this paper, we did not consider subclassifications of farms based on their productive specialization, such as organic producers or livestock farms. Nevertheless, subsequent research must incorporate this information to expand the findings and provide a more comprehensive characterization of the market concentration dynamics in the agricultural sector. Because our objective was to consider the largest possible spatiotemporal sample, we included European regions with complete (non-missing) information for the entire period under study. Although more recent classifications were available, we selected the NUTS 2010 nomenclature due to its comprehensive coverage of the 27 EU member states during the 2010–2020 period. The selected dataset contains comprehensive data from 236 regions.

[1] As of August 2025, the "Main farm indicators by NUTS 2 regions" open database also contains information for 2010, 2013, 2016, 2020, and 2023. For 2023, a dedicated analysis of the effects of the major geopolitical events that occurred in previous years on the European agricultural market would be required. Such events constitute insightful research opportunities that should be seized.

We computed concentration indices for both farmland (i.e., utilized agricultural area) and production (i.e., standard output of farming), considering the stratification of agricultural farms into $K = 11$classes[2] of economic size based on increasing standard output values. Taking advantage of the number of farms and the cumulated standard output for each stratum in a region, we calculated the Gini indices for production and farmland following Cerqueti et al. (2024), which rely on the Gini index specification for grouped data described in Brown (1994). Specifically, let d be the index for production ($d = P$) and farmland ($d = L$), and let $j = 1, \ldots, K$ be the index for the economic strata. We then computed the Gini index for each region $s = 1, \ldots, 236$as follows:

$$\boldsymbol{Gini_{ds}} = \frac{\boldsymbol{N_s}}{\boldsymbol{N_s - 1}} \left[1 - \sum_{j=1}^{K} \left[(\boldsymbol{Q_{dj}} + \boldsymbol{Q_{dj-1}}) \times (\boldsymbol{F_{dj}} - \boldsymbol{F_{dj-1}})\right]\right]$$

where $d = \{P, L\}$ represents the production (P) or farmland (L) values, N_s is the total number of farms in region s, $Q_{dj} = \sum_{i=1}^{j} q_{di}$is the cumulative proportion of production or farmland up to the j -th ordered class (with q_{di} being the regional share of production or farmland associated with the i -th ordered class over the total), and $F_{dj} = \sum_{i=1}^{j} f_{di}$ is the cumulative proportion of farm holding up to the j -th ordered class (with $f_{di} = \frac{N_{si}}{N_s}$ being the regional share of farms associated with the i -th ordered class over the total number of farms in the region under the constraint $\sum_{i=1}^{K} N_{si} = N_s$). In short, $Gini_{Ps}$ corresponds to the Gini index for the production (standard output) in region s, while $Gini_{Ls}$is the Gini index for farmland in region s. Given that we utilized yearly data for 2010, 2013, 2016, and 2020, we computed a Gini index for each year and region.

From a statistical perspective, the Gini index can be interpreted as a measure of either statistical dispersion (i.e., variability) or statistical concentration (Giorgi & Gigliarano, 2017). Whereas the latter measures the agricultural market's concentration in terms of the economic capacity of farms, the latter gauges it in terms of land owned by farm holding (i.e., physical size). By definition, the Gini index is a normalized metric lying between 0 and 1, or, equivalently, between 0 and 100 if rescaled as a percentage (Giorgi & Gigliarano, 2017). A Gini index value equal to 0 is expected when all farms have the same standard output or the same hectares of land (i.e., the perfect equal distribution scenario). Conversely, a value close to 1 (or 100) represents a situation of high concentration in which almost all the land or standard output is owned by a very restricted number of farm holdings, leaving only a very small amount to the remaining companies. In the extreme case of a Gini index value of exactly 1 (or 100), the entire agricultural land (standard output) of a region would be owned (produced) by a single farm holding (i.e., the full concentration scenario).

In this paper, we describe the spatial and temporal evolution of agrobusiness concentration by comparing the two Gini indices to establish an empirical relationship between the concentration of production (as a proxy for the farms' economic size) and the concentration of farmland (as a proxy for the farms' physical size). To do so, we employed a sample covering a time frame subsequent to that of Ezcurra et al. (2008), namely, 2010 to 2020, and all regions of the EU27 countries.

We performed an exploratory analysis by studying the evolution through space and time of the linear correlation between the concentration of agricultural land and the concentration of agricultural production. We also investigated the temporal dynamics of spatial autocorrelation measures that can describe the influence of the Gini index recorded in neighboring regions on that observed in each European region to assess the presence of spatial spillovers in market concentration across regions. Although our study does not directly imply any causal relationship between physical concentration and economic concentration, the next paragraphs will thoroughly examine how these two measures may evolve simultaneously in the EU agricultural market, without assuming any causal relationships.

When examining the correlation between concentration measures, a direct and positive relationship is generally expected; however, careful consideration is still required. Clearly, if the Gini index value of farmland is equal to 1 (i.e., one firm owns all the land in a region), a production Gini index value of 1 is directly implied. On the contrary, a Gini index of farmland close to 0 does not directly imply a low Gini index value of production. Two points support this view. First, even if the land is homogeneously distributed, some of it could be "inactive," leading to an uneven distribution of standard output. Second, even if most of the land is productive, two regions with the same land Gini index value could have higher or lower levels of production concentration for different reasons: for instance, farms in one region could have higher productivity levels due to differences in

[2] The Eurostat database used to build the area-level concentration measures refers to a large set of farm indicators by organic farming, utilized agricultural area, economic size (i.e., standard output), and type of agricultural holding aggregated at the regional (NUTS-2) level. Eurostat classifies farms by standard output as follows: 0 euros; over 0 euros to less than 2,000 euros; from 2,000 to 3,999 euros; from 4,000 to 7,999 euros; from 8,000 to 14,999 euros; from 15,000 to 24,999 euros; from 25,000 to 49,999 euros; from 50,000 to 99,999 euros; from 100,000 to 249,999 euros; from 250,000 to 499,999 euros; 500,000 euros or over.

Table 1. Conceptual framework.

	High concentration/disparity in the standard output	Low concentration/disparity in the standard output
High concentration/ disparity in land distribution	There is substantial variation in both farm size and standard output. Higher output levels are associated with greater production capacity. There may be economies of scale and scope, with larger farms driving total sector output.	Disparity in standard output is not driven by unequal land size. This may be due to capacity constraints unrelated to the total size of the farm, or to industry and regional specialization, or to economies of scope favoring smaller farms (while economies of scale may be neither relevant nor present).
Low concentration/ disparity in land distribution	Although the size of the land is homogeneous, productivity and standard output vary substantially. This may reflect differentiation within the sector and thus farm specialization. Although farms have the same land size, they produce and focus on different products, resulting in different standards of output. Scale and farm capacity do not drive the disparity in the standard output.	The region has farms of similar size that produce a similar standard output. This may indicate productivity homogeneity within the region.

land-use productivity (e.g., organic vs. non-organic production, crops vs. livestock, etc.) but also due to the cost structure and market characteristics of the farms. Finally, the link between the two levels of inequality depends primarily on the possible presence of economies of scale, scope, and capacity in the agricultural sector. Table 1 displays the conceptual framework, highlighting how different structural configurations of this sector may arise.

As shown in Table 1, we anticipated that, at the NUTS-2 regional level, most regions would fall into either the north-west configuration (i.e., high disparities in both land concentration and standard output) or the south-east configuration (i.e., low disparities in both indicators). The geographical configuration we considered distinguishes between 236 regions in the EU, and each region may cover a substantial amount of land. By contrast, the north–east configuration (i.e., low disparity in standard output combined with high disparity in land concentration) and the south configuration (i.e., high disparity in standard output but low disparity in land concentration) are likely to occur in smaller regions, where specialization may play a more significant role. Therefore, we expected a positive association between the two disparity indicators given that our analysis concerns large regions (defined at the regional level). This is in line with the possible dynamics of both Gini indices. A decline in the Gini index value for farmland could mean either that some micro farms are acquiring other small plots of land and becoming larger or that a large area of land has been sold to a number of other farms. The possible change in the Gini index for standard output could be driven by potential economies of scale following this reduction in land concentration. If economies of scale are relevant, a decrease in land concentration could lead to a decrease in the heterogeneity of standard output as farms become more similar in terms of physical size.

The spatial dependence analysis revealed local patterns in the spatial distribution of the agricultural market, which result in the coexistence of sub-areas with nonhomogeneous characteristics (see, for instance, Ezcurra et al., 2008). Ezcurra et al.'s (2008) findings regarding agricultural productivity suggest at least two sub-areas: north-central Europe, oriented toward animal farming, with a relatively large share of cereal and forage crops, and southern Europe, specializing in the production of vegetables and permanent crops. This confirms the hypothesis of dualism in the European agricultural market discussed by Kearney (1991) and Gutierrez (2000), which also provide evidence of spatial dependence among regions between 1980 and 2001; that is, neighboring regions tended to register similar levels of gross value added per worker in the agricultural sector.

To make our findings comparable with the existing literature, we employed exploratory spatial data analysis techniques (Elhorst, 2010; LeSage, 2008) designed to measure the degree of spatial dependence of agricultural concentration and its temporal evolution. In particular, we estimated the dependence between regions using Moran's statistic for both global and local spatial autocorrelation (Anselin, 1995).

4. EMPIRICAL RESULTS

4.1 National and regional patterns of farmland and production concentration

We begin the empirical analysis by presenting a combination of country-level and regional-level evidence regarding the spatiotemporal dynamics of the Gini indices for production and farmland. The primary findings are outlined in Table 2, which synthesizes the evolution of the phenomenon between 2010 and 2020, emphasizing country-specific characteristics with respect to temporal and territorial (i.e., intra-country) dynamics. A close examination of the available data revealed significant variations among European countries. Specifically, farmland exhibited lower concentrations than standard output. This suggests that overall land productivity was characterized by significant heterogeneity both between and within countries.

Figure 2 shows the minimum, average, and maximum Gini index at the country level for both standard output (left panel) and agricultural farmland (right panel). We computed the yearly average Gini index by country according to the following two-step procedure. First, we summed the annual number of farm holdings, hectares, and standard output of all regions (NUTS-2) in a given country (NUTS-0) along the available dimensions, excluding economic size (i.e., organic farming, utilized agricultural area, and farm type of agricultural holding). Then, we calculated the national Gini index by aggregating the economic size classes as described in Section 3. The minimum and maximum values represent the lowest and highest concentration values recorded among the regions in a given country. For a more detailed view, Table S1 of the Supplementary Materials displays the numerical value of the average Gini index by country and year for both standard output and hectares, and Table S2 reports country- and year-specific intra-country variability. The latter was computed as the root mean squared error of the available regional concentration measures from the national average in Table A1, which acted as the barycenter.

Although the average values remained broadly stable over time, some country-specific patterns emerged. The two Gini indices had similar values only for Bulgaria, Croatia, Hungary, Romania, and Slovakia. We also identified a group of countries with relatively low levels of the Gini index in Central Europe. Specifically, France, Finland, the Netherlands, Belgium, and Austria exhibited an average farmland Gini index value below 40%, with a production Gini index ranging between 50% and 65%. Germany and Slovenia displayed relatively homogeneous market concentration as well. Figure 3 shows the Gini index at the regional NUTS-2 level for both farmland size (first row) and production (second row) in the four years considered.

Figure 4 and Figure 5 show the raw change (i.e., the net difference) and the relative change in the indices between 2010 and 2020, respectively. The analysis provides a more granular and informative picture of the European agricultural sector, capturing dynamics that are lost at the aggregate level. Notably, the Gini index for standard output invariably exceeded that of farmland in all NUTS-2 regions. Despite the inherent physical limitations imposed by land size, this outcome was not entirely unexpected. A more homogeneous distribution of land does not guarantee a more homogeneous standard output (Table 1); however, a higher Gini index of standard output suggests a considerable concentration of land ownership compared to the actual distribution of land. This phenomenon may be attributed to several factors, primarily related to the efficiency of the production process. First, economies of scale can generate a higher standard output at a growing rate: even a moderate increase in the available land surface may result in a more than proportional increase in standard output due to improved land-use efficiency. Second, smaller farms may have access only to comparatively cheap machinery and equipment, which may be outdated, potentially reducing overall productivity; in contrast, larger farms may be able to use more advanced and efficient machinery to maximize the use of available land. Lastly, capital investment tends to be more efficient for larger farms.

We identified France and the Netherlands as the countries with the lowest Gini index values observed, both for standard output and farmland. Between 2010 and 2020, France experienced a visible decline in the Gini index, with the southern region constituting a notable exception as it saw either no change or a modest increase. The decline is predominantly attributable to the jump occurred between 2016 and 2020, as illustrated in Table 2. Furthermore, the Gini index appears to have decreased slightly over time, with a more pronounced decline observed in farmland concentration. However, the region of Provence-Alpes-Côte d’Azur in the south saw its hectare index value rise—an exception to the overall trend. Overall, the evidence suggests a decline in regional heterogeneity, defined by variations in land size, over time.

Germany and Spain exhibit highly distinctive patterns. We observed a discrepancy in the levels of the Gini index in German regions, with lower indices in western and southern regions than in eastern ones. This discrepancy was consistently confirmed over the period considered and reflects historical dualism in the national development process, which was only partially resolved by the reunification of the country in the 1990s. There is also some evidence – albeit modest – of this difference for standard output. Meanwhile, the situation in Spain was somewhat different. In 2010, northern regions had a lower degree of concentration than southern regions as concerns size. However, in the period under consideration, the northern regions saw a substantial increase in

Table 2. Summary of the main empirical results on the Gini index for farmland and production.

	Farmland Gini Index		Production Gini Index	
Country	Time variation	Intra-country differences	Time variation	Intra-country differences
Austria (AT)	Constant after 2013	Some differences detected, but province heterogeneity decreases over time	Constant after 2013	Minor differences detected
Belgium (BE)	Negligible	Minor differences detected	Negligible	Minor differences detected
Bulgaria (BG)	Decreasing in the time horizon considered	Minor differences detected	Increasing until 2016, then slightly decreasing between 2016 and 2020	Minor difference detected, but province heterogeneity decreases over time
Cyprus (CY)	Increasing until 2016, then slightly decreasing between 2016 and 2020	/	Slight increase over time	/
Czech Republic (CZ)	Constant over time	Minor differences detected	Slight increase over time	Minor differences detected
Germany (DE)	Slight increase over time	Some differences detected, especially between East and West Germany	Increase over time	Some differences detected, especially between East and West Germany
Denmark (DK)	Increasing over time	/	Increase over time	/
Estonia (EE)	Considerable time variations	/	Constant until 2016, then slightly decreasing	/
Greece (EL)	Considerable decrease between 2013 and 2016	Some differences detected	Small time variations detected; Jump in 2020	Minor differences detected
Spain (ES)	Slight increase until 2016	Considerable differences, especially between Northern regions and Southern regions	Constant over time	Minor/negligible differences
Finland (FI)	Increase over time (jump in 2020)	Minor/negligible differences	Slight increase over time	Minor/negligible differences
France (FR)	Slightly increasing until 2016, then sharply decreasing; large volatility	Minor differences detected, but province heterogeneity seems to decrease over time	Slightly decrease over time	Minor differences detected
Croatia (HR)	Considerable time variations	Considerable differences, but province heterogeneity seems to decrease over time	Increasing over time	Considerable differences detected
Hungary (HU)	Constant until 2016, then sharply decreasing	Minor/negligible differences	Small time variations detected, but very similar 2010 and 2020	Minor/negligible differences
Ireland (IE)	Small time variations detected	Minor/negligible differences	Small time variations detected, but very similar 2010 and 2020	Minor/negligible differences
Italy (IT)	Sharp decrease between 2010 and 2013	Regional differences detected, but not differentiated between northern and southern Italy	Time variations detected, but very similar 2010 and 2020 levels	Regional differences detected, but not differentiated between northern and southern Italy
Lithuania (LT)	Slightly increasing over time	/	Slightly increasing over time	/
Luxembourg (LU)	Constant over time	/	Slightly increasing over time	/
Latvia (LV)	Strongly increasing over time	/	Slightly increasing over time	/

(Continued)

Table 2. (Continued).

	Farmland Gini Index		Production Gini Index	
Malta (MT)	Strongly decreasing over time; Large drop in 2020	/	Decreasing until 2016, then increasing	/
Netherlands (NL)	Small time variations detected; Noticeable drop between 2013 and 2016	Minor/negligible differences	Decreasing until 2016, then constant	Minor/negligible differences
Poland (PL)	Constant over time	Considerable differences detected	Slightly increasing over time	Minor differences detected
Portugal (PT)	Constant over time	Considerable differences detected	Slightly increasing over time	Minor differences detected
Romania (RO)	Large and positive time variations	Considerable differences detected	Increasing over time	Considerable differences detected
Sweden (SE)	Increasing over time	Negligible differences	Increasing over time	Negligible differences
Slovenia (SI)	Small time variations detected	Negligible differences	Constant until 2016, then slightly increasing	Negligible differences
Slovakia (SK)	Slightly decreasing over time	Negligible differences	Slightly decreasing over time	Negligible differences

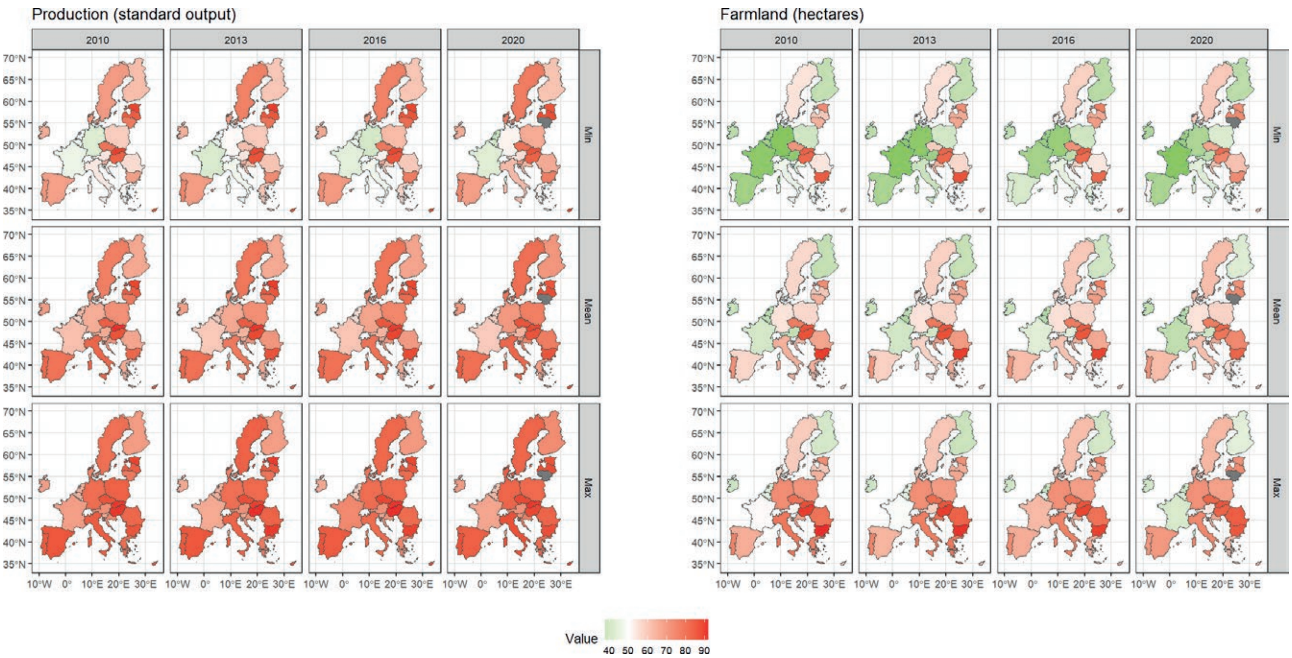

Figure 2. Maps of descriptive stats for Gini index from 2010 to 2020 in Europe. Note: Gini index is reported in a 0-100 scale. By rows are reported the minimum (Min), the average (Mean), and the maximum (Max) Gini index by country and year computed aggregating the available regional values. The yearly average Gini index by country is computed as follows. First, the annual number of farm holdings, the hectares (HA), and the standard output (SO) of all the regions (NUTS-2) belonging to a given country (NUTS-0) are summed across the available dimensions excluding the economic size (i.e., organic farming, utilized agricultural area, and farm type of agricultural holding). Then, the national Gini Index is computed by aggregating the economic size classes as described in Section 3. The minimum and maximum values represent the lowest and highest concentration values recorded among the regions belonging to a given country. Regarding Lithuania (LT), the last available information from Eurostat regards 2016. Thus, Gini index and the corresponding descriptive statistics for 2020 are not available (grey region).

