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 110.50$t^{-1}CO_{2eq.}$ 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.

JEL Codes: Q15, Q18, Q54, H23

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 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, 2014; 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 GHGs, 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 (COP26) in Glasgow to cut CH_4 emissions

[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.

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 as a result 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, and cattle in particular.[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 reduction target to the same livestock categories (i.e., specialised cattle, pig and poultry farms) targeted by the proposed revision of the European IED, as it appears to be the most likely policy objective, based on recent developments.[4]

This study's simulation also allows us to estimate the market-clearing permit price to obtain a self-sustaining policy tool. We do so by exploiting the heterogeneous abatement costs of farms and assessing the characteristics (including the specialisation) of farms that could be most heavily impacted by such a policy.

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). In this study we use the agroeconomic supply model called AGRITALIM (AGRIcultural TerritoriAL

[2] COM (2022)156 final, at https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52022PC0156 (accessed 08/11/24).

[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.

tIme economic; Dell'Unto et al., 2025; Coderoni et al., 2024a; Cortignani and Coderoni, 2022; Dell'Unto et al., 2023). The model is calibrated with microdata surveyed in 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); the model's emitting units are the specialised livestock farms of the 2020 sample of the FADN. 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 paper examines 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). According to Aguilera et al. (2021) despite the large share of emissions that can be attributed to livestock production, the mitigation of these emissions is an underrepresented area in the research efforts in the Mediterranean agriculture.[5] This tool reflects all the characteristics that, according to Auld et al. (2014), a policy tool should have to create positive behavioural change, i.e.: built-in flexibility (that is firms' discretion to decide how to meet an environmental target), defined time frames, and expenditure instruments (tax or subsidy in this case). 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; Van Doorslaer et al., 2015). Our study is unique in combining these approaches.

Moreover, we conduct our assessment using a micro-based modelling approach, allowing us to capture farms' heterogeneous abatement costs (Cai et al., 2016). It is worth noting that, 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

[5] Moreover, 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.

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 emission intensities at the baseline, that reflect management intensity, even in the absence of explicit mitigation strategies (see Section 3). The simulation aims to exogenously identify the price that could yield a predetermined reduction target through a self-financing scheme[6]. 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 and data used and the simulated scenario, Section 4 presents the results, Section 5discusses 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.

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

However, there are many challenges in applying the PPP in agricultural GHG mitigation, including the difficulty of monitoring, reporting and verification (MRV) for a non-point source of pollution that is also linked to high levels of heterogeneity of farms environmental performances (European Commission: Directorate-General for Climate Action 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., 2024a). 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; Ehlers et al., 2021; 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, or 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).

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

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

paid by the government to farms, there would be no burden on government funds (apart from the MRV system).

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

3.1 Data and sample used

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. The use of the FADN database allows for some proxies of environmental pressure (e.g., input use) to be linked to economic indicators, and for economic and environmental performances to be appraised at the farm level.

The FADN survey sample is randomly drawn from the structural survey of the Italian National Institute of Statistics and provides representative data along three dimensions: geographical region (location), economic size and farm specialisation; this latter is of interest here. The survey does not cover all farms, but only those which, due to their size, can be considered professional and market-oriented (i.e., with a standard output higher than 8,000 EUR per year); consequently, the FADN sample is not fully representative of the entire national agricultural sector.

The fact that only professional farms are considered in FADN is relevant for this study. Given that many transaction costs associated with MRV are fixed expenses that are independent of farm size, there are considerable MRV-related obstacles to the implementation of mitigation targets for the whole agricultural sector (Bellassen et al., 2015). In fact, including the smallest farms would imply covering relatively high MRV costs compared to the low environmental benefit associated with small amount of GHG reduced. Literature has therefore concluded that optimal coverage is achieved when the marginal benefit (GHG reduction) is equal to the marginal cost (for MRV) of adding another emitter (Ancev et al., 2008). Thus, the approach followed here – of including only professional farms rather than all emitters – seems suitable for achieving higher cost-effectiveness.[9]

The analysis is limited to farms that specialise in cattle, pig and poultry. Those were the targeted animal categories included in the proposal for the revision of the European IED, which excludes specialised sheep and goat farms, along with non-specialised livestock farms.