the hectare Gini index, indicating an increase in concentration, on average, while southern regions demonstrated negligible or minimal change. The latter pattern was not observed for standard output. In Spanish regions, the Gini index value of standard output was relatively high, with minimal variation between areas. Moreover, the

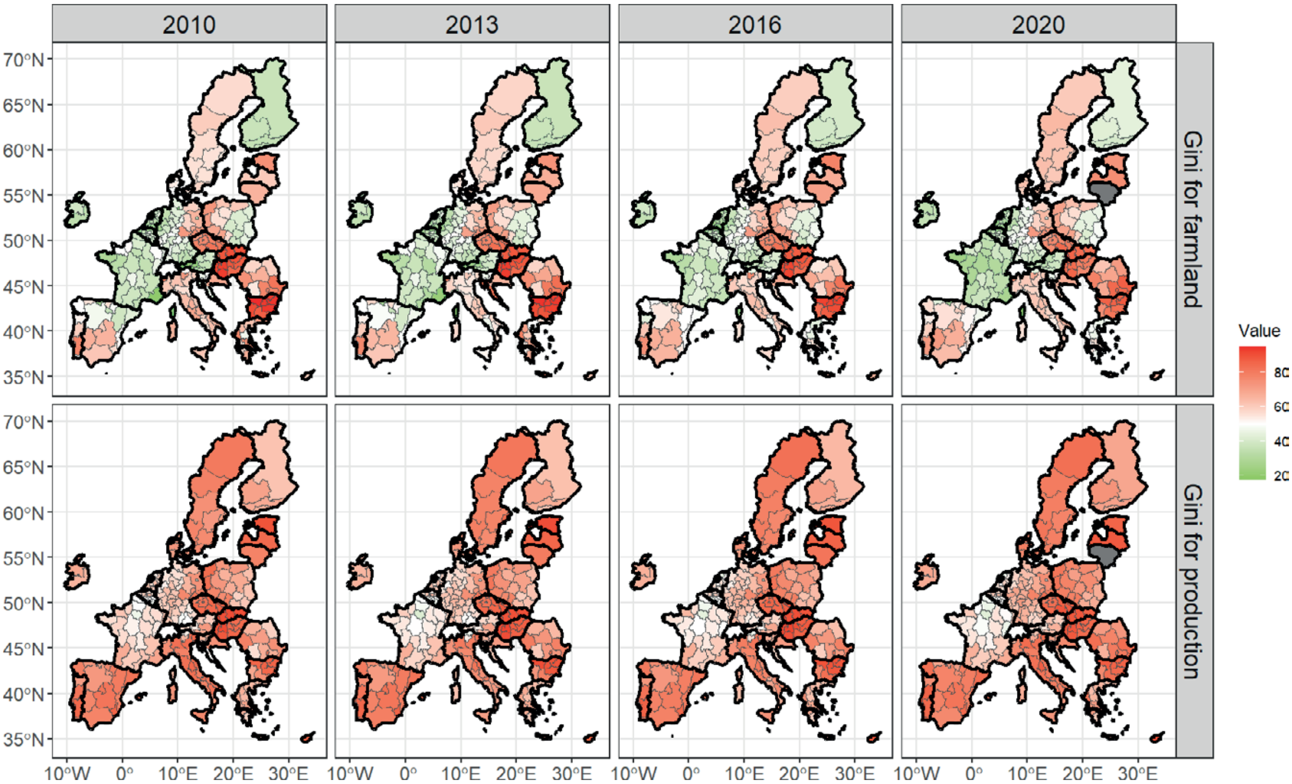

Figure 3. Maps of Gini index for production and farmland from 2010 to 2020 in Europe. Note: Gini index is reported in a 0-100 scale. Regarding Lithuania (LT), the last available information from Eurostat regards 2016. Thus, Gini index for 2020 is not available (grey region).

pattern in the southern Spanish regions was similar to that of Portuguese regions, in terms of both hectares and standard output.

We observed relevant differences between western and eastern areas in Poland as well. The western region had larger Gini indices than eastern ones, especially areas bordering Germany and the Czech Republic. Between 2010 and 2020, this gap reduced thanks to increased concentration in eastern regions, although the average production Gini index at the country level slightly rose during this period.

The two Scandinavian countries included in the sample (Finland and Sweden) had markedly divergent Gini index values, with Finland receiving lower values than Sweden for both standard output and hectares. Furthermore, we observed an increase in the Gini index in both countries between 2010 and 2020. However, no substantial disparities emerged for either country at the NUTS-2 level.

Next, we thoroughly examined Gini index patterns for Austria and Italy. Austria had both a relatively low farmland Gini index and a low production Gini index, comparable to the averages of western Germany. Interestingly, between 2010 and 2020, the farmland Gini index increased in western Austria (i.e., Vorarlberg, Tirol, and Salzburg regions), with no relevant change in standard output concentration; instead, standard output concentration decreased in Kärnten and Steiermark, regions in which the farmland Gini index slightly increased in the same period. In Italy, the time patterns of the two Gini indices appeared to be regionally specific. We observed a substantial decline in the farmland Gini index in most regions, with notable values recorded in Sardinia, Lazio, and Abruzzo. Conversely, slight increases were evident in Emilia-Romagna and Marche. The production Gini index seemed relatively stable over time, with slight decreases in certain regions and negligible increases in others. Consequently, the size and output concentration of these two countries were still marked by significant heterogeneity and regional specificity. In contrast to the east–west dualism characteristic of Germany and Poland, Italy showed a classical but less pronounced north–south differential. In addition, the country's homogeneous values in both land and production suggested a lack of divergence in these domains.

The time patterns in Greece's Gini index values are of particular interest. In 2010, Greece's average Gini index was similar to that of Western Germany. The

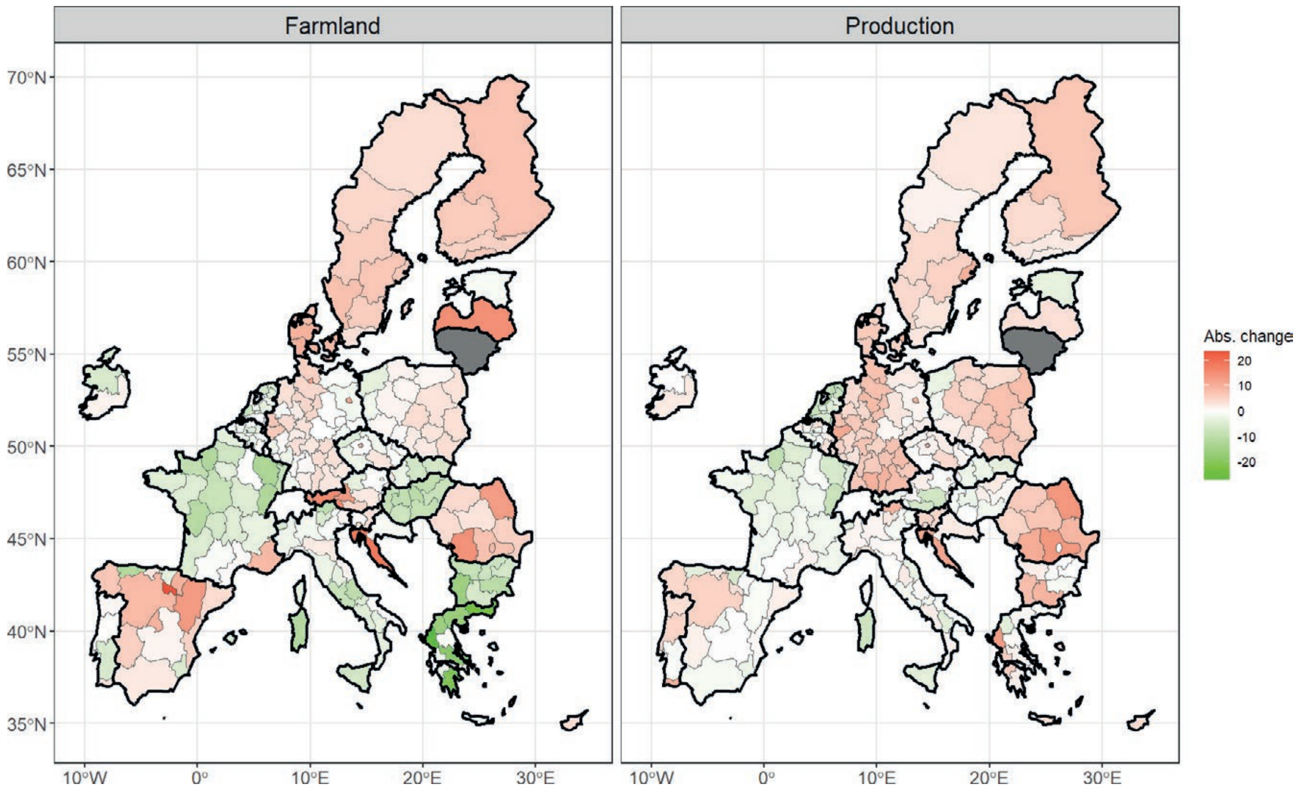

Figure 4. Maps of raw change in Gini index for production and farmland from 2010 to 2020 in Europe. Note: Variations of the Gini index is computed as the difference between the regional (NUTS-2) Gini index for 2020 and the Gini index for 2010. As the Gini index are computed on a 0-100 scale, also the variations are in the same scale. Regarding Lithuania (LT), the last available information from Eurostat regards 2016. Thus, Gini index and the corresponding variation is not available (grey region).

largest absolute decrease in our sample was observed in most Greek regions over the 10 years under study. However, during the same period, we observed different variations in the production Gini index: while land size became more homogeneous, the standard output became much more concentrated. This phenomenon was particularly salient in the Ipeiros region, where the production Gini index saw the most substantial increase, alongside a pronounced decline in the farmland Gini index.

Some countries in central and eastern Europe had remarkably high Gini index values, although the patterns were heterogeneous. In 2010, Bulgaria exhibited one of the highest farmland Gini indices on record. This index declined throughout the nation's territory over the subsequent decade. Concurrently, the production Gini index rose modestly, particularly in the southwestern, south central, and northwestern regions. A similar pattern was noted in Hungary and Slovakia, which differed only in the minimal or negligible increase in standard output concentration. Meanwhile, Ireland, the Netherlands, and Belgium had similarly low Gini indices with little variation over the decade.

Eventually, some important differences in border areas should be highlighted due to their similar physical characteristics (e.g., mountainous areas between Italy and Austria and between France and Spain) and weather conditions, especially in terms of rain, wind, and solar irradiance. Accordingly, we observed similarities in agricultural land concentration in some cross-border areas: the Portugal–Spain border, a large part of central Europe comprised of France, the Netherlands, Belgium, Austria, and western Germany, a smaller part of central Europe including eastern Germany, western Poland, and the Czech Republic, and, lastly, Hungary and Slovakia. For other cross-border areas, the picture remained fragmented, and common patterns cannot be easily defined.

4.2 Common and index-specific dependence patterns in farmland and output concentration

As illustrated in Figures 6 and 7, a moderately strong linear correlation (i.e., the R value indicates the Pearson's correlation coefficient) existed between the two indices

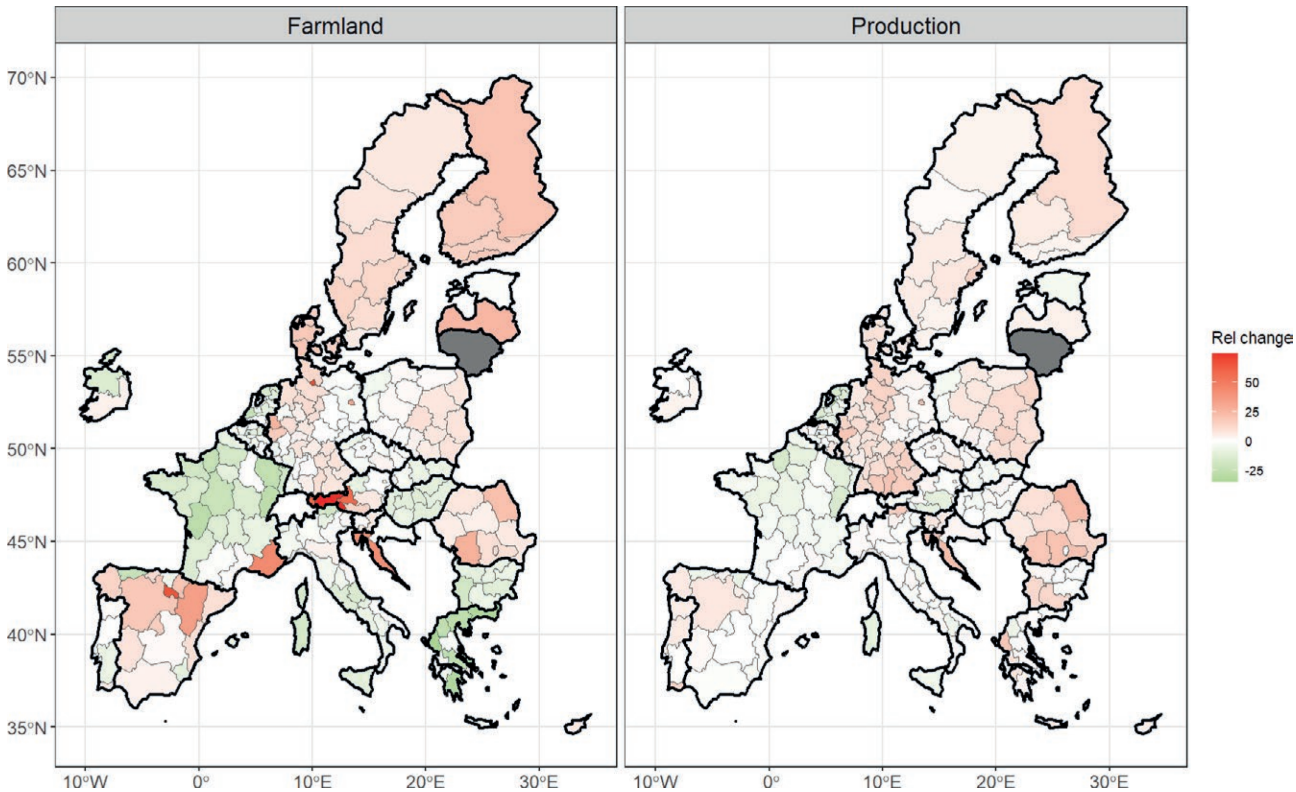

Figure 5. Maps of relative change in Gini index for production and farmland from 2010 to 2020 in Europe. Note: Relative variations of the Gini index are computed as the ratio of the difference between the regional (NUTS-2) Gini index for 2020 and the Gini index for 2010 and the regional Gini index for 2010. Thus, it does coincide with the ratio of the raw (absolute) variation and the Gini in 2010. Relative variations are reported in a percentage scale. Regarding Lithuania (LT), the last available information from Eurostat regards 2016. Thus, Gini index and the corresponding relative variation is not available (grey region).

at the year level, as well as between the change in the two indices between 2010 and 2020. The graphs reveal a direct and unambiguous relationship between the farmland Gini index and the production Gini index.

Figure 6 indicates an increasing positive linear correlation between the concentration index for hectares and standard output during the decade. This is corroborated by the growth rates documented in Figure 7, which demonstrate a positive correlation between the increments in the Gini index for production and for farmland concentration, proving that the two concentration measures consistently varied simultaneously over time for most regions. Furthermore, Figure 6 reveals that although the range of the Gini index for standard output (horizontal axis) remained constant, the range of the farmland Gini index (vertical axis) narrowed slightly due to a decline in the maximum Gini index values and a concurrent rise in the minimum levels.

Further, the spatial dependence analysis (see Table S3 of the Supplementary Materials) demonstrated the presence of a strong positive autocorrelation between EU regions for both production and farmland concentration. This finding supports the hypothesis that adjacent regions tend to register similar levels of statistical concentration, generating clusters of regions with either similarly high or similarly low values. In this regard, spatial clusters transcend national borders, forming contiguous clusters of regions that can be traced back to historical-political events and processes. Once again, the evidence supports the hypothesis of a dichotomy between north-central and southeastern Europe. The results presented in Figure 8 are consistent with those of Ezcurra et al. (2008), which highlight the European dualism characterized by the presence of distinct geographical regions on the continent: regions in southern Europe, such as Spain and Italy, and eastern Europe, including Romania and Hungary, exhibit notably high production and farmland concentrations, while regions in the Netherlands, Belgium, and France have significantly lower levels. A very similar clustering structure was also confirmed by Cerqueti et al. (2024). Extending the notion of spatial autocorrelation within a cluster-

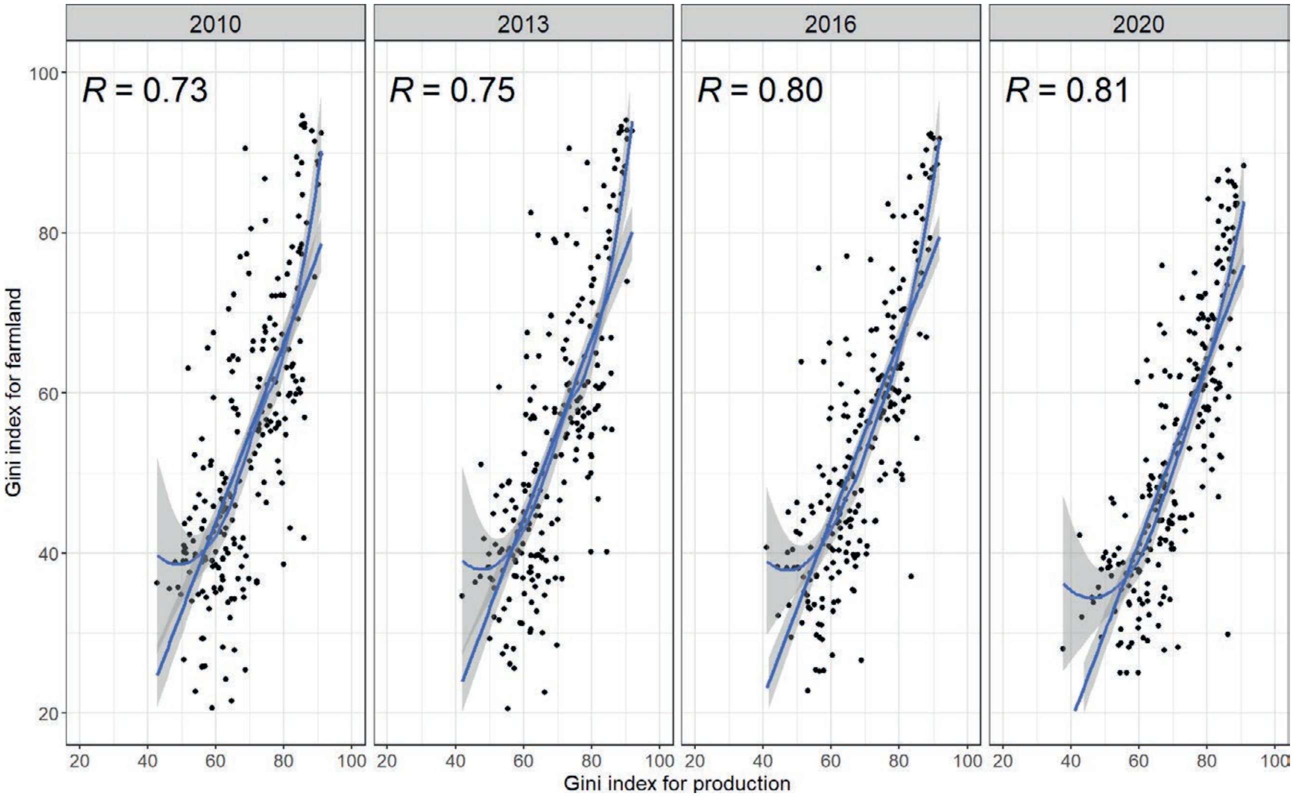

Figure 6. Correlation between Gini index for production and farmland. Note: the R value reported on top of each figure represents the Pearson's linear correlation coefficient.