We consider the whole 2020 Italian FADN sample of these specialised livestock farms in this study to retain the representativeness of the study in terms of livestock categories. Because the FADN sample is not constant between years, using average values among two or three consecutive periods would have meant losing the representativeness of the work.[10]

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 (see among others: Coderoni and Vanino, 2022; Dabkiene et al., 2020; Baldoni et al., 2017). We thus reconstruct farm-level CH_4 emissions from manure management and enteric fermentation and convert them in tonnes of CO_{2eq}.[11] One of the main value added of the approach here used to estimate CH_4 emissions is that, for enteric fermentation (that represent the bulk of national CH_4 emissions here considered), it allows reflecting management intensity, by leveraging on FADN data on milk production at the farm level (for details on emissions calculation please refer to the appendix A in the supplementary

[9] It is worth noting that, although the sample refers only to professional farms, the GHG emissions produced by the livestock categories represented in this analysis and reported to the population universe of the Italian agricultural farms, represent 70% (11.1 $MtCO_{2eq}$ against 15.85 $MtCO_{2eq}$) of 2021 emissions of CH_4 from the same livestock categories in Italy (as reported in the National Inventory Report; ISPRA, 2023).

[10] An analysis on FADN datasets for the years 2019 and 2021 revealed only slight differences with the 2020 sample composition in terms of the main variables characterising different farm types (number of farms, LSUs, UAA, OI). Thus, opting for average values would not have affected results in a relevant way.

[11] Hereafter, when mentioning CO_{2eq} emissions, we mean missions from CH_4 converted into CO_{2eq}

materials). This makes possible to provide results that reflect farmers' optimization behaviours that depend also on the different micro-level emissions intensity performances, thus letting farm-level heterogeneity emerge in the solution of the model.

Table 1 describes some general characteristics of cattle, pig and poultry farms in the sample. Variables reported include the total number of farms in the Italian sample, the utilised agricultural area (UAA), the number of LSUs reared, and the total and average levels of OI and CH_4 emissions.

Table 1. Description of farm sample for the different farm specialisations.

	Farms	Total UAA	Total LSU	Total OI	Total CH_4 emitted	Average CH_4 emitted	Average CH_4 to be curbed[a]
	n.	*Ha*	*n.*	*EUR ,000*	t^{-1} CO_{2eq}	t^{-1} CO_{2eq}	t^{-1} CO_{2eq}
Dairy cattle	931	40,189	99,782	76,868	321,580	345.4	103.6
Beef cattle	466	22,368	35,849	19,436	74,740	160.4	48.1
Mixed cattle	153	7,717	9,282	4,947	24,924	162.9	48.9
Pig	158	6,491	69,603	19,999	22,116	140.0	42.0
Poultry	78	1,025	32,391	11,776	6,306	80.8	24.3
Total	1,786	77,790	246,907	133,025	449,666	251.8	75.5

[a] Average quantity of baseline CH_4 emissions to be curbed at farm level to meet the 30% reduction target

Source: Authors' elaborations

Cattle farms (60.0% of which specialise in milk production) represent 86.8% of the farms in the sample and produce 93.7% of emissions. Cattle farms rear 58.7% of LSUs on 90.3% of UAA and generate 76.1% of OI. Dairy cattle farms have the highest emissions produced both totally and on average, as well as the highest average quantity to be curbed per farm to meet the 30% mitigation target. The lowest total emissions among cattle farms is produced by mixed farms, while beef farms are intermediate (Table 1). However, on average, these two groups of farms produce a very similar amount of emissions. Pig farms rear 28.2% of LSUs, generate 15% of OI and are responsible for 4.9% of emissions. Finally, poultry farms rear 13.1% of LSUs, generate 8.9% of OI and account only for 1.4% of emissions. Compared to dairy cattle farms, these latter groups of farms produce about 40% and 20% of emissions, respectively.

3.2 AGRITALIM model with integrated system of tax and subsidy and GHG mitigation target

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. [12] The estimation of CH_4 emissions from livestock farms is a feature only recently included in the model (Cortignani and Coderoni, 2022; Coderoni et al. 2024a) 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. This reduction target was selected because it represents 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 the target reduction (i.e., more than by 30%) and receive a subsidy for each unit of emissions (tonne CO_{2eq}) avoided above the target.