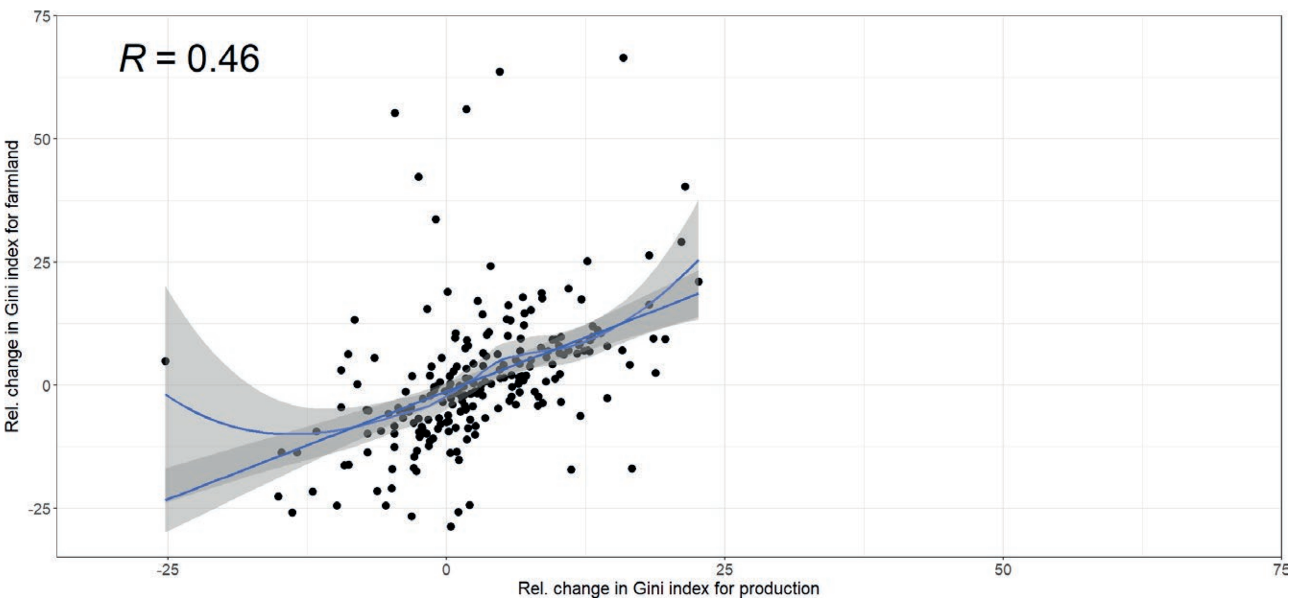

Figure 7. Correlation between relative changes in Gini index for production and farmland. Note: the R value reported on top of the figure represents the Pearson's linear correlation coefficient.

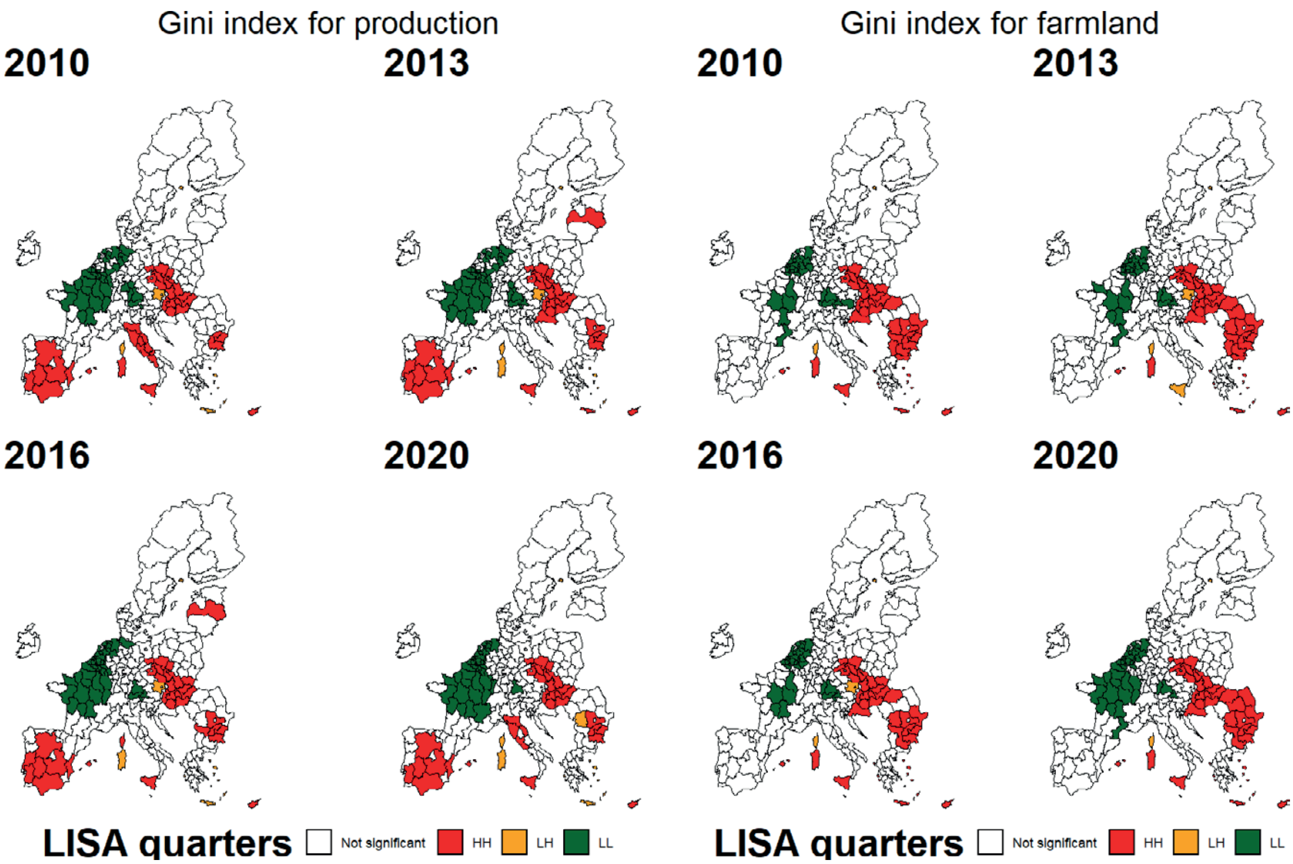

Figure 8. Spatial autocorrelation using local Moran's index. Note: LISA stands for Local Indicator of Spatial Autocorrelation (Anselin, 1995). Regions are grouped into five non-overlapping clusters or quarters, that is, high-high (HH) group (i.e., regions with high concentrations are surrounded by highly-concentrated neighbors); low-low (LL) group (i.e., regions with low concentrations are surrounded by lowly-concentrated neighbors); high-low (HL) group (i.e., regions with high concentrations are surrounded by lowly-concentrated neighbors); low-high (LH) group (i.e., regions with low concentrations are surrounded by highly-concentrated neighbors); non-significant area in which local autocorrelation index is not statistically significant.

based framework, the authors ascertained that European regions can be categorized into three macro-regions (e.g., Germany, Benelux, and the northeastern French regions form a homogeneous cluster) with group-specific determinants of agricultural production concentration. Figure 9 shows the robustness of these results, where spatial autocorrelation remained positive for a considerable number of spatial lags and values increased from 2010 to 2020

4.3 Discussion and further considerations

The present study offers novel evidence of the fragmentation of the European agricultural sector, a phenomenon characterized by remarkable heterogeneity as concerns both farmland and production concentration. Spatial heterogeneities are evident within and between countries, with noticeable clusters of neighboring highly concentrated regions contrasting with clusters of adjacent regions with significantly lower concentrations. Such clusters transcend national boundaries and often correspond to areas with known common historical and political processes (e.g., former Soviet bloc countries). We identified various time patterns that, however, vary significantly on both a national and an intra-national scale. Furthermore, we employed spatial autocorrelation analysis to identify cross-country areas exhibiting analogous patterns of land and output concentration.

The cross-country analysis revealed that, at the aggregate level, a more equal distribution (or less unequal) distribution of land and standard output was found in the area delimited to the west by Austria and western Germany, to the east by France, to the north by the Netherlands, and to the south by southern France and Austria. In contrast, Central (from eastern Germa-

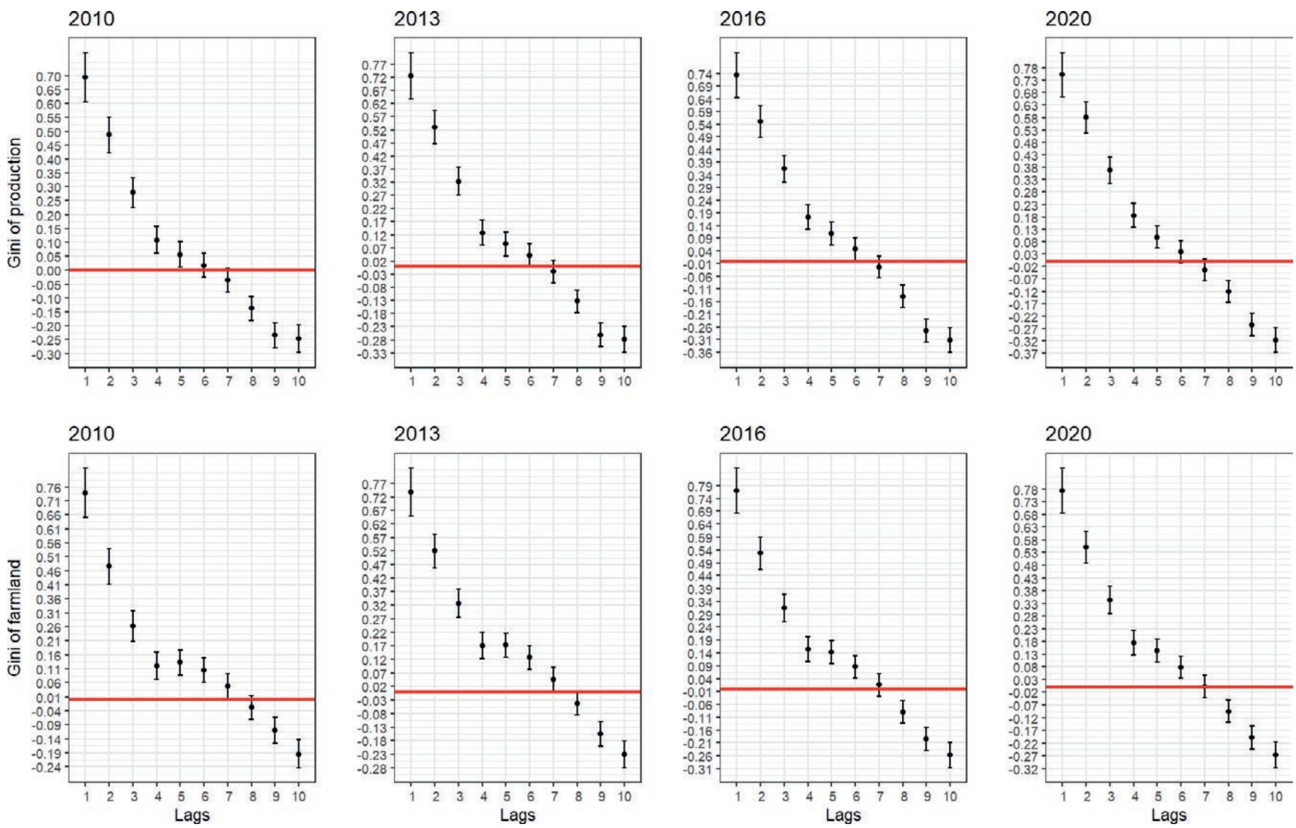

Figure 9. Global Moran's spatial autocorrelogram.

ny) and Eastern Europe seemed to have a more unequal distribution in both indicators, especially the Czech Republic, Hungary, Romania, Bulgaria, and Slovakia. At the end of the 20th century, Central and Eastern European countries underwent significant changes in their agricultural sector, in particular in their approach to land distribution and migration from rural areas. Specifically, as van Vliet et al. (2015) argue, land use was strongly impacted by the shift to post-socialism, given that under socialism, most land was collectivized following "optimization" schemes run at the central level. The de-collectivization of lands and the return to private holdings, therefore, had significant effects on land usage and the migration from very poor rural areas. This could explain why these countries are now characterized by a highly unequal distribution of land, as large firms may have accrued monopolistic power and also acquired many small firms. Levers et al. (2018) showed that between 1990 and 2006, low-intensity and de-intensifying land systems dominated in Europe's east, in stark contrast to the dynamics in western Europe. Additionally, some countries in Southern Europe (namely, Spain, Italy, Portugal, and Croatia) seemed to have, on aggregate, a similar level of disparity, slightly higher than France and western Germany or the Benelux countries. Mediterranean European areas have different characteristics in terms of soil, degradation related to climate change, and other factors such as farmland abandonment (a common issue in Europe) compared to central Europe (e.g., see García-Ruiz & Lana-Renault, 2011; Malek et al., 2018).

Our analysis revealed interesting results within countries, often connected to the European historical paths. A key finding is represented by the marked differences in the national orientation toward land management. For instance, the difference between western and eastern Germany is connected to the country's historical dualism. In Spain, we found clear differences in terms of hectares disparity between northern and southern regions. This may result from differences in the climate, geography, and soil quality, which have consequences for the type of farming and the need for smaller or bigger firms, in some cases. Further, land abandonment has differed between the rural areas of regions like the Pyrenees and those of other regions (García-Ruiz, 2010). In contrast to these results, we did not find evidence of a clear difference in land distribution between northern and southern Italy (for a specific insight on Italy we refer the reader to Corti et al., 2013, which present an overview of the soil management practices through the time and in the different Italian physiographic districts, analysing their effects on soil conservation and fertility).

The development of rural areas remains one of the primary challenges of the EU's CAP strategy (Viaggi, 2008; Viegas, 2021). The capacity of the member states and the EU to facilitate the revitalization of rural areas and, thereby, counteract the ongoing process of desertification, enables enhanced social and territorial cohesion while also serving as a response to the substantial climate-related challenges confronting the region. Implementing the agroforestry mosaic, as one of the main eco-schemes[3] provided for in current CAP regulations, requires understanding the advantages of ensuring the viability of a scale of production that has been relegated to secondary importance for decades. Small and medium-sized farms recognize the productive potential of vast abandoned areas, which can be allocated to forestry and plant or animal production, feeding short marketing circuits, boosting local economies, and helping prevent the fires that have devastated much of Europe's forests in recent years.

5. CONCLUDING REMARKS

The academic agenda on regional disparities among European farms is still evolving. The literature so far has largely focused on the influence of spatial disparity on productivity levels across regions. In contrast, the present analysis contributes to the scientific debate by providing a clear map of the statistical concentration of agricultural land size and production at the regional level for the EU27 countries. Furthermore, we presented novel evidence concerning the temporal evolution of the agricultural sector's concentration during the 2010–2020 decade.

This work calls for follow-up research. First, although the present analysis does not explicitly consider farm typologies, the evolution of the distribution of agricultural systems likely plays a role in shaping land and output concentration. According to Eurostat typology data, the past decade has seen notable shifts across EU regions, including the decline of small-scale grazing livestock holdings in Southern and Eastern Europe and the consolidation of field crop and granivore systems in more capital-intensive areas. These alterations may offer a partial explanation for the higher concentration in production we observed, particularly in regions where high-productivity systems (e.g., granivores, horticulture) have expanded. Concurrently, land concentration may have increased in regions where permanent crop systems, which are frequently associated with substantial estates, have gained ground. These structural shifts appear to align with broader CAP dynamics favoring scale and capital investment, and they may reinforce spatial inequality between farming systems. Therefore, a more detailed disaggregation contrasting organic and non-organic producers, as well as crops and livestock farmers, could enrich the literature on the drivers of concentration. It would also help determine whether the substantial heterogeneity in output can be attributed to these specific agricultural enterprises.

Furthermore, policy changes have contributed to the evolution of land and output concentration over the past decade. In particular, the reforms of the CAP (including the decoupling of direct payments, the introduction of greening measures, and the promotion of competitiveness and modernization) may have disproportionately benefited larger and more capitalized farms. These farms frequently possess a strategic advantage in meeting subsidy requirements and absorbing compliance costs, which may indirectly accelerate consolidation trends. Although the present analysis does not formally isolate the effects of policy, these institutional dynamics can reasonably be expected to interact with market forces in shaping structural inequality. Accordingly, future research could further explore the causal impact of specific CAP instruments on concentration patterns at the regional level.

Lastly, given the growing importance of sustainable agronomic practices, researchers should examine whether changes in regional farmland and output concentrations are associated with changes in pollution levels. This could assist policymakers in assessing whether a more equitable land distribution could contribute to a concrete reduction in the environmental impact of the agricultural industry and support climate-change mitigation policies.

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[3] Eco-schemes provide support to farmers who implement agricultural practices beneficial to the environment and climate. These measures reward and incentivize farmers for acting towards more sustainable farm and land management with the objective of preserving public goods.

"SCARFACE - Sequestering CARbon through Forests, AgriCulture, and land usE" (2024-ATEQC-0048).

Data availability and codes: Data used in the paper are public (source Eurostat). Since we use only public data, no Special Permission is need to use copyrighted material from other sources (including the Internet). All results presented in this paper can be reproduced using the R software. The codes were developed entirely by the authors. Fore reproducibility purposes, all the scripts and the data are made public through the following GitHub folder https://github.com/PaoloMaranzano/SB_PM_MV_AgroMarketConc.git

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Applying the Global Methane Pledge to the italian livestock sector

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Abstract. The Global Methane Pledge was launched by the EU and the US with the aim to cut 30% of methane (CH_4) emissions by 2030. Livestock systems are major contributors to CH_4 emissions. This study assesses a combined tax and subsidy policy tool applied at the farm level that would allow to reach the 30% reduction target for livestock CH_4. The simulation is performed with the Positive Mathematical Programming model AGRITALIM calibrated using the Italian commercial livestock farms as represented by the Farm Accountancy Data Network. The micro-based model simulates at the farm level the imposition of a tax on each unit of emissions that exceeds the targeted amount, or the grant of a subsidy for each unit of emissions that is reduced above the target. The simulation exploits the heterogeneity of farmers' behaviour to reach a market-clearing permit price of one tonne of emissions to obtain a self-sustaining policy tool that would equate the amount of taxes and subsidies paid. Results point that with a price of EUR 110.50t-1CO_{2eq}. the system would self-sustain itself. Higher negative impacts are foreseen for less productive beef and mixed cattle farms as a result of the profitability and emission intensity of their activities. Findings could be used to help policymakers understand the diversified impacts of the target on farms and evaluate possible compensation they could provide for a more just transition.

Keywords: GHG emissions, mathematical programming model, carbon tax, carbon subsidy, carbon price, short-lived GHG.

1. INTRODUCTION

Establishing plans to reduce the greenhouse gas (GHG) emissions produced by the world's livestock systems is essential, given the expanding global population and the anticipated 20% increase in demand for terrestrial animal products by 2050 (FAO, 2023).

Despite continuous advancements in production efficiency, GHGs from livestock systems continue to pose a serious problem, as they account for a large portion of global emissions (Cerutti et al., 2023). In particular, the Intergovernmental Panel on Climate Change (IPCC, 2021) has identified agricultural production, primarily livestock, and the use of fossil fuels as

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major contributors to the rise in atmospheric methane (CH_4) emissions. These emissions are second only to carbon dioxide (CO_2) in their overall contribution to climate change (Milich, 1999). On a molecular level, CH_4 is more powerful than CO_2; thus, although it is less persistent in the atmosphere, it has a significant effect on climate change (IPCC, 2021; Gernaat et al., 2015).[1] Additionally, CH_4 contributes to the formation of tropospheric ozone, a potent local air pollutant with serious health effects (European Commission, 2020). Consequently, cutting CH_4 emissions improves air quality and slows the rate of climate change.

In recent years, there has been a worldwide political focus on CH_4 (European Commission, 2020; Minister of Environment and Climate Change, 2023; Magnapera et al., 2025). The United States (US)-China Joint Glasgow Declaration specifically points the urgent need for greater action to reduce CH_4 (Wang et al., 2021). In New Zealand, the Zero Carbon Amendment Bill targets a net zero budget for GHG, including a separate target to reduce biogenic CH_4 emissions (New Zealand Ministry for the Environment, 2024).

To put forward a global action, in 2021, the European Union (EU) and the US launched the Global Methane Pledge (GMP) at the 26th Conference of Parties in Glasgow to cut CH_4 emissions by 30% by 2030. As part of its commitment to the GMP, the EU submitted the Methane Action Plan (European Union, 2022), which outlines existing policies and further activities under development that are expected to reduce CH_4 emissions until 2030 and beyond. The plan describes the expected impact on CH_4 emissions from agriculture because of the proposed revision of the Industrial Emissions Directive (IED)[2] that, for the first time, was intended to target cattle farms as well as the pig and poultry farms already subject to the (old) Directive. The proposal to include cattle farms in the revised IED did not pass after much debate within the co-decision mechanism. However, by the end of 2026, the EU Commission plans to publish a report with solutions that will more comprehensively address emissions from the rearing of livestock, focusing on cattle.[3]

In this context, this work aims to simulate a combined tax and subsidy scheme to illustrate the likely impacts of the GMP's proposed CH_4 reduction target of 30%. The simulation applies this target to the same livestock categories (i.e., specialised cattle, pig and poultry farms) targeted by the proposed revision of the IED, as it appears to be the most likely policy objective, based on recent developments.[4]

The assessment requires a model that is based on micro-level (i.e. farm-level) data that allow representing farms' heterogeneity in terms of productive and structural features (Baldi et al., 2024; Heckelei et al., 2012). In this study we use the agroeconomic supply model called AGRITALIM (AGRIcultural TerritoriAL tIme economic; Dell'Unto et al., 2025; Cortignani and Coderoni, 2022; Dell'Unto et al., 2023). The model is calibrated with microdata surveyed of the Farm Accountancy Data Network (FADN) that include information on aspects regarding economic, financial, productive, market, policy and structural features of farms. The model was recently implemented to account for GHG emissions at the farm level (Coderoni et al., 2024a). Impacts are evaluated focusing on the number of livestock units (LSUs) reared, the level of CH_4 emissions and the operating income (OI) of farms.

Compared to the literature to date, this is the first assessment of a hybrid policy tool that proposes the simultaneous application of tax and subsidy to the sole livestock sector of one important livestock-producing country (Italy).[5] Previous works have considered either a tax to incentivise farms to reduce emissions or a subsidy for those farms that reduce this negative externality (see, among others: Acosta et al., 2023; Fellmann et al., 2018; Himics et al., 2018; Pérez Domínguez et al., 2016).

Moreover, we conduct our assessment using a micro-based modelling approach, allowing us to capture farms' heterogeneous abatement costs (Cai et al., 2016). At this stage of the analysis proposed, the only mitigation strategy allowed is the reduction of LSU as the aim of the study is not to assess the possible benefits and costs of eventual mitigation options, but to show the impact of the application of the GMP to the Italian livestock sector in a short-term scenario, with no possible changes to the production technology. However, the GHG estimation approach here adopted, allows the model to capture farms' optimizing behaviours characterized by different

[1] CH_4 is a so-called short-lived GHG (i.e., it has a strong initial climate impact that rapidly drops after 20 years, unlike CO_2). This attribute has significant consequences for calculating its effect on global warming and some stakeholders have urged that a distinct regime is needed for long-lived and short-lived GHGs. At present, however, CH_4 and CO_2 emissions belong to the same policy frameworks at the EU and national level.

[2] COM (2022)156 final, at https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52022PC0156 (accessed 08/11/25).

[3] https://environment.ec.europa.eu/topics/industrial-emissions-and-safety/industrial-and-livestock-rearing-emissions-directive-ied-20_en#farming-under-the-ied-20 (accessed 08/11/2025).

[4] Specialised sheep and goat farms, along with non-specialised livestock farms, fall outside the scope of the original directive, and including them in the revised IED has never been part of the debate for its revision.

[5] Running a search on the Scopus database (search string: "emission trading system" OR "ets" AND livestock AND "eu*") did not yield any paper that addressed the same issue with a similar approach.

emission intensities at the baseline, that reflect management intensity, even in the absence of explicit mitigation strategies (see Section 3).

The simulation also aims to exogenously identify the price that could yield a predetermined reduction target through a self-financing scheme[6] by exploiting the heterogeneous abatement costs of farms. In contrast, previous studies mainly imposed a price on emissions and evaluated environmental and economic impacts (see, among others: Coderoni et al., 2024a; Pérez Domínguez et al., 2020).

The rest of the paper proceeds as follows: Section 2 reviews some pertinent literature on the economics behind the proposed approach, Section 3 presents the models, data used and the simulated scenarios, Section 4 presents the results, Section 5 discusses their implications, and Section 6 presents our conclusions.

2. BACKGROUND OF THE ANALYSIS AND LITERATURE REVIEW

Although there has been substantial political attention on curbing CH_4 emissions, reaching this objective remains difficult. GHG emissions are environmental externalities that lack a market price; thus, farmers are unable to internalize their global impact on society (Acosta et al., 2023; Millock and Nauges, 2006). Consequently, in Europe, the Scientific Advisory Board on Climate Change (2024) recommends that, through a legislative proposal set to begin after 2030, the EU should extend the pricing regime of GHG emissions to all key emitting sectors, including agricultural, food and land use. This change would give farmers a definite financial incentive to lower emissions and increase removals. This vision advances what the European Court of Auditors (2021) previously recommended that the EU should assess the potential of applying the polluter pays principle (PPP) to agricultural emissions.

Many challenges exist in applying the PPP in agricultural GHG mitigation, including the difficulty of MRV for a non-point source of pollution that is also linked to high levels of heterogeneity of farms environmental performances (European Commission et al., 2023; Coderoni, 2023). Farmers' performances can in fact vary according to many structural features (farm size, typologies, etc.) that inevitably translate into behavioural heterogeneity. Consequently, homogenous policies will produce heterogeneous responses (Stetter et al., 2022; Esposti, 2022; Coderoni et al., 2024b). Moreover, even when farms show similar structural and behavioural characteristics, site-specific agronomic, ecological and biophysical variables can lead to uneven environmental effects (OECD, 2022).

These multiple and complex sources of heterogeneity are among the reasons that over the last two decades, analysts and stakeholders have advocated for agri-environmental policies with a more tailored design (Erjavec and Erjavec, 2015; Mahmoud and Hutchings, 2020). However, not all farm characteristics are easily targetable due to practical or political constraints (Coderoni et al., 2024b). Moreover, information asymmetries prevent policymakers from tailoring policies to those farms that can more effectively mitigate emissions, as they are unaware of farms' individual abatement costs.

In the context of information asymmetries, economic theory indicates that market-based policy instruments, like a tax or a tradable permit system for emission rights (a so-called emissions trading system-ETS), are the most cost-effective way to abate emissions without knowing the cost structure of each farm (NERA, 2007). Both ETS and carbon taxes leave the decision of how much to pollute to the regulated parties, which are better informed about the costs and benefits of mitigation options (NERA, 2007). Thus, regulated parties will abate the amounts of GHG that equal their marginal costs of abatement. In the absence of uncertainty, an efficient level of abatement could be achieved under either policy, even if their distributional effects are different (Walter 2020; McKibbin and Wilcoxen, 2002)[7]. A pure emissions tax would generally induce large transfers of income from firms to the government general funds, while the ETS would generate revenue for the governments only through the (eventual) initial auction of emission permits (Carl and Fedor, 2016). Additionally, it would represent a financial transfer from more to less polluting entities. Thus, some ETS-type of instruments have been shown to be less regressive than carbon taxes, and even slightly progressive (Roberts and Thumin, 2006). As a result, ETSs are usually more politically acceptable than carbon taxes. Moreover, an ETS allows for reaching an environmental objective by setting a GHG reduction target in a cost-effective way, without knowing the abatement costs of each firm (as convenience assessments are left to individual cost-benefit analysis). Instead, to reach a desired emission reduction, a carbon tax should be fixed at its optimal level; otherwise, the environmental outcome is uncertain (NERA, 2007).

[6] It is worth specifying that Monitoring Reporting and Verification (MRV) costs and transaction costs were not considered in this study.

[7] As showed by Weitzman (1974), however, in the presence of uncertainties on marginal benefits and costs, taxes and permits are not equivalent. In this case, the relative slopes of the two curves determine which policy would cause a minor welfare loss for society.

To attain a more desirable balance of trade-offs, alternative market-based policy designs could capitalise on the advantages of both the carbon tax and the ETS. Hybrid tax-subsidy schemes offer a potential solution (OECD, 2019; Povitkina et al., 2021).[8] One of these hybrid approaches could take the form of a joint tax and subsidy that applies both the PPP and the provider gets principle (PGP) to CH_4 emissions mitigation. This scheme would apply an environmental standard (in this case, the reduction of 30% CH_4 emissions) to each farm and establish a tax on each unit (tonne) of emissions that exceeds the imposed reduction target or pay a subsidy for each unit of emissions that is reduced above the target.

Farmers can decide to pay the tax while continuing to emit above their threshold, or they can receive the subsidy by reducing emissions below this threshold, according to their economic convenience. If this approach is designed so that the total amount of taxes paid by polluting farms equals the subsidies paid by the government to farms, there would be no burden on government funds (apart from the MRV costs).

This combined policy tool mimics an ETS in terms of incentives, as it leaves farmers free to decide their most convenient action. Meanwhile, policymakers can continue to ignore individual abatement costs. Unlike the ETS, however, this system does not generate government revenue, as taxes are recycled back to subsidised farmers. Moreover, if the price of the incentive (tax or subsidy) is fixed in advance by the regulatory scheme, the uncertainty that usually exists in the likely future permit price can be reduced, thus encouraging investment decisions (Pezzey, 2003).

3. MATERIALS AND METHODS

The data used in this study are derived from the 2020 Italian FADN, the only harmonised microeconomic database that merges data on farm structure, input use, output produced and economic variables (European Council, 2009) with reference to specialised cattle, pig and poultry farms.

To estimate GHG emissions, we adopt an approach already used in the literature to achieve a farm-level indicator of GHG emissions adapting the IPCC methodology at the micro level (Coderoni and Vanino, 2022; Dabkiene et al., 2020; Baldoni et al., 2017). We performed the analysis using the AGRITALIM model, an agroeconomic supply model that uses much of the information reported in the FADN dataset on economic, financial, productive, market, political and structural aspects. The model allows to consider information about farms' geographical areas, altimetric levels and farm types (Cortignani et al., 2022; Dell'Unto et al., 2023); however, for the purpose of this study, results are shown only for farm specialization, OI and LSU.[9] The estimation of CH_4 emissions from livestock farms is a feature only recently included in the model (Cortignani and Coderoni, 2022) and, for the purposes of this study, we further enrich it by implementing an integrated tax and subsidy system to achieve a reduction of 30% of CH_4 emissions from the baseline, to mimic the objective set by the GMP. Our study assumes that this reduction target is equal among all CH_4-emitting units.

To reach this target, we used an alternative system of tax or subsidy, modulating the unitary amounts of the incentive to achieve the mitigation target and an equilibrium between the total amount of tax paid and subsidies received by farmers. The model is constructed so that, at the farm level, two alternatives exist: (1) maintain the productive level (and emissions) and pay a tax on each unit of emissions (tonne of CO_{2eq}) exceeding the 30% target reduction, or (2) reduce emissions more than by 30% and receive a subsidy for each unit of emissions avoided above the target.

The methodology used to estimate CH_4 emissions and the mathematical structure of the model for each farm are presented in Appendix A-Supplementary materials.

4. RESULTS

The results of the simulation involve various technical-productive and economic aspects. All results distinguish between the group of farms that would pay the tax and the group of farms that would receive the subsidy, with reference to the different livestock categories.

Table 1 reports the total emissions produced at the baseline by the different farm types, the quantity of emissions curbed to meet the mitigation target, and the emissions produced above (ΔE^+) and below (ΔE^-) the mitigation target (tonnes of CO_{2eq}). To ensure completeness, we also report the total amount of taxes and subsidies paid.

The total emissions curbed (under Tax and Subsidy, i.e.: 134,964 t^{-1} CO_{2eq}) represent, as expected, 30% of baseline emissions (Table 1).

[8] Such a scheme could encourage the adoption of low-emission technologies by returning emissions tax income to firms (Ollier and De Cara, 2024).

[9] Other results are available upon request.

Table 1. Baseline emissions, emissions curbed under simulation scenario and deviations from the mitigation target (t CO_{2eq}) and total amounts paid for farms opting for the tax or the subsidy.

	Tax				Subsidy			
	Baseline CO_{2eq}	CO_{2eq} curbed	ΔE^+	Total taxes (€)	Baseline CO_{2eq}	CO_{2eq} curbed	ΔE^-	Total subsidies (€)
Dairy cattle	198,234	34,976	24,494	2,706,554	123,347	56,378	19,374	2,140,795
Beef cattle	35,791	6,894	3,843	424,657	38,948	22,992	11,307	1,249,470
Mixed cattle	14,014	3,443	762	84,163	10,910	5,677	2,403	265,583
Pig	18,965	1,649	4,040	446,455	3,151	1,715	770	85,035
Poultry	4,865	437	1,023	112,997	1,441	804	371	41,031
Total	271,870	47,400	34,161	3,774,825	177,797	87,564	34,225	3,781,914

Source: Authors' elaborations.

The unit value of emissions that is calibrated to achieve the mitigation target, is of course the same for tax and subsidy and is equal to EUR 110.50 t^{-1} $CO_{2eq.}$ This would be like the clearing-market price, if there was a market. Thus, the total taxes paid by farms that produce emissions exceeding their threshold (EUR 110.5 × ΔE^+) nearly equals that of subsidies granted to farms that reduce emissions below their threshold (EUR 110.5 × ΔE^-).[10] This result suggests a neutral impact on public finances (without considering implementation and transaction costs).

It is worth noting that farms opting for the tax produce 60% of baseline emissions but contribute only 35% to the mitigation effort. The majority (68%) of the mitigation effort is sustained by dairy cattle farms. Despite this, this category continues to produce the highest volume of emissions exceeding the mitigation threshold (ΔE^+). In contrast, beef and mixed cattle farms exhibit a large prevalence of emissions reduced below the mitigation threshold (ΔE^-). As for pig and poultry farms, the quota of ΔE^+ emissions largely exceeds that on ΔE^- emissions.

Table 2 reports the impacts on the LSU yielded by the different farm types and overall, along with their CO_{2eq} emissions. Moreover, it provides information on the percentage incidence of the amount of the subsidy received and the tax paid, and the percentage of farms opting for the subsidy, both within each type and overall. The absolute values of LSU number and CO_{2eq} emissions for the different farm types at the baseline and under simulation are graphically represented in Figure A.1 (Appendix B-Supplementary materials).

A strict relationship binds the reduction of CH_4 emissions and the number of LSUs, in the absence of any feasible mitigation option that reduces the amount of CH_4 emitted per LSU, like modifications of manure management practices, vaccination against methanogenic bacteria, feed rations supplementation (Magnapera et al., 2025), etc. Such options were not considered at this stage of the analysis, because the objective here is not to appraise the possible benefits and costs of these mitigation options; thus, curbing emissions was possible only by reducing the number of LSUs. Therefore, impacts shown must be considered as a worst-case or short-term scenario, in which it is not possible to change the production technology.

In the overall results, farms opting for the tax reduced their emissions (and number of LSUs) much less than those opting for the subsidy.

Regarding the different farm types, cattle farms (in particular, mixed and beef cattle) are most likely to opt for the subsidy. Thus, cattle farms are the only type to receive an amount of subsidies that exceeds the taxes paid, due to the relevant reduction of emissions they achieve. On opposite, only a limited share of pig and poultry farmers opt for the subsidy. Pig farms were the least likely to adopt the subsidy, and they received the lowest number of subsidies compared to the taxes paid. To understand the technical and economic motivations behind these farms behaviours, Table 3 and the corresponding Figure A.2 in Appendix B show the values of three key indicators for the different farm types and overall: (*i*) methane emission intensity (MEI; i.e., tonnes of CH_4 in CO_{2eq} divided by the LSUs), (*ii*) profitability per LSU (PLSU; i.e., OI divided by the number of LSUs)

[10] Perfect equality between the two values (taxes and subsidies) cannot be achieved for technical reasons. Since price calibration is external to the model, a more precise calibration (e.g., to the level of EUR cents) would theoretically bring the total amount of taxes and subsidies to perfectly balance, but this would also cause issues in model resolution. In practice, as farms cannot simultaneously be subject to both the tax and the subsidy, and given their inherent heterogeneity, it is highly unlikely (though theoretically possible) that the two groups of farms (those paying the tax and those receiving the subsidy) would be perfectly identical, for example, in terms of LSU.