The mathematical structure of the model for each farm is specified in the following equations (1–6)[13].

$$max_{\boldsymbol{X}} = \boldsymbol{C}\,\boldsymbol{X} - \boldsymbol{TL}\,\boldsymbol{\Delta E^{+}} + \boldsymbol{SL}\ \ \boldsymbol{\Delta E^{-}} \qquad (1)$$

[12] Other results are available upon request.

[13] The specification of the AGRITALIM model in terms of crop hectares and number of livestock units is here used to represent farmers' decision-making process as farmers usually choose the hectares to cultivate and the number of animals to rear, rather than output quantities (yields and production levels are a subsequent outcome of these choices). From a primal perspective, the two types of models (the one that uses as the decision variable the output quantity and the one that uses crop hectares and number of livestock units) are fully solvable and yield the same solution. Also, from a dual perspective, a model with yields as outcome variable is fully solvable, as demonstrated for example in Cortignani and Severini (2012).

$$s.to\ \boldsymbol{A}\,\boldsymbol{X} \leq \boldsymbol{B} \qquad [\boldsymbol{\lambda}] \tag{2}$$

$$\boldsymbol{LE} = \boldsymbol{UE}\,\boldsymbol{X} \tag{3}$$

$$\boldsymbol{LEB} = \boldsymbol{UE}\,\boldsymbol{X^0} \tag{4}$$

$$\boldsymbol{LER} = \boldsymbol{LEB}\ \boldsymbol{tel}\% \tag{5}$$

$$\boldsymbol{LE} - \boldsymbol{\Delta E^+} + \boldsymbol{\Delta E^-} = \boldsymbol{LER} \tag{6}$$

In these equations, ***C*** is the unitary income of the various ***X*** production activities, ***TL*** is the tax level for ΔE^+ emissions above the farm threshold of emissions, and ***SL*** is the subsidy level for ΔE^- emissions below the farm threshold of emissions.

As shown more in detail in Appendix A, the objective function of the model is represented by the OI and it results from the optimal combination of activities and inputs. Farms' OI represents the difference between revenues (including financial support from the First Pillar of the Common Agricultural Policy), variable costs and part of the fixed costs linked to the annual depreciation of fixed capital endowments.[14]

The model is subject to the following structural constraints: In Equation (2), ***A*** is the matrix of technical coefficients and ***B*** is the matrix of resources availability. Equation (3) calculates the ***LE*** level of total emissions from the ***UE*** unitary emissions and the level of ***X*** variables under simulation. Equations (4)–(5) calculate the ***LEB*** level of observed emissions in the baseline (X^0) and the ***LER*** level of targeted emission level obtained by multiplying ***LEB*** by the desired targeted emission level (***tel%***; for a reduction target of 30%, the targeted emissions level is 70% of the baseline). Equation (6) refers to the relationship between ***LE*** and ***LER***: for each farm, at equilibrium, the level of final emissions (***LE***) must be equal to the level of target emissions (***LER***) plus(minus) the emissions reductions(increase) incurred. It should be noted that $\boldsymbol{\Delta E^+}$ and $\boldsymbol{\Delta E^-}$ are both non-negative variables,

[14] Annual depreciations of fixed capital endowments arise only when the corresponding structural variables change and therefore represent activity-related or quasi-fixed costs, rather than fixed costs in the strict accounting sense. Depreciation costs are calculated by dividing the replacement value of the relevant assets by their technical lifetime, as reported in FADN.
It is worth mentioning here that, although some long-term factors regarding new investments (i.e., the depreciation costs), are taken into account, the proposed model is not dynamic as the time factor is not explicitly modelled. Therefore, the analysis conducted is short-term, but it also considers some long-term factors.

so they measure the absolute size of the deviation in emissions from the farm threshold. For each farm, only one value can be greater than zero, and the deviation cannot be positive and negative for the same farm. This means that $\boldsymbol{\Delta E^{+}}$ and $\boldsymbol{\Delta E^{-}}$ are selected in a minimizing way.