Table 2. Impacts on the LSU number and on CO_{2eq} emissions of farms opting for the tax, for the subsidy and average (Δ% under the simulation with respect to baseline) and percentage incidence of the amount of the subsidy received and the tax paid and of farms opting for the subsidy on total farms.

	Tax		Subsidy		Average		Subsidy/Tax	Subsidised farms
	LSU	CO_{2eq}	LSU	CO_{2eq}	LSU	CO_{2eq}	%	%
Dairy cattle	-17.6	-17.6	-45.7	-45.7	-28.5	-28.4	79.1	41
Beef cattle	-18.8	-19.3	-57.7	-59	-39.4	-40.0	294.2	41.2
Mixed cattle	-23.6	-24.6	-51.5	-52	-36.2	-36.6	315.6	56.2
Pig	-8	-8.7	-56.5	-54.4	-15.9	-15.2	19	11.4
Poultry	-7.2	-9	-57.5	-55.8	-18.7	-19.7	36.3	16.7
Total	-13	-17.4	-51.4	-49.2	-25.5	-30	100.2	38.7

Source: Authors' elaborations.

Table 3. Average values of MEI, PLSU and MeP for the two groups of farms that opt for paying the tax or receiving the subsidy, under the Baseline and the Simulation.

	Tax			Subsidy		
	MEI	PLSU	MeP	MEI	PLSU	MeP
Baseline						
Dairy cattle	3.25	903	278	3.18	562	177
Beef cattle	2.12	751	355	2.05	356	173
Mixed cattle	2.74	682	249	2.61	350	134
Pig	0.33	323	995	0.28	100	357
Poultry	0.19	427	2,189	0.19	151	780
Total	1.63	606	371	2.21	400	181
Simulation						
Dairy cattle	3.25	1,004	309	3.18	1,010	318
Beef cattle	2.11	868	412	1.99	865	434
Mixed cattle	2.71	824	304	2.58	713	276
Pigs	0.32	342	1,059	0.29	231	788
Poultry	0.19	454	2,375	0.20	355	1,761
Total	1.55	653	421	2.30	815	354

Source: Authors' elaborations.

and (*iii*) methane productivity (MeP; i.e., the OI generated by one tonne of CH_4 in CO_{2eq}).

The first section of the table (Baseline) shows the value of the indicators at the baseline for the two groups of farms that opt for paying the tax or receiving the subsidy; the second section (Simulation) reports the same information for the same groups under the simulation.

The results in the last row of the Baseline section reveal that farms opting for the subsidy tend to have a lower value of PLSU and MEI than those opting for the tax, and this is true across all the different farm types. The higher share of cattle farms among those opting for the subsidy leads the average value of MEI to be higher for farms opting for the subsidy, even though the values of the different farm types are lower than those opting for the tax.

Relevant differences also emerge among farm types. Dairy cattle farms exhibit the highest MEI and PLSU, while the highest MeP is found among beef cattle farms opting for the tax, as they tend to have a low MEI compared to the other cattle farms in this group. The highest value of MeP within the whole sample is associated with poultry farms, which have the lowest MEI and an intermediate level of PLSU. Pig farms exhibit an intermediate MEI, which, in combination with the lowest PLSU, leads to intermediate MeP values.

Similar considerations are seen when analysing the values of the indicators of the different farm types under the Simulation scenario. It is worth highlighting that PLSU and MeP increase compared to the baseline, even doubling in the case of the farms opting for the subsidy. This result is partly explained since 35% of farms opting for the subsidy would have a negative OI in the baseline, if the contribution from the Common Agricultural Policy (CAP) First Pillar payments were not included. Thus, these farms probably prefer to cut production, forgoing the CAP coupled support and opting for the CH_4 reduction subsidy. These farms also demonstrate a slight increase in MEI values in contrast with the farms opting for the tax.

When analysing the impacts on the single farm types opting for the tax, it is necessary to consider how reducing the number of LSUs (and emissions) affects mixed cattle farms, in comparison with other types of farms. As shown in Table 3, these farms exhibit the lowest value of MeP along with a still-high value of MEI (second only to dairy cattle farms). When looking at the farms opting for the subsidy, the drop in production activities is particularly dramatic for beef cattle, poultry and pig farms.

Table 4. Impacts on OI of farms opting for the tax, for the subsidy and average, with and without the impacts of taxes and subsidies on farms' budget (Δ% under the simulation with respect to baseline).

	With taxes and subsidies			Without taxes and subsidies		
	Tax	Subsidy	Average	Tax	Subsidy	Average
Dairy cattle	-8.4	-2.4	-6.7	-3.5	-12.2	-5.9
Beef cattle	-6.3	2.8	-3.1	-2.9	-15.8	-7.4
Mixed cattle	-7.8	-1.2	-5.9	-5.4	-19.4	-9.5
Pig	-2.8	0.7	-2.7	-0.5	-6.9	-0.8
Poultry	-1.3	-0.2	-1.2	-0.2	-3.8	-0.5
Total	-6.3	-1.1	-5.0	-2.6	-12.8	-5.0

Source: Authors' elaborations.

Table 4 shows the impacts on OI of the different farm types and overall. The left section reports actual impacts on OI, including the economic cost of reducing production activities, as necessary to meet the mitigation target, and the financial impacts of taxes and subsidies on farms' budgets. In the right section of Table 4, we considered only the impacts of activities that reduced production, excluding the financial impact of taxes and subsidies on farms' budgets. The absolute values of OI generated by the different farm types under baseline and simulation are graphically reported in Figure A.3 (Appendix B).

The overall results in the left section of Table 4 indicate that farms opting for the subsidy are nearly compensated for OI losses due to the reduction in their production activities (–1.1%), while tax burden reduces the OI of the farms opting for this instrument by 6.3%. When excluding the financial impacts of tax and subsidy, the situation is reversed. The much milder reduction of production activities undertaken by the farms opting for the tax would determine equally mild impacts on their OI (–2.6%). Instead, the negative impacts on OI are much stronger for the farms opting for the subsidy (–12.8%), although this impact is far less than proportional to the level of reduction of productive activities these farms undertake (–51.4% of LSU, as reported in Table 2). This less-than-proportional reduction of OI with respect to the level of production activities is due to the strong increase of PLSU and MeP that occurred for these farms in the simulation (Table 3).

When examining the different farm types and considering the financial impact of tax and subsidy, cattle farms (particularly dairy cattle and mixed cattle) are the most negatively affected due to having the highest MEI and lowest MeP (Table 3). Even when excluding the financial impact of tax and subsidy, the worst impacts again affect mixed cattle farms, since these farms more frequently opt for the subsidy and receive the highest amount of subsidies with respect to taxes paid. For the same reason, the opposite occurs considering the average impacts on OI of pig and poultry farms, which make less recourse to – and thus receive a lower share of – the subsidy.

To provide evidence of the wide heterogeneity between farms' performances, Table 5 shows baseline values of OI and CH_4 emitted and the impacts on these variables from the application of the combined economic policy tool, together with their Coefficients of Variation (CV).

As evidenced by the high values of CV, a large heterogeneity characterises the farm types under analysis at the baseline, with beef and mixed cattle farms being the most heterogeneous both in terms of OI and of CH_4 emitted. Instead, dairy cattle farms show the lowest heterogeneity in terms of emissions, indicating that the high level of emissions is a characteristic inherent to this type of farming (in line with the value MEI values reported in Table 4). Under simulation, these farms experiment the worst impact on OI with the highest level of heterogeneity, closely followed by beef cattle farms. Instead, both the extent of the impacts and their variability gradually reduce in mixed cattle, pig and poultry farms. Thanks to the lowest MEI, these latter two farm types

Table 5. Average value of OI (EUR ,000) and CH4 (t) at the baseline and Δ% under simulation, and respective Coefficients of Variation (CV).

	Baseline OI		Baseline CH_4		Δ% OI		Δ% CH_4	
	Average	CV	Average	CV	Average	CV	Average	CV
Dairy cattle	82.6	231.4	345.4	141.9	-27.0	-897.7	-29.9	-62.8
Beef cattle	41.7	334.8	160.4	237.9	-26.2	-787.4	-32.6	-75.0
Mixed cattle	32.3	387.1	162.9	291.1	-6.4	-412.0	-37.7	-65.1
Pig	126.6	166.8	140.0	145.1	-5.9	-360.5	-13.3	-137.0
Poultry	151.0	215.5	80.8	199.5	-2.4	-167.3	-13.8	-138.4
Total	74.5	250.7	251.8	176.2	-22.1	-926.3	-29.1	-75.1

Source: Authors' elaborations.

show lower CH_4 reductions, although with the highest heterogeneity. For the opposite reason, cattle farms (particularly mixed ones) reduce the most their emissions, with a halved level of variability.

Relevant heterogeneity also exists among different geographical location of Italy (see Table A2 in the Appendix C).

A sensitivity analysis was finally performed to evaluate the eventual different impacts derived from imposing d reduction targets (-25% and -35% with respect to baseline level of emissions). The overall results indicate that the extent of the impacts on OI, LSU and emissions increase in a consistent way as the mitigation target becomes more ambitious (Table A3 in Appendix D).

5. DISCUSSIONS AND POLICY IMPLICATIONS

This study simulates the application of the GMP mitigation target to the Italian livestock sector through a mechanism alternatively combining taxes and subsidies. The proposed policy instrument is exogenously built to approach financial self-sufficiency. The heterogeneity of farms' characteristics and productivity, shown in Table 5, make this outcome likely. As the degree of homogeneity increases, the instrument might become less efficient in reaching this objective, as farms' relative convenience would converge.

The choice to reduce emissions or pay taxes drives the optimisation behaviour based on farm-level abatement costs (represented in this case by the opportunity cost of production, i.e., PLSU) and emissions' performances (MEI and MeP).

When examining the impacts generated, it is worth noting that a reduction of emissions is currently possible in the model only by reducing the number LSU. As specified, in fact, our model does not consider any simulated mitigation option for reducing emissions per LSU while retaining animals. Indeed, as stressed by European Commission et al. (2023), for cattle farms in particular, GHG abatement using technical options has limited emissions reduction potential. Therefore, these farms primarily need to reduce livestock numbers, as it is inherently tied to the level of GHG emissions (USDA, 2004). Reducing LSUs thus represents the most direct (and drastic) mitigation measure. Of course, impacts on OI are much lower in this study than those estimated by Coderoni et al. (2024a) for the introduction of a tax (of a maximum of 100 EUR per tonne of CO_{2eq}) alone, as, in this case, farmers can choose to opt for mitigating emissions or paying taxes. However, impacts on LSUs are almost identical. In particular, the simulated impacts on production (specifically of farms opting for the subsidy) are remarkable. The average reduction in LSUs in farms opting for the subsidy exceeds 50%, with peaks of –56.5% and –57.5% for pig and poultry farms. For these farm types, it is notable that almost 30% showed high dependence on the CAP First Pillar payment in the baseline, indicating that they are inefficient in producing OI without the subsidy. In the presence of such taxation, they have opted to reduce their herd size and receive the subsidy.

In this scenario, however, it is likely that many of the most impacted farms will be forced to exit the market or drastically modify their productive specialisation in the medium to long run. These impacts must be considered as the bottom line in case no policy intervention is undertaken to facilitate the adoption of alternative mitigation options by farmers and no spontaneous adoption by the latter occurs. Indeed, it may not be realistic to expect farmers to spontaneously adopt mitigation options, particularly in the short run. Implementing these measures could contribute, on the one hand, to mitigating the impact on production levels, but on the other hand, it requires having financial resources available to invest, and thus increases production costs.

Usually, in the presence of a price on carbon, rational farmers adopt technologies for mitigating GHG emissions if these technologies improve their economic sustainability; thus, what really matters in implementing these measures is the interplay between mitigation potential (that would reduce the amount of tax to pay or increase the subsidy to receive) and the costs of its implementation (Auld et al., 2014; Blandford and Hassapoyannes, 2018; Bakam et al., 2012). In addition, if the reduction targets are relevant, impacts on LSUs are as well, unless not all farms apply the mitigation measures (Coderoni et al., 2024a). Thus, the policy should provide support to cover the cost of mitigation technologies and ensure the effectiveness of the strategy.

Our results show that the choice to reduce productive activities, as well as the level of reduction with respect to the mitigation target, can be explained by considering three proxies of productivity and efficiency performance at the farm level, with respect to CH_4 emissions produced. The first (MEI) pertains to CH_4 emission intensity. The second (PLSU) relates to the profitability (in terms of OI) of each LSU. The third (MeP) combines the information from the first two, quantifying the productivity or profitability (OI) of each unit of CH_4 emissions (expressed in CO_{2eq}). The modelling tool's optimisation of OI involves increasing PLSU and MeP in the presence of taxes and subsidies. In general, the higher PLSU in the farms opting for the tax prevents them from reducing the LSUs to the level necessary to achieve the mitigation target. On the contrary, farms with lower PLSU opt for the subsidy because it is convenient to reduce emissions far below the mitigation target, along with reducing their production level. This makes it possible for these farms to (*i*) receive the subsidy on the quota of curbed emissions below the threshold and (*ii*) reduce the production costs in the presence of a lower baseline PLSU. This means that only farms with higher productivity will continue to emit more than the mitigation target (paying the tax), while the others will reduce their emissions below the target (receiving the subsidy).

An interesting aspect is that farms opting for the tax manage to reduce their CH_4 emissions more than proportionally to the number of LSUs, while reducing emissions is more "costly" in terms of LSUs for the farms opting for the subsidy (although they reach higher levels of reduction). However, subsidised farms achieve a less-than-proportional reduction of emissions with respect to the number of LSUs. This is because their lower baseline MEI, which slightly increases under the simulation.

It is also interesting to note the strong increase, under the simulated scenario, of the average value of PLSU and MEI, particularly for farms opting for the subsidy. This increase could also result from reducing the herd size for those farms that would have not been profitable (without CAP support) in the baseline and thus opt for reducing inefficient production units if taxed.

Results in terms of GHG reduction with respect to the GHG price are not directly comparable to other studies that simulate the introduction of an ETS or the pricing of GHG emissions. We only address CH_4 emissions from the Italian livestock sector, while other studies usually consider applying an ETS or an emission price to the whole agricultural sector (at the European or country level) (see among others: Pérez Domínguez et al., 2020). However, some comparisons are possible with other works in the literature. For example, the market-clearing price derived in this study, which would permit reaching the 30% GHG reduction target, is 110.50 EUR t^{-1} CO_{2eq}. Isbasoiu et al. (2020) and Pérez Domínguez et al. (2020), who calculated a similar GHG price (100 EUR t^{-1} CO_{2eq}), estimate a GHG reduction of 25%. Furthermore, in terms of subsidies, this emission price is similar to other payments made under the Italian CAP (e.g., agro-environmental payments to reduce ammonia emissions or livestock-related eco-schemes).

5.1 Policy implications

The results presented here, being the first ex-ante modelling of the application of the GMP to Italian livestock sector, could be useful to appraise the impacts of such target on different specialisations, to provide a policy to support the transition to more heavily affected farms. Besides, they could provide a preliminary indication of the tentative price to be applied to livestock emissions to reach this ambitious target.

In terms of policy tool efficiency and efficacy, the analysed instrument combining a tax and a subsidy, like an emission standard, allows for reaching a desired reduction target, but unlike the standard, it also compensates virtuous behaviour with the subsidy (thus pursues the PGP).

Similarly to the ETS, this tool allows for reaching the environmental objective by addressing the heterogeneity of farms' performances in terms of mitigation potentials, thus overcoming information asymmetries between the polluter (farm) and the policymaker. Unlike ETS, this system does not foresee a mechanism for the market of credits; thus, part of the implementation costs should be lower (as, for example, there is no need for a registry for the credits), although MRV issues remain. MRV matters are linked to two main (interlinked) problems: complexities and costs. MRV complexities are present because agricultural emissions are challenging to quantify. The sector is a non-point source of pollution, and emissions derive from all agricultural activities across the rural landscape (Smith et al., 2014). Usually, there is a direct proportion between estimation accuracy and the cost of estimation itself. This brings us to the second relevant issue: MRV costs. MRV costs per tonne of GHG reduction are primarily driven by the size of the source. Significant transaction costs associated with MRV are thought to be fixed expenses that are independent of farm size (Bellassen et al., 2105). This fact heavily influences the discussion on the cost-effectiveness of including small farms in the system. An "on farm" ETS option, like the one simulated here, although excluding small non-professional farms, would include farmers as direct participants, bringing much higher complexity and administrative costs compared to "downstream" and "upstream" options that involve dairy and meat processors or fertiliser and feed sellers as participants (European Commission et al., 2023). Although the availability of proxy data can reduce these costs, as some data required for MRV is already collected under existing agricultural regulations and applications for subsidies under the CAP – and synergies could be established with the IED (European Commission, 2022) – significant information remains to be collected to have a proper estimation at the farm level.[11]

[11] Indeed, a proper estimation of agricultural GHG emission is a very complex issue and the private sector initiatives have worked extensively on data quality for the agricultural measures to be included the Science

Another aspect to consider in implementing such a policy tool is that subsidising farmers to reduce their emissions might be less efficient and potentially more market distortive than the alternative approach based on taxation, beyond the risk of overcompensating farmers for reducing emissions (OECD, 2019; 2022). In this approach, the potential for creating a distorting effect is partly counterbalanced by the fact that the money needed to pay the subsidy is self-financed from the environmental tax implemented by the same scheme. This method yields a neutral impact on public finances (excluding MRV), as well as an income transfer between farms. Here, funds are transferred from pig and poultry farms to cattle farms. The latter benefit most from the subsidy, both in terms of the number of farms and the amount of subsidy received, but a similar redistributive effect also occurs among these farms (e.g. from dairy to beef and mixed farms).

In terms of policy implications, it is also necessary to reflect on impacts on employment[12], territorial protection and control of the territory by more extensive livestock farms, as well as on carbon leakage. We consider these factors in the absence of relevant modifications of consumers' behaviour towards the consumption of animal products.[13] Sustained internal demand is likely to lead, at least in part, to relocating production to countries where no emissions mitigation policy is in place, with a consequent increase in imports from outside the EU.

Finally, the overall policy coherence should be assessed (Coderoni, 2023). While such a policy framework could be coherent with the IED and the Farm to Fork Strategy, it may conflict with coupled income support for livestock under the CAP (European Commission et al., 2023).

5.2 Limitations of the study

Among the limitations of the study, the AGRITALIM model cannot consider changes in internal demand and international trade dynamics. However, the impacts it estimates – with a 25.5% reduction of reared LSUs for Italy alone – will hardly avert such a phenomenon, which a substantial body of literature warns about (Pérez Domínguez et al., 2016; Dumortier et al., 2012; Caro et al., 2017). This risk could be reduced through multilateral agreements with countries exporting in the EU, free allocation of GHG permits to farms or a Carbon Border Adjustment Mechanism (European Commission et al., 2023).