The model does not impose a constraint of equality between the total amount of taxes paid for emissions exceeding the farm threshold and the subsidies received for emissions reduced below the farm threshold. Instead, this constraint was obtained exogenously by reiterating the simulation with different price levels until equilibrium was reached. Here is where the exploitation of the high heterogeneity in the abatement costs for farms of the sample occurs. Since the farms are very different, the same unitary amount of tax and subsidy splits the sample between those opting to pay the tax (for which the opportunity cost of reducing emission is too high compared to the tax) and those opting to receive the subsidy (for which the opportunity cost of reducing emission is too low compared to the tax). The emergence of the market-clearing price that should be fixed for the unit of emissions to build a system that is almost self-financing results from exploiting this heterogeneity. It should be noted here that the concept of self-financing refers to the fact that the total amount of subsidy that should be paid to farmers who reduce emission below the threshold is paid by taxes from farmers who continue emitting above the threshold. This concept excludes all the implementation and transaction costs incurred, including MRV costs. The equality is, indeed, not perfect (see Section 4), since further adjustments of the unit value of tax and subsidy would be needed. However, in this study, making these adjustments would have created problems in the model resolution phase, since it is very unlikely (though theoretically possible) that the two groups of farms (paying the tax and receiving the subsidy) are perfectly equal in terms of, e.g., number of LSU.

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 farm types (dairy cattle, beef cattle, mixed cattle, pig, and poultry).

Table 2 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.

Table 2. 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.

In the overall results, ΔE^+ and ΔE^- emissions are nearly equal.[15] 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). 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^-). This result suggests a neutral impact on public finances (without considering implementation and transaction costs).

[15] 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 perfect 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.

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 amount 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 3 reports the impacts on the LSU number 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 1 (Appendix B in the supplementary materials).

Table 3. 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.

First, it is worth noting that 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; thus, curbing emissions was possible only by reducing the number of LSUs. In fact, this study does not consider technological mitigation options because the objective here is not to appraise the possible benefits and costs of these mitigation options. 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 4 and the corresponding Figure 2 in Appendix B in the supplementary materials 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) 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 with reference to the same groups for the values assumed by the indicators under the simulation.

Table 4. 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.

	Baseline					
	Tax			Subsidy		
	MEI	PLSU	MeP	MEI	PLSU	MeP
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					
	Tax			Subsidy		
	MEI	PLSU	MeP	MEI	PLSU	MeP
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.

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 pig and poultry farms and other types of cattle farms. As shown in Table 4, 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 5 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 5, 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 3 (Appendix B in the supplementary materials).

Table 5. 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.

The overall results in the left section of Table 5 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 3). 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 4).

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 4). 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 6 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).

Table 6. Average value of OI (EUR ,000) and CH_4 (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

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 reduce the lowest their CH_4 emissions, although with the highest heterogeneity. For the opposite reason, cattle farms (and particularly mixed cattle farms) reduce the most their emissions, with a halved level of variability.
Relevant heterogeneity also exists among different territorial areas of Italy (see Table A1 in the Appendix C-Supplementary materials). Differences among territorial areas stem from the different distribution of farm types within them and from their own peculiarities. A detailed analysis of these aspects falls out the scope of this study, but some general considerations can be made. Farms located in the Regions of central Italy show the highest heterogeneity in baseline OI, despite a lower average than farms operating in northern Italy. As for emissions, the largest heterogeneity occurs in the insular Regions, which however are characterised by the lowest average. Considering the negative impacts on OI, the Regions of northern Italy show the highest magnitude, both in terms of variability and on average. Instead, the highest variability among farms and the strongest average emissions reduction occur in the insular Regions. 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 A2 in the Appendix D-Supplementary materials).

5. Discussions and Policy Implications

This study simulates the impacts of the application of GMP mitigation target to the Italian livestock sector, simulating a policy tool that combines a tax and a subsidy that single farms can choose between to reach the overall national target.

At the farm level, a tax is imposed on each unit of emissions that exceeds the targeted amount, while a subsidy is granted for each unit of emissions that is reduced above the target. By opting for the tax, a farm can produce CH_4 emissions exceeding its targeted reduction of emissions, potentially keeping the emissions unchanged with respect to its baseline. If a farm instead opts for the subsidy, it chooses to reduce CH_4 emissions more than the mitigation target, thus contributing more than the standard to climate change mitigation.