Another limitation of the study is the assumption that the emissions distribution across farms in a particular year (in this case, 2020) represents an adequate baseline on which to base a tax and subsidy regime, as individual farmers could claim that the baseline year chosen is not representative of their farms. While not fully relevant to the ex-ante simulation here proposed, this issue should be adequately considered in case of actual implementation of such policy tool.

Another means of improving the modelling tool would be to incorporate technological mitigation options that could function as an alternative to reducing the number of LSUs.

6. CONCLUSIONS

The present study employed a micro-level economic modelling approach to assess the results of a combined policy tool to curb CH_4 emissions from Italian cattle, pig and poultry specialist farms.

The results highlight the heterogeneity of farmers' behaviour, as influenced by the profitability and emission intensity of their livestock activities. In general, the analysed policy instrument would yield a stronger negative impact on less productive farms (i.e., beef and, particularly, mixed cattle). These farms are characterised by a much higher MEI than pig and poultry farms and a lower PLSU than dairy cattle farms. Consequently, the share of farms opting for the subsidy is highest among these farms, with dramatic production losses. Insights from this research could be used to help policymakers understand the diversified impacts of such a policy framework on livestock farms and the possible compensation they could provide to specific specialisations and territories.

Future research could replicate the study by simulating different minimum farm sizes (in terms of LSUs or income) to be included in the framework to assess the cost-effectiveness of the policy, according to different point of obligations design. Moreover, the model could be implemented considering alternative and combined technical mitigation options to assess the mitigation potential of the sector and more properly estimate impacts on productions allowing technological progress. This could be more easily implementable with database improvements that could capture the presence and

Based Target initiative (SBTi) (https://sciencebasedtargets.org/blog/the-sbti-flag-updates) (accessed 08/11/2025).

[12] European Commission et al. (2023) identifies the presence of livestock as an important risk-reduction strategy for vulnerable rural communities, the use of a threshold level of LSUs for the smallest farms should be carefully considered.

[13] For an assessment of the importance of integrating economic and environmental policies to enhance global food sustainability see Frontuto et al. (2025).

impacts of different mitigation measures (e.g. with the transition to the Farm Sustainability Data Network). Lastly, future studies should simulate the impacts of a likely CAP reform that divert financial resources to direct support to agricultural incomes, to direct support for GHG emissions reduction.

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Short communication

Circular Biobased Europe Joint Undertaking: driving innovations towards sustainable agriculture and growth in rural areas

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Abstract. The Circular Bio-based Europe Joint Undertaking (CBE JU) is a public-private partnership that supports research and innovation fostering the transition towards a competitive, sustainable, and low-carbon economy in Europe. CBE JU and its projects represent a significant business opportunity for the primary sector, and in particular for farmers. The deployment of circular bio-based innovations can help diversify farmers' activities and generate new sources of income. Since 2022, about 130 million euros have been made available by CBE JU to develop bio-based solutions with the potential to support sustainable agricultural practices and boost rural economies. In addition, 84 entities from the primary sector are participating in CBE JU projects. The manuscript aims at analysing the major findings associated with primary producer involvement in the CBE JU programme and elaborate on the specific actions undertaken to ensure that the primary sector can benefit from participating in innovative bio-based value chains.

Keywords: bioeconomy, primary sector, biorefineries, bio-based industries, public-private partnership.

1. INTRODUCTION

The unprecedented trend of global warming, climate change, degradation of the natural ecosystems and increased pollution calls for immediate actions. In response, the European Union (EU) has put in place the European Green Deal, a growth strategy that aims to create a fair, prosperous society with a competitive and resource-efficient economy aiming to achieve net-zero greenhouse gas emissions by 2050 (European Commission, 2019).

To reach these ambitious goals, a transition from a fossil- to a bio-based economy is needed. New innovative, sustainable and circular bio-based products, that reach high technical levels of performance and fully meet market requirements, should be developed so that they can successfully replace their current fossil-based counterparts. In addition, the sustainable and local sourc-

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ing of biomass, including all types of bio-based side streams, and the reuse, recycling and upcycling of resources will play a key role in ensuring that bio-based systems are sustainable and efficient in the use of natural resources.

Building on the success of its predecessor, the Bio-Based Industries Joint Undertaking (BBI JU), the Circular Bio-based Europe Joint Undertaking (CBE JU) is a pivotal instrument to implement this vision at European level, as it facilitates transition from fossil fuel dependency, aligning with the goals of the EU Green Deal within the multifaceted policy scenario that govern the bioeconomy and the bio-based sector (European Commission, 2021; Johnson et al., 2021; Mengal et al., 2018; Ruiz Sierra et al., 2021).

Policy development in the bio-based sector and in the bioeconomy area at large have received increasing attention in recent years. In April 2023, the EU Council endorsed conclusions highlighting the bioeconomy's potential to support the environmental and climate objectives of the European Green Deal (General Secretariat of the Council, Special Committee on Agriculture, 2023). The bioeconomy is seen as a key factor in enhancing EU competitiveness, reducing fossil fuel dependency, and improving food security. In particular, the Council stressed the role of bioeconomy in fostering socially and economically viable rural areas, engaging primary producers in climate action, and promoting job creation and equal opportunities across the EU. Additionally, it emphasised the need for sustainable solutions in rural regions and the importance of providing diversified incomes for stakeholders in the bioeconomy, including landowners and small businesses, through new value-added chains and business models.

More recently, in 2024, the final report of the Strategic Dialogue on the Future of Agriculture acknowledged the necessity of collaboration between public and private sectors, as strong public-private partnerships in which rural actors actively participate can help turn niche into norm to support the development and implementation of bioeconomy initiatives (Members of the Strategic Dialogue on the Future of EU Agriculture, 2024).

In addition, in 2024, the European Commission (EC) has proposed a series of targeted actions to boost biotechnology and biomanufacturing in the EU, offering innovative solutions to societal challenges (European Commission, 2024). Biotechnologies which fall into the remit of CBE JU's field of action hold great promise for modernising not only the bio-based industrial sector but also agriculture, forestry, food and feed industries at European level.

Altogether, these important political inputs have constituted the basis for the new Bioeconomy Strategy, that was adopted in November 2025 (European Commission, 2025) and aims to advance innovation and maintain the EU's leadership in the bioeconomy. The new Bioeconomy Strategy proposes actions to unlock the potential of bioeconomy innovations, so that they can reach the market, and will represent a major step forward in the evolving EU economic and political context. Particular attention is given to the role of the primary sector and the significance of biomass sustainability and availability for strengthening and supporting the bio-based sector across Europe.

In this overall scenario, the objective of this article is to present the activities that CBE JU has performed to ensure that primary sectors benefit from the economic, social, and environmental opportunities offered by circular and bio-based innovations, including the creation and establishment of a dedicated CBE JU working group on primary producers. Data derived from the first three years of programme implementation demonstrates how the effort that has been taken contributed to enhance the role of primary producers in circular bio-based systems and value chains. Lastly, the article is presenting cases of projects where the involvement of the primary sector is exemplary and showcase the potential impact of the primary sector in the deployment of bioeconomy, with a specific attention to the first-of-a-kind biorefineries that represent a peculiarity of CBE JU funding strategy.

2. CBE JU: A PUBLIC-PRIVATE PARTNERSHIP TO SUPPORT THE GREEN DEAL OBJECTIVES

The CBE JU is a EUR 2 billion Public-Private Partnership between the EU, represented by the EC, and the Bio-based Industries Consortium (BIC), a not-for-profit organisation representing the private sector across the bio-based industries. It is established for the 2021-2031 period under Horizon Europe, the EU's research and innovation framework programme (European Commission, 2021).

Key objectives of CBE JU are to i) accelerate the innovation process and development of bio-based innovative solutions, ii) support the market deployment of mature bio-based innovative solutions and iii) ensure a high level of environmental performance of the bio-based industrial systems. In particular, CBE JU seeks to bridge the gap between the development of new bio-based innovations and their market deployment by promoting research and innovation collaborative projects which integrate stakeholders throughout bio-based value chains, including the primary sector, as vital biomass suppliers. CBE JU aims at de-risking investments, encouraging collaboration, establishing new value chains, and tackling strategic challenges to build a sustainable and prosperous bioeconomy. It ultimately contributes to boosting European competitiveness on the global scale while at the same time reducing dependency and increasing strategic autonomy.

CBE JU also aims to enhance the role of the primary sectors in the European bioeconomy with their involvement in new value chains. This is reflected across all the frameworks and activities that CBE JU is performing, from the Council Regulation establishing the Joint Undertakings to the CBE JU Strategic Research and Innovation Agenda (SRIA) and the CBE JU annual work programmes, which are setting the basis for the annual publication of calls for proposals (European Commission, 2021; Bio-Based Industries Consortium, 2022).

CBE JU is a central pillar in establishing Europe's bio-based sector as a global leader, and the overall CBE JU project portfolio is composed of 220 projects, including 138 projects funded by the predecessor BBI JU and 82 projects funded by CBE JU up to call 2024. Over 1714 participants from 46 countries have been engaged in CBE JU funded projects, among which 38% are SMEs.

Aligned with Horizon Europe, the CBE JU is funding projects through open calls for proposals. In particular, early-stage development (TRLs 3–5) is funded by research and innovation actions (RIAs). Innovation actions (IAs) are represented by two different type of actions: demonstration projects (IA-DEMO) that aim at scaling up the technology and validating business cases (TRL 6–7), and flagship projects (IA-FLAG) that are operating at a pre-commercial scale (TRL 8), and aim to support innovations that have already been demonstrated but not yet applied or deployed at industrial and commercial scale in the EU (first-of-a-kind innovation). Lastly, CBE JU is funding coordination and support actions (CSAs), that address non-technological challenges, such societal awareness, capacity building, education and skills, among others. Table 1 shows the portfolio of projects funded by CBE JU (and its predecessor BBI JU) divided per type of action and with their associated budget.

The main application areas covered by the CBE JU projects are bio-based chemicals, biopolymers and bioplastics, food and feed ingredients, packaging, construction materials, crop protection and fertilisation solutions, and textile as shown in Figure 1.

The main types of feedstocks used in CBE JU projects are agriculture-based feedstock, including residues and by-products from the agri-food industry, followed by forest-based feedstock, including lignocellulosic side streams and wood residues, and finally aquatic feedstock, including aquatic organisms and biomass from fisheries and the aquaculture sector and their residues. Other relevant feedstock for CBE JU projects includes side streams from industry, including black liquor from the pulp and paper industry and dairy process side streams, as well as biowaste, including Organic Fraction of Municipal Solid Waste (OFMSW), and biogenic gases. (see Figure 2).

It is therefore noteworthy to underline the importance of primary and secondary biomasses linked to the agricultural, forestry and marine ecosystems in the overall CBE JU portfolio, representing about 90% of the feedstocks addressed by the CBE JU projects.

3. CHALLENGES OF THE PRIMARY SECTOR INTEGRATION IN THE BIOBASED INDUSTRY AND OPPORTUNITIES OFFERED BY CBE JU TO FARMERS

Enhancing business opportunities for primary producers in cooperation with the rest of the stakeholders involved in the development of new innovative bio-based value chains and promoting bioeconomy in rural areas are at the core of CBE JU's priorities.

Farmers are recognised in the context of CBE JU as crucial actors of the value chains as they are providing biorefineries with different types of biomasses (including residues, side streams and by-products) which are converted into high-value bio-based products and mate-

Table 1. Number of projects funded for Type of Action and relative share in the overall CBE JU portfolio until call 2024.

Type of Action	Number of funded projects	Total budget	Share of project	Share of total budget	Technology Readiness Level (TRL)
Innovation Action – Flagship	19	333 m€	10%	26%	3-5
Innovation Action – Demonstration	76	516 m€	34%	41%	6-7
Research and Innovation Action	100	383 m€	45%	30%	8
Coordination and Support Action	25	37 m€	11%	3%	---
Total	220	1269 m€			

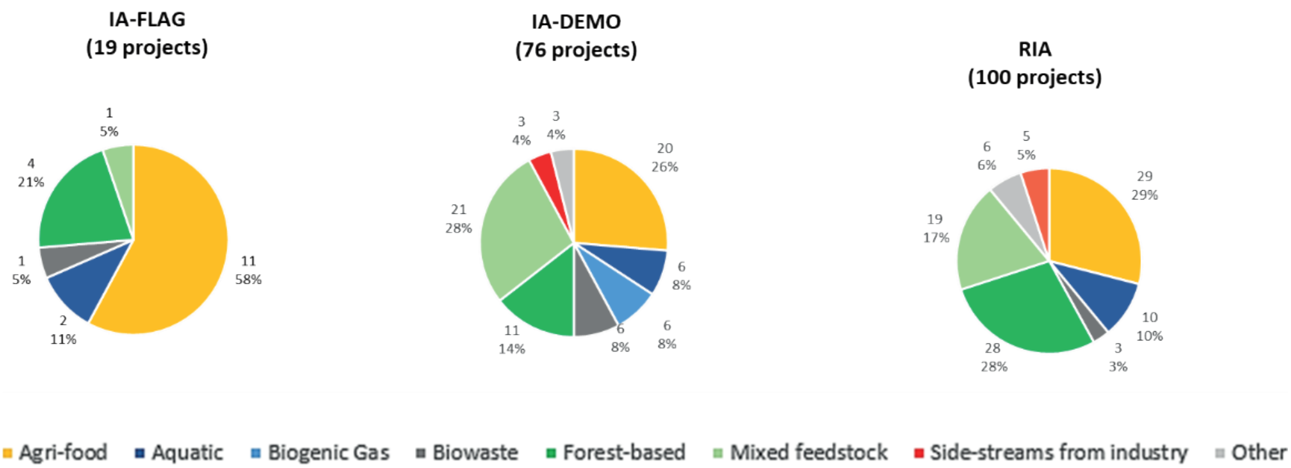

Figure 1. Number of CBE JU projects by main area of application and type of action. CSA projects are not included being horizontal actions to support CBE JU programme.

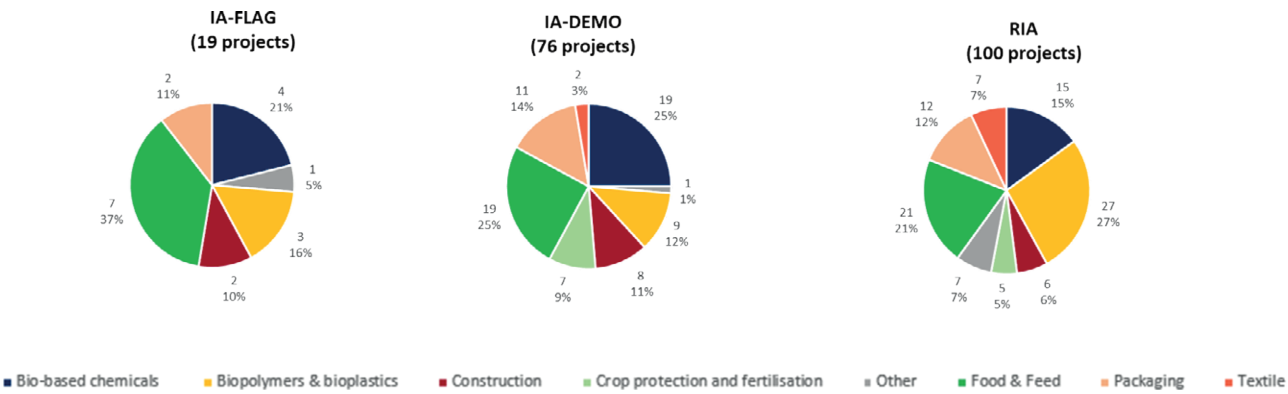

Figure 2. Number of CBE JU projects in relation to their main feedstock divided per type of action.

rials. The economic activities along the biorefinery processes have the potential to bring new sources of income for primary producers including farmers and therefore boosting local economies in rural areas where they are located. In addition, farmers are also end-users of the innovations delivered by the CBE JU-funded projects which are developing bio-based crop protection and fertilisation solutions with a high environmental performance. These innovations include bio-based fertilisers, bio-based pesticides, biostimulants, or biodegradable and bio-based plastics used in agricultural practices. These bio-based products represent a real alternative to conventional products being more sustainable (i.e., having a reduced carbon footprint, minimising the impact on natural land, protecting soil quality and productivity, minimising the emission of chemicals) and supporting ecosystem restoration, greener agricultural practices (including organic farming), decarbonisation and reduction of EU dependency on imports of raw materials used to produce fertilisers.

In order to better understand the main challenges and opportunities for primary producers in the bioeconomy sector, a "Study on the participation of the agricultural sector in the BBI JU: Business Models, Challenges and Recommendations to enhance the impact on Rural Development" (Innovarum, 2019) has been conducted to be used as foundation for the draft of the CBE JU SRIA.

The primary sector plays a fundamental role in the deployment of circular bio-based innovations, significantly influencing the sustainability and success of the broader bio-based economy. As key suppliers of biomass, primary producers provide the essential raw materials needed for bio-based processes. At the same time, they act as both producers and end-users of bio-based products and innovations, making their engagement vital for creating fully integrated, circular value chains. Despite their potential to drive sustainability and innovation, several barriers hinder their full participation and the extent to which the primary producers can benefit from these opportunities. One of the core challenges is a lack of awareness regarding the opportunities presented by circular bio-based innovations. Many primary producers remain uninformed about how these innovations can enhance their operations, improve efficiency, and offer new revenue streams. Even when information is available, there is often hesitation to embrace change, stemming from concerns about altering well-established business models. The transition toward bio-based solutions also may require significant adjustments to traditional agricultural or forestry practices, leading to uncertainty about economic viability, technical feasibility, and market demand. Several communication-related issues further limit primary producers' ability to engage in bio-based innovation (e.g., language used is too complex, inappropriate interlocutors at the primary producer level, insufficient exchanges between primary producers and industry).

From a value chain perspective, primary producers are often only marginally integrated into the bio-based value chains and they are facing technological risks and uncertainties as building a new supply chain takes many seasons and years, with high risk for the primary sector and with limited short-term results.

By addressing these challenges, primary producers can be empowered to take an active role in circular bio-based innovation, ensuring that they do not just remain suppliers of raw materials but also benefit from the transformative opportunities that this growing sector offers.

Consequently, the CBE JU SRIA underlined that there is still room for further outreach and mobilisation of primary biomass suppliers from the agriculture sector which had already been identified as the group that needs to play a bigger and more specific role in the bioeconomy and bio-based value chains (Bio-Based Industries Consortium 2022; Innovarum, 2019; Bio-Based Industries Joint Undertaking, 2019).

Among the priorities established in the CBE JU SRIA for the primary sector, it is proposed i) to engage and integrate primary producers in sustainable circular bio-based systems and value chains; ii) to improve the primary sector's involvement in the value chains with the aim of ensuring high quality and quantity of feedstock, while they are rewarded with a proper share of the profit; iii) to revive and revitalise rural, coastal, and peripheral regions through the development of appropriate technological solutions, and inclusive involvement and empowerment of local bioeconomy actors (including the primary sector).

In the SRIA, it is also foreseen that CBE JU actions will implement a value chain approach to ensure that all the relevant actors in the bio-based system, including the supply chain, i.e. primary producers, are appropriately involved in the selected project proposals and are represented to the largest possible extent in the project consortia.

Therefore, the CBE JU has launched in 2024 dedicated communication campaigns in EU countries that are included in the list of widening countries under Horizon Europe and that were underrepresented through the BBI JU programme implementation, as well as targeted specific stakeholder groups, such as primary producers. Communication material is adapted to the local language to reach a higher impact. The communication addresses local communities with a message on creating new kinds of jobs and alternative income sources in rural and coastal areas.