The proposed policy instrument is exogenously built to approach financial self-sufficiency. The heterogeneity of farms' characteristics and productivity, shown in Table 6, 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 in the study, a reduction of emissions is currently possible only by reducing the number of animals (LSUs). As specified, in fact, our model does not consider any technical or technological mitigation option for reducing emissions per LSU while retaining animals. European Commission: Directorate-General for Climate Action et al. (2023) stress that for cattle farms in particular, abatement using technical options has limited emissions reduction potential. Therefore, these farms primarily need to reduce livestock numbers, as the number of LSUs is inherently tied to the level of GHG emissions (USDA, 2004). Reducing LSUs represents the most direct (and drastic) mitigation measure. Of course, impacts on OI are much lower 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 likely 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; Moran et al., 2010). 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 (i.e., the ratio between emissions and the number of LSUs reared). 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 (in terms of 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 number of 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 in excess of 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, these farms achieve a less-than-proportional reduction of emissions with respect to the number of LSUs. This is because they have a lower baseline MEI than the farms opting for the tax, 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

In terms of policy implications, the results presented here could be useful as they represent the first ex-ante modelling of the application of the GMP to Italian livestock sector, thus, they could be used to appraise the impacts of such target on different specialisations, to provide a policy to support the transition for more heavily affected farms. Besides, they could provide a preliminary indication of the tentative price required for livestock emissions to reach this ambitious target.

In terms of policy efficiency and efficacy, the analysed tool 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 purses the PGP).

From the policymaker perspective, like the ETS, this tool allows for reaching the environmental objective by addressing the heterogeneity of farms' performances in terms of mitigation potentials that overcome information asymmetries between the polluter (farms) 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 issues 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: Directorate-General for Climate Action 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 EU 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.[16]

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 an environmental tax. This method yields a neutral impact on public finances (without accounting for implementation and transaction costs), as well as an income transfer between farms. In the case simulated by this study, funds are transferred from pig and poultry farms to cattle farms. The latter

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

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).

It is therefore necessary to reflect on losses in terms of employment[17], territorial protection and control of the territory by more extensive livestock farms, as well as carbon leakage. We consider these factors in the absence of relevant modifications of consumers' behaviour towards the consumption of animal products.[18] 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.

Moreover, policy coherence analysis should be assessed overall (Coderoni, 2023). While such a policy framework could be coherent with the IED, the Farm to Fork Strategy, animal welfare legislation and the CAP, it may conflict with coupled income support for livestock under the CAP (European Commission: Directorate-General for Climate Action 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 (Arvanitopoulos et al., 2021; Pérez Domínguez et al., 2016; Van Doorslaer et al., 2015; 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: Directorate-General for Climate Action, 2023).

[17] European Commission: Directorate-General for Climate Action 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.

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

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 tool combines a tax on farms whose emissions exceed a set threshold and a subsidy on farms that reduce emissions below the threshold. This threshold is a 30% reduction target (with respect to the 2020 baseline) as set by the GMP. Farmers are thus free to decide whether to pay the tax on GHGs emitted above the threshold or to reduce emissions below this threshold and receive a subsidy. They make this decision according to their economic profitability, as determined by the optimisation positive mathematical programming model. Furthermore, the proposed policy instrument is financially self-sufficient because of the heterogeneity of farms' characteristics and productivity. This heterogeneity causes the farms to split among those opting for the tax (i.e., those with higher productivity) or the subsidy (i.e., those with lower productivity). The exogenous setting of a GHG mitigation target also allows the simulation to determine the market-clearing price of CH_4 emissions that would allow Italy's livestock sector to reach this target.

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 in order 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 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.

References

Acosta A., Cicowiez M., Nicolli F., Rostan F. (2023). Economic, social and environmental effects of reducing dairy methane emissions through market-based policies: An application of the Livestock Policy Simulation Model, Journal of Policy Modeling 45 (2023) 345–361, https://doi.org/10.1016/j.jpolmod.2023.02.006

Aguilera E., Reyes-Palomo C., Díaz-Gaona C., Sanz-Cobena A., Smith