As a last and relevant operational instrument to foster the primary sector engagement in the bio-based industry, CBE JU has created a working group on primary producers (WG PP) that has been officially launched in June 2025. This is an action group the scope to propose specific actions to address the challenges faced by the agricultural, forestry and aquaculture & fisheries primary sector and to harness opportunities offered by circular bio-based innovations. The objectives are i) to empower primary producers to play an active and rewarding role in circular bio-based value chains; and ii) ensure they benefit from the economic, social, and environmental opportunities these systems offer (supported by long-term, sustainable, and feasible business models). The WG PP is a group of 78 stakeholders (by June 2025) and consists of organisations representing the agricultural, forestry, fisheries, and aquaculture primary sectors across Europe. The WG PP remains open to incorporate additional primary producers who wish to join the initiative in the future, ensuring broader representation across both sectors and regions. Among the concrete outcomes expected from the WG PP is the development and implementation of an Action Plan over the three years period 2026–2029, with the possibility of extending the work in a later phase, depending on the results achieved and future decisions. The action plan is drafted by the members of the working group, being tailor-made, to cover the specific needs and priorities of the primary sector. While the specific actions and the roadmap to achieve them will be defined by the WG PP over the next year, it is already anticipated, based on the SWOT analysis presented in Figure 3 and feedback gathered during the consultative workshop held in February 2024 (Circular Bio-Based Europe Joint Undertaking,

Strengths:	Weaknesses:
– Primary producers are at the forefront of the bio-based value chains. – Direct processing and conversion of biomass at source (primary producers as operators of biorefineries, instead of 'just' biomass suppliers). – Incremental demand for biomass and increasing demand for circular bio-based products from industry and consumers. – Long tradition to cooperate in market-oriented value chains. – Possibility to use different forms of cooperation to strengthen the organisation of the primary sector, e.g., farmers' cooperatives (among themselves, and with industry and regional stakeholders), ensuring the direct and indirect participation of their members in the opportunities offered by the circular bioeconomy. – National support (e.g., farmers' support from national advisory services plus their enhanced role under CAP). – Existence of hubs, training centers, and capacity-building initiatives in rural areas.	– Primary producers do not always/fully benefit from the opportunities offered by cooperation with the bioeconomy/circular bio-based sector. – Mistrust & reluctance about new crops and potential opportunities offered by such crops, including their residues and new farming systems. – Insufficient engagement/cooperation of primary producers in the bio-based value chains (missing integration) and difficulty in maintaining motivation over the years. – Insufficient innovation capacity. – A volatile market for biomass as input to the bio-based sector. – Lack of skills, administrative burden, and language barriers encountered by primary producers to engage in new value chain development through participation in R&I projects. – Individual primary producers' involvement in bio-based value chains, in general, is more difficult than if they are represented by the cooperative or other types of organisations serving their interests. – Replicability of business models in different regions highly affected by local factors
Opportunities:	Threats:
– New business opportunities for primary producers based on the efficient use of biomass and valorisation side streams from primary production & crop residues to produce high added-value materials. – Novel business models with environmental benefits, e.g., via circulation of nutrients and new sustainable, diversified production systems. – Revitalisation of the economic sustainability of unused or abandoned rural areas granting benefits to primary producers that provide ecosystem services. – Innovations as a lever for rural regeneration and generational renewal. – Benefits of participating in new innovative value chains: reduce the risk and accelerate the work, networking at the EU level, working closely together with other partners in so-called innovation ecosystems.	– Difficulties in cooperation and an unlevel playing field between large companies/cooperatives and SMEs/individual primary producers (e.g., feasibility of long-term contracts between the primary sector with industry). – Lack of credibility of long-term economic viability of novel bio-based business models and associated technical barriers, e.g., building a new supply chain takes many seasons and years with high risk and very limited short-term results. – Too complex or not clearly communicated environmental requirements, including the competing demands for the use of land: biomass use for food and feed production, carbon storage, biodiversity (set-aside), etc. – Climate change impact and/or other unexpected threats to primary production. – Societal issues, including rural depopulation and aging (the average age of EU farmers is +60 years, and the new generation may not be interested). – Policy, legal & regulatory barriers: e.g., validity of 'new' crops not included in the actual CAP implemented at a national level, difficulty to use abandoned lands, barriers linked to logistics & transport of waste across regions, bio-based sector not considered among the national CAP plans and Operational Groups, fragmented legislative framework, etc.

Figure 3. SWOT analysis summarising the main findings of the CBE JU analysis on the problems and opportunities on the participation of primary producers in the biobased innovation development.

2024), that the actions will focus on different key areas of activity. The first area of activity focuses on raising awareness and improving understanding of the opportunities that circular bio-based innovations offer to primary producers. This includes reaching out to as many producers as possible, using the appropriate tools and language to ensure accessibility and impact. To continue, other areas of activities focus on strengthening cooperation of the primary sector with the industry and other stakeholders; deploying feasible business models; and enhancing knowledge exchange on innovation. Furthemore, activity focused on creating synergies and collaboration as well as capitalising on existing efforts and building on the work of established networks such as the EU CAP Network EIP AGRI Operational Group and various EU-funded projects are also sought. Finally, the last area of activity will concentrate on widening participation by mobilising primary producers from regions with unexploited potential and actively engaging them in bio-based value chains (Circular Bio-Based Europe Joint Undertaking, 2025).

4. HIGHLIGHTS ON FARMER PARTICIPATION IN CBE JU FUNDED PROJECTS

The CBE JU annual work programmes are designed to support the primary sector's appropriate involvement and representation to the largest possible extent in the consortia in the selected project proposals. Several CBE JU topics are highly relevant and attractive for the agricultural primary sector (indicative list provided in table 2). Also, the expected outcomes, as described in the topic text, envisage positive impacts for farmers and rural areas, such as: engaging with primary producers to ensure that the solutions are meeting their requirements and needs; generating new incomes for farmers; delivering skilled job opportunities in rural areas; supporting the revitalisation of rural areas; fostering cooperation between farmers and bio-based industries; supporting capacity building, training and education for farmers, etc.

In addition, CBE JU-funded projects – particularly those at higher TRL (6-8), all Innovation Actions, including flagships – are requested to implement the Multi-Actor Approach as part of their methodology to ensure an effective engagement with primary producers by involving them in the project activities, including the design and use of the bio-based solutions. This guarantees that the farmers' requirements and needs are well-considered from the beginning of the development of any innovation and in the building up of a new value chain. Synergies with measures and initiatives undertaken in the frame of the Common Agricultural Policy (CAP), as for example EIP Agri and the EIP Agri Operational Groups, and with the CAP networks are also reflected in several topics, where specific requirements are included in the topic texts and to be implemented in the project.

To monitor the progress of the CBE JU programme implementation with regard to the strategic participation and integration of feedstock producers and suppliers towards large-scale valorisation of sustainable biomass, a dedicated Key Performance Indicator has been set - KPI 1.1. number of primary producers, involved as project beneficiaries and/or engaged in value chains at project level.

This strategic support framework of CBE JU reaps the benefits. Analysing the data reported by projects from the first three calls - complemented by a detailed study of the indirect participation of primary producers - it is worth highlighting that since 2022, 84 organisations from the agricultural, forestry, and aquatic primary sectors have received a total of about 8.5 million euro in CBE JU funding. 61 out of 84 primary producers are farmers (agricultural primary producers; Figure 4, left panel), which means that farmers represent 73% of the primary sector actors involved in CBE JU projects. This is in line with the fact that agri-based feedstocks represent the major share of feedstock addressed by CBE JU projects (Figure 2).

Primary producers are involved in CBE JU projects, both as beneficiaries (direct participation) or in other ways (indirect participation). Indirect participation can take different forms such as contracts as biomass providers, contracts to perform validation services of end-products, involvement in advisory bodies, etc. In this regard, an interesting aspect to explore is the comparison between the figures of direct and indirect participation in CBE JU-funded projects as about 40% of farmers are

Table 2. List of topics published in CBE JU calls for proposals relevant for farmers.

CBE JU Call	Type of action and title of the topic
2022	IA-02-Cooperative business models for the sustainable mobilisation and valorisation of agricultural residues, byproducts, and waste in rural areas
	RIA-05-Sustainable fibres biorefineries feedstock
2023	IA-01 Small-scale biorefining in rural areas
	IA-02 Production of safe, sustainable, and efficient bio-based fertilisers to improve soil health and quality
	RIA-01 Phyto-management; curing soil with industrial crops, utilising contaminated and saline land for industrial crop production
2024	IAFlag-01 Bio-based value chains for valorisation of sustainable oil crops
	IAFlag-03 Bio-based value chains for valorisation of sustainable natural fibre feedstock
	IA-01 Bio-based materials and products for biodegradable in-soil applications
	RIA-03 Sustainable, bio-based alternatives for crop protection
	CSA-01 New forms of cooperation in agriculture and the forest-based sector
	CSA-03 Supporting the CBE JU Deployment Group on Primary Producers

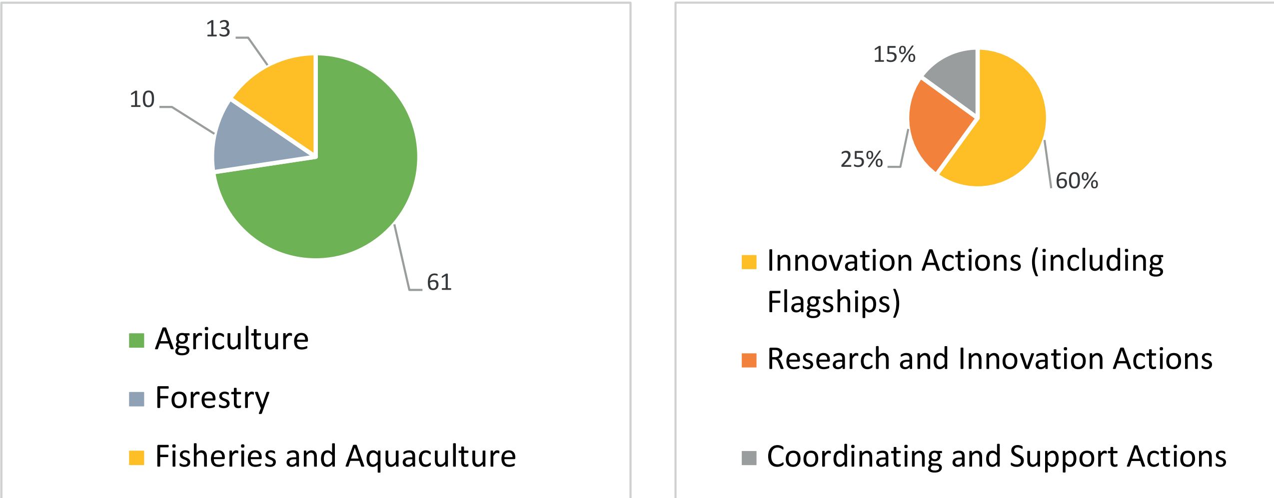

Figure 4. Participation of primary producers in CBE JU projects (2022, 2023 and 2024 calls). On the left, distribution of participation among primary sectors as a percentage of total primary producer participation. On the right, distribution of participation per type of funded action as a percentage of total primary producer participation.

direct participants while 60% are indirect participants. This indicates that farmers are interested in participating in CBE JU-funded projects, but not always as direct beneficiaries, and many prefer other forms of involvement that allow them to be engaged in these projects without bearing the administrative burden that come with formal project participation. This approach enables farmers to network and benefit from technical innovations while keeping their focus on their core activities.

Another aspect analysed in this publication is the involvement of primary producers in the different types of projects that CBE JU is funding (figure 4, right panel). The figures show that the involvement is particularly relevant in innovation actions, including flagships, where the full value chain is covered, and their role is vital to supply biorefineries with locally sourced biomass and/or to test the bio-based solutions as final end-users. In fact, since 2022, 60% of primary producers are involved in innovation actions and flagships, while 25% are in RIAs and 15% in CSAs.

5. EXAMPLES OF CBE JU FUNDED PROJECTS SIGNIFICANTLY INVOLVING PRIMARY PRODUCERS

Among the different CBE JU projects that represent new opportunities for farmers, a selection of exemplary cases where the involvement of farmers is particularly relevant is presented below.

The BRILIAN project has been conceived to support the adoption of sustainable and cooperative business models in rural areas, for the valorisation of agricultural by-products seeking to increase and diversify primary producers' income.[1] The ROBOCOOP-EU project develops circular regional business models for the use of waste streams from three agricultural sectors: grape, olive and stone fruit cultivation.[2] The project will offer new commercial opportunities in rural areas of Extremadura, Spain; Apulia, Italy; and West Macedonia, Greece. Another interesting example is MANUREFINERY project that will develop innovative ways to convert livestock manure into bio-based animal feed and fertilisers [3]. The project will help reduce the environmental impact of livestock farming and create alternative income sources for farmers on four sites in Romania, Slovenia and Spain. These are only a few examples of Innovation Actions among many others that are carried out with the support of CBE JU.

Particularly interesting is the case of the flagships funded by CBE JU. In fact, CBE JU flagship projects cover the full value chain from biomass supply to the delivery of end products and considering their location close to the source of biomass. This is particularly relevant in term of creation of economic impact at territorial level. In this context, the role of farmers in the value chains as biomass suppliers but also end-users, together with the expected cooperation that will be forged between primary producers and biorefinery operators, has a high potential to support them by

[1] Available at: https://www.cbe.europa.eu/projects/brilian
[2] Available at: https://www.cbe.europa.eu/projects/robocoop-eu
[3] Available at: https://www.cbe.europa.eu/projects/manurefinery

Table 3. Summary of the CBE JU Flagship up to Call 2024 and distribution for geographical area, main feedstock and main area of application.

Name of the project	Country of location	Main feedstock	Area of application
CERISEA	France	Agri-food	Bio-based chemicals
PEFERENCE	The Netherlands	Agri-food	Biopolymers and bioplastics
FIRST2RUN	Italy	Agri-food	Bio-based chemicals
PLENITUDE	The Netherlands	Agri-food	Food and feed
LIGNOFLAG	Romania	Agri-food	Other
TERRIFIC	Italy	Agri-food	Biopolymers and bioplastics
SUSTAINEXT	Spain	Agri-food	Food and feed
RUNFASTER4EU	Italy	Agri-food	Bio-based chemicals
AFTERBIOCHEM	France	Agri-food	Bio-based chemicals
FARMYNG	France	Agri-food	Food and feed
CIRCLE	The Netherlands	Agri-food	Bio-based chemicals
SCALE	France	Aquatic	Food and feed
PROTEUS	Norway	Aquatic	Food and feed
CIRCULAR BIOCARBON	Spain and Italy	Biowaste	Biopolymers and bioplastics
SWEETWOODS	Estonia	Forest-based	Construction
EXILVA	Norway	Forest-based	Biopolymers and bioplastics
VIOBOND	Latvia	Forest-based	Construction
WOODCELL	Estonia	Forest-based	Biopolymers and bioplastics

diversifying their business opportunities and sources of income.

Table 3 summarises the status of the CBE JU Flagships projects funded until call 2024 with a focus on where the biorefinery plant is located and which is the main associated feedstock.

An example of a flagship project that aims at achieving zero-waste and circular-by-design industrial process in a rural region in Europe is SUSTAINEXT[4]. The project is turning an existing production plant into a digitalised circular biorefinery to produce healthy plant extracts and functional ingredients from medicinal and aromatic crops – rosemary, camomile and lemon verbena – on disused tobacco fields in Extremadura, Spain. It also deploys solar panels to enhance soil use and provide clean energy as well as agricultural side streams – olives, cardoons and pomegranates – to showcase how underexploited biological raw materials can be upcycled. The project will generate value and new jobs for the region, showing the positive impact of pursuing the European Green Deal objectives. The project's model is easily adaptable and replicable and can run on renewable energy.

Another relevant example is the AFTERBIOCHEM flagship project [5]. The EU is the world's largest producer of sugar beet, with about 140 000 sugar beet growers and around 27,000 direct jobs in sugar beet processing. AFTERBIOCHEM is building the first biorefinery for transforming the sugar industry's side streams – mainly pulp and non-food waste – into bio-based molecules of industrial interest, for the flavourings, fragrances, hygiene products, pharmaceuticals, antimicrobials and polymers sectors in Carling Saint-Avold, France. This will increase the economic and environmental sustainability of the sugar beet industry. In addition, the process will be flexible enough to adapt to alternative feedstocks in the future.

6. CONCLUSION

Analysing the CBE JU funded projects, some key messages can be drawn on the main elements that are contributing to make a compelling proposal a successful project. In particular, while aligning with the CBE JU objectives and directly contributing to the EU Green Deal, circular economy and bioeconomy goals, successful projects have shown how the involvement of actors across the entire bio-based value chain, from biomass producers to end-users, is a very relevant prerequisite to provide the conditions that make a brilliant ideas a potential market success. In addition, SMEs play a crucial role in the CBE JU programme, accounting for one-third of participants and receiving a corresponding nearly one-third of the total funding. Their leadership is also evident, with one in four projects coordinated by an SME, reinforcing their vital contribution to driving innovation and project execution within the bio-based

[4] Available at: https://www.cbe.europa.eu/projects/sustainext

[5] Available at: https://www.cbe.europa.eu/projects/afterbiochem .

sector. Accelerating the innovation process for bio-based solutions and fostering technology transfer are part of core objectives of successfully funded CBE JU projects. Therefore, it is notewhorty that universities and research centres, representing one-quarter of all CBE JU participants, are key providers of innovative bio-based solutions for the projects. Building consortia founded on a strong multi-actor approach with a robust impact potential in term of societal, economic and environmental benefits is also pivotal to drive the market deployment of the biobased sector in Europe in a fair and sustainable way. To this regard, successful projects are mastering effective approaches to strengthen the link between circularity, bioeconomy and availability of sustainable biomass in the real life. This is very important to ensure that the farmers play a strategic role in the biobased transformation and are clearly positioned in the biobased value chains. This strong integration between the primary production and the biobased industry is expected to be further enhanced in the longer term, leading to systemic benefit from these collaborations.

As shown by CBE JU, there is a clear trend of supporting research and innovation aimed at enhancing competitiveness while at the same time ensuring high environmental protection, food security and the decarbonisation of the economy. The circular bio-based innovations developed in CBE JU projects are instrumental in achieving this goal. They will be crucial to make the most of the available sustainable biomass, including wastes, side streams, non-food crops, and cultivations in marginal lands to develop circular bio-based solutions in replacement of fossil-based products. These innovative solutions have the potential to protect ecosystems, reduce the utilisation of external inputs, ensure food security, support nature restoration, while diversifying the business models and income streams of the primary sectors. The expected rewarding cooperation between farmers and the rest of the biorefinery operators will also be important to ensure a proper and fair share of the profit among all the actors involved in the value chain.

The potential of CBE JU to support farmers is high and the partnership's legal framework is extremely supportive, with measures incentivising their involvement in project activities but also beyond that, empowering farmers and enhancing their role in the circular bio-based value chains, as is proved with the launch of the WG PP. Several projects from BBI JU have already finished and demonstrated impacts for the primary sector and rural development. Under CBE JU, some of the projects resulting from the first three calls for proposals are already delivering concrete results and impacts. The project outcomes over the next years will be crucial to further understand the challenges and the opportunities for the involvement of farmers in the European circular bio-based value innovations and the impacts of the promotional CBE JU activities on that.

Altogether, the achievements of CBE JU and the findings related to the integration of primary sector and biobased industry will represent a solid and significant basis, substantiated by concrete outcomes and exploitable results, for the future of the bioeconomy research and innovation support in Europe in the next future.

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Short communication

The cost of joining forces: collective organisations and the economic performance of dairy farms in South West England

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Abstract. This note highlights the importance of sale agreements for the economic performance of dairy farms in South West England. The reduction in public intervention in milk supply governance led to market coordination through supply chain agreements (SCAs), resulting in unbalanced power dynamics that reduced farmers' bargaining power and made them vulnerable to unfair practices. Collective organisations are seen as a solution to protect farmers. Using Coarsened Exact Matching, the paper estimates the effect of collective organisation participation on selling prices, production costs, and markup in a sample of 200 farms in Somerset and Devon. The results show that collective organisations are associated with 7.3% higher production costs and 23 percentage points lower markup, mainly due to costs associated with milk collection, transport, storage, marketing, and adherence to strict quality standards. However, these costs are counterbalanced by secured market access, stronger negotiating power, and better alignment with market demand. These findings underscore the need to further investigate collective governance in developed agricultural markets.

Keywords: dairy farming, collective organisations, markup, coarsened exact matching.

1. INTRODUCTION

This note highlights the importance of sales arrangements for the economic viability of farms, analysing the case of dairy farming in Somerset and Devon, England. With the abolition of milk quotas in 2015, the dairy sector experienced a shift towards a more market-driven model. Moreover, since Brexit the United Kingdom (UK) has moved away from the European Union's Common Agricultural Policy (CAP) and developed a new framework centred on the Environmental Land Management (ELM) schemes. While ELM emphasizes environmental sustainability and productivity, it does not directly address key challenges for small producers, particularly those arising from vertical and horizontal relationships with other companies in the supply chain.

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The English dairy sector has particularly experienced the effects of these changes. Since 2015, the number of dairy farms in England declined by about 3.3% every year[1]. Continued pressure on dairy margins contributed to the decline, with growth of milk-to-feed price ratios of only 0.8% per year insufficient to generate sustainable profits[2]. In addition, the abolition of the quota system changed the mechanism for aligning milk production to consumer demand, giving a more important role to supply chain agreements (SCAs). Within this evolving supply chain, smaller UK dairy producers deal directly with larger companies – both upstream (e.g., feed and energy suppliers) and downstream (e.g., dairy processors and retailers) – which have greater bargaining power and often set their private quality standards (Sexton, 2012). The growing gap in access to market information between farmers and their trading partners can also lead to unfair trading practices, further disadvantaging smaller producers (Fałkowski et al., 2017).

With the deregulation of the dairy market, reduced policy support, and concentrated market power, competitive pressures on milk producers have intensified. This motivates the development of alternative forms of contractual relationships. Collective organisations such as cooperatives can offer farmers improved bargaining power, better access to affordable inputs, and enhanced price stability. Most research on welfare distribution within agricultural supply chains focuses on price transmission (Bakucs et al., 2014), with few studies on contracts' effects on farmer welfare, largely in developing countries (Bellemare and Bloem, 2018). Exceptions include Michalek et al. (2018) on Slovak farms and Verhaegen and Van Huylenbroeck (2001) in Belgium. There are, however, no studies examining collective organisations' impact on the economic performance of UK dairy farmers. Using survey data from 200 dairy farmers in Devon and Somerset and a Coarsened Exact Matching (CEM) approach (Porro and Iacus, 2009; Iacus et al., 2012), we estimate the effect of participating in a collective organisation on selling prices, production costs, and markup. Additionally, with penalised regression, we explore which agreement and farmer's characteristics are linked to participating in collective organisations. The findings show that selling through a collective organisation results in 7.3% higher production costs and approximately 23 percentage points lower markups. These increased costs stem from milk collection, transportation, storage, marketing, promotion services, and the production of milk that meets the collective organisation's strict standards. However, these costs are offset by guaranteed market access, stronger bargaining power with retailers and processors, and better alignment with market demand, helping to prevent oversupply and the price volatility that can come with it.

The paper is organised as follows: Section 2 provides a conceptual framework for our research question. Section 3 describes the CEM and the penalised regression methodologies and provides an overview of the data. Section 4 shows the results. Finally, Section 5 provides a discussion of the results and concludes.

2. CONCEPTUAL FRAMEWORK

We adopt a transaction cost framework (Williamson, 1989) to analyse how farmers' decisions to either participate in a cooperative or sell through the spot market affect their performance. According to this framework, farmers are assumed to choose the option that minimises their overall transaction costs. Participation in a collective organisation is widely associated with enhanced bargaining power, improved market access, and lower transaction costs – such as those related to searching for buyers, negotiating terms, and enforcing agreements (Alho, 2015). In addition, collective arrangements can help reduce market uncertainties. However, while transaction costs may be lower within cooperatives, other types of costs can increase. These may include compliance with higher quality standards, coordination of logistics, and administrative overhead. Despite these additional costs, cooperatives often benefit from greater bargaining power through the pooling of commodities and resources, which can lead to higher farm-gate prices.

Based on this framework, we expect that joining a collective organisation has a positive effect on the price received by farmers. This hypothesis is frequently supported in the empirical literature, although the evidence comes primarily from developing countries (Grashuis and Su, 2019). In contrast, the effect on overall costs is less clear, as the reduction in transaction costs may be offset by increased production and coordination expenses. As a result, the net impact on farmers' markup depends on whether the price premium is sufficient to compensate for potential additional costs.

[1] Calculated on AHDB data extracted on 18 December 2024 from https://ahdb.org.uk/dairy/GB-producer-numbers
[2] Calculated on AHDB data extracted on 18 December 2024 from https://ahdb.org.uk/dairy/milk-to-feed-price-ratio

3. METHODOLOGY AND DATA

To reduce the imbalance in covariates between the treated and control groups and to evaluate the differences in outcomes between them, we use the Coarsened Exact Matching (CEM), a counterfactual matching methodology. To match a treated unit with similar control units, the CEM first coarsens each variable into substantively meaningful groups and then performs an exact match based on these coarsened data. Finally, it retains only the original (uncoarsened) values of the matched data. It is relevant to mention that higher coarsening (higher number of strata) is associated with a lower level of imbalance, which comes however at the expense of a higher drop in observations. After preprocessing data with CEM, the analysis can follow using a simple difference in means provided by a linear regression of outcome on treatment (for details see Porro and Iacus, 2009; Blackwell et al., 2009; Iacus et al., 2012). A limitation of our data is that we observe covariates only for the survey year, and not before the treatment (i.e. selling through a collective organisation). Therefore, we cannot ensure covariate balance in the pretreatment period, nor can we confirm their independence from participating in a collective organisation. Consequently, this analysis should not be interpreted as causal, but rather as a more accurate estimate compared to a simple comparison between treated and control groups.

In the second step, we investigate agreements and farmers' characteristics associated with participation in a collective organisation using a penalised regression approach. In particular, we apply (logit) LASSO, Elastic Net, and Ridge. Penalised regressions add a 'penalty' to the estimated coefficients, forcing them towards zero (LASSO and Elastic Net) or exactly to zero (Ridge), therefore reducing model complexity and allowing for the selection of explanatory variables. We use these methods to select supply chain features and farmers' characteristics associated with collective organisation agreements among 30 different explanatory variables.

3.1 Data description

Because of the lack of data on SCAs, we use survey data from a small but representative sample of 200 dairy farmers in Devon and Somerset (South West England). The sample includes 88 farms from Somerset and 112 from Devon. The total farm population in the two regions is approximately 1,300. With this sample size, the survey maintains a 5% margin of error (within the commonly accepted threshold ≤ 10%). In these two counties, there are approximately 20% of all English dairy farmers. The survey was conducted by telephone interviews in November-December 2017 and the questions covered refer to the 2016-17 financial year.

The binary treatment variable distinguishes between farms selling milk exclusively through a collective organisation – cooperatives, producer organisations (POs), inter-branch organisations (IBOs), or farmers' unions and associations – or through individual businesses with a bilateral contract (e.g., retailers). The outcome variables are milk selling price (€/litre), production costs (€/litre), and markup (%). The markup is calculated as follows:

$$markup = \frac{sellingprice - productioncosts}{productioncosts} \tag{1}$$

To enhance comparability between farms using different sales channels, we consider only those with exclusive contracts (i.e., towards a single collective organisation or individual business). Among the 200 farmers, 173 have an exclusive selling agreement. We considered 4 observations as outliers, i.e. those with a markup lower than the 1st and greater than 99th percentile of the sample distribution. After removing farmers with incomplete data and outliers, the final sample size for the analysis is 169 observations. Summary statistics of all the variables are presented in Table S1. 43.8% of farms in our sample participate in a collective sale agreement. The average selling price in our sample is about 0.25 euro per litre of milk, while the production cost is about 0.21 €/litre. The average markup is about 36%.

We use the CEM approach to reduce covariates imbalances among farmers. Covariates used for matching are the age (4 categories) and the education of leading farmers (4 categories), total milk production (litres), hectares used for milk production (ha), herd size (number of cows), yield (litre/cow), and full-time workers. In the Appendix, we provide a description of the strategy used to select the "preferred" cutpoints combination used for performing the CEM. Table S2 shows the covariates imbalances before and after matching. We focus on the 'Multivariate L1 distance' that represents the overall imbalance with respect to the full joint distribution (including interactions) of the covariates between the treated and control groups. Panel A shows a value of L1 before matching equal to 0.865. It represents a baseline reference for the unmatched data. A good matching solution would produce a reduction in such a statistic. After considering different alternative cutpoints to define the coarsening, we select those that reduce the value of the multivariate L1 distance, preserve statistical power, and minimise the loss of observations (see Appendix). Panel B shows a value of L1 after matching equal to

0.637, which is about 23 percentage points lower than the unmatched case (with 107 farmers being matched). Furthermore, Table S3 presents a more standard covariates (average) imbalance and a t-test for the difference in average values that never rejects the hypothesis that they are equal to zero.

4. RESULTS

Table 1 presents our main findings. The estimated coefficient for the treatment variable in column 1 shows that selling milk through a collective organisation rather than to individual businesses is associated with a slightly higher average selling price (0.003 €/litre), although not statistically significant. As shown in column 2, collective sales have statistically significant higher production costs of 0.015 €/litre (about +7.3% of the average costs). This increase in costs leads to a significant reduction in markup of 23 percentage points (column 3).[3] A back-of-the-envelope estimate suggests that the sample average farmer selling exclusively through a collective organisation would face a revenue increase of €5,550 and an increase in total costs of €27,750, based on average annual milk production of 1,850,000 litres. Robustness checks, such as unmatched OLS, the addition of covariates, and a Propensity Score Matching support these findings (see Table S4). Qualitatively similar results are reached using 150 different combinations of cutpoints in the CEM algorithm (see Figure S1).

To understand why SCAs with collective organisations imply higher production costs and lower markup, we further investigate five categories of agreements' characteristics associated with collective organisations using penalised (logit) regression, namely: i) special contract clauses (contract duration, services, producer protections); ii) pricing methods; iii) timing of milk delivery and pricing; iv) costs associated with the agreement; and v) required quality and production standards. Given a large number of variables (30 in total), we apply penalised regression methods (namely, Ridge, LASSO, and Elastic Net) to select those variables with higher predictive power.

Table A5 shows the standardised coefficients of the selected variables associated with the LASSO and Elastic Net estimations, while Figure S2 shows the absolute value of the standardised coefficients from the Ridge estimation. We then run a standard logit model regressing

Table 1. Regression results after CEM of selling to a collective organisation on farmer's outcomes.

	(1) Selling price €/litre	(2) Production costs €/litre	(3) Markup %
Collective (binary)	0.003	0.015*	-0.233*
	(0.006)	(0.008)	(0.126)
Observations	107	107	107
R^2	0.002	0.030	0.038

Note: the treatment variable 'collective' is = 1 if the exclusive sale is through a collective organisation, 0 otherwise. Standard errors in parentheses are robust to heteroskedasticity. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

the binary variable that identifies the agreement with a collective organisation on the selected variables. Table 2 shows the estimated coefficients.[4]

Dairy farmers selling through a collective organisation are more likely to get paid after the milk delivery and to receive a price that is based on the yearly organisation's profit. This SCA is also more likely to be associated with logistics (collection, storage, transport, handling, etc.), and marketing costs. Looking at the overall sample (Table 2, column 2), dairy farmers selling through a collective organisation are more likely to comply with higher quality standards for the milk (e.g., taste and nutritional content), increasing production costs. Conversely, they are less likely to receive a price based on production costs, therefore, their milk prices do not follow the volatility of input costs. Finally, they are less likely to comply with animal welfare standards.

To better understand the reasons why dairy farmers sell through collective organisations, we perform an additional analysis on two groups of variables: i) the farmers' perception towards the SCA; ii) the farmers' risk-taking attitude. These variables are measured on a 1-5 Likert scale (1 = strongly disagree, 5 = strongly agree) and they are analysed using a logit regression. Complete questions are available in the Appendix.

Table 3 summarises the results. Farmers who do not have alternative options are not associated with collective organisations. This implies that farmers do have other opportunities to sell their milk. Similarly, farmers stating that the sale agreement provides more stable prices from year to year than alternative buyers are less likely to rely on collective organisations. This means that cooperatives/PO offer less stable prices. However, they offer

[3] The sample size decreases from 169 to 107 observations after applying CEM. This reduction may raise concerns about generalizability and statistical power (see Appendix for further discussion). The statistical (post) power tests for each outcome (price, costs, and markup) are 0.21, 0.72, and 0.82, respectively.

[4] Note that we are not interested in the magnitude of the coefficients or their causal interpretation. We aim to highlight the presence or absence of relevant features in the case of collective organisations.

Table 2. Logit model using selected variables from LASSO and Elastic Net describing agreements' characteristics associated with collective organisations.

	(1) Matched obs. Collective	(2) Whole sample Collective
Payment after delivery	2.365***	3.195***
	(0.826)	(0.783)
Price varies with the share of profits	1.556***	1.855***
	(0.553)	(0.481)
Logistic costs	1.059**	0.918**
	(0.510)	(0.457)
Marketing costs		0.537
		(0.445)
Price varies with production costs		-0.957*
		(0.540)
Quality standards		2.057**
		(0.883)
Animal welfare standards		-2.393***
		(0.853)
Observations	97	161
Pseudo R2	0.25	0.34

Note: the dependent variable 'collective' is = 1 if the exclusive sale is through a collective organisation, 0 otherwise. The explanatory variables are all binary variables ('yes' = 1, 'no' = 0). The exact questions are provided in the Appendix. Eight farmers did not answer all the questions included, therefore the number of observations is lower than in Table 1. Standard errors in parentheses are robust to heteroskedasticity. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

more opportunities for negotiating prices, an advantage less likely when engaging with individual businesses (e.g., retailers). A negative perception is that farmers who see delays in payments are more likely to be associated with a collective organisation. Looking at the risk attitudes, farmers with higher attitudes towards production risks (such as adopting new milking regimes, new fodder, and new breed of cow), marketing, and pricing risks are less likely to be associated with collective organisations. Conversely, attitudes toward financial risks (e.g. new investments) increase the propensity to sell through a collective organisation. These results suggest that farmers seek stable market access and protection and to this end, they are willing to accept price volatility, higher costs and financial exposure which can be faced through a higher predisposition to taking financial risks.

5. DISCUSSION AND CONCLUSION

Sales agreements are fundamental to the economic viability of farms. Using a sample of farmers in Somerset and Devon, England, in this note we present the results of an empirical analysis showing that dairy farmers face a tradeoff between benefits and costs when selling through collective organisations. The benefits consist especially in market coordination, through higher negotiating power with respect to retailers and processors, and alignment with market demand to avoid oversupply that can lead to milk price volatility. Without the milk quota system, the pricing mechanism of the collective organisation is the main tool to regulate supply. Different types of collective organisations adopt different pricing mechanisms. A&B pricing mechanisms – farmers receive A prices on defined volumes of milk agreed in advance, while any excess of milk delivered is paid a B price discouraging overproduction – are among the most common tools to keep supply and demand tightly controlled. Larger cooperatives, such as ARLA, buy all the milk delivered but rely on their ability to export to tighten the supply reducing the need for price adjustments and allowing farmers to expand.

Table 3. Farmers' perception and risk attitudes and their association with collective organisations.

	(1) Matched Collective	(2) Whole sample Collective
No alternative options for selling milk	-0.213	-0.156
	(0.168)	(0.122)
Higher prices than alternative buyers	-0.119	-0.013
	(0.231)	(0.165)
More stable prices than alternative buyers	-0.400*	-0.497***
	(0.242)	(0.165)
More possibilities for negotiating prices	0.302	0.292*
	(0.205)	(0.154)
There are delays in the payments	0.166	0.295
	(0.269)	(0.224)
The costs of this sale agreement are too high	0.278	0.087
	(0.237)	(0.184)
Willingness to take production risks	-0.266	-0.382**
	(0.226)	(0.173)
Willingness to take marketing and price risks	-0.191	-0.062
	(0.248)	(0.187)
Willingness to take financial risks	0.600***	0.487***
	(0.230)	(0.168)
Observations	91	154
Pseudo R^2	0.12	0.12

Note: Explanatory variables are on a 1-5 Likert scale. The exact questions are provided in the Appendix. Ten farmers did not answer all the included questions, therefore the number of observations is lower than in Table 1. Standard errors in parentheses are robust to heteroskedasticity. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

However, these benefits come with costs that with deregulation have been partially shifted from public support to farms. Farmers pay for services such as milk collection, transport and storage, and for marketing and promotion. Moreover, farmers make products to the collective organisation's specifications, owning full responsibility for the competencies and capital needed for the process technology. Indeed, farmers selling through collective organisations show a higher propensity to take financial risks, such as taking loans for investments. However, these costs are the price farmers pay for having some confidence that their milk supply has a buyer and a decent price, instead of having to hope for a spot contract most probably not aligned with retailers' price.

The shift of costs from public support to individual farms highlights the need for nuanced policy that accounts for the dual role of collective associations as both market coordinators and informal insurance mechanisms. While farmers face higher costs and often receive lower prices due to stricter quality requirements, CAs offer significant value by reducing exposure to price volatility, thus stabilising farm income and lowering financial risk. Policymakers should recognise this implicit insurance function and consider supporting it through targeted instruments, such as subsidies for compliance with quality standards, investment support for required technologies, or risk-sharing mechanisms like income stabilisation tools.

While this note provides some evidence of the tradeoffs farmers face with respect to selling practices and how SCAs affect their economic performance in a developed country, it has important limitations. First, the estimates cannot be considered causal, as we lack information on pre-treatment periods. Second, the results are based on a limited sample of farms from only two counties in England. Therefore, the findings cannot be generalised to the national level, nor to other developed countries. Finally, we are unable to clearly identify the mechanisms that lead farmers to participate in collective organisations, even when it may result in a lower markup. Further research is needed to explore both collective and contractual arrangements in modern agricultural markets. A critical step in this direction would be to improve the current lack of data on SCAs, with larger samples across multiple sectors and countries to analyse.

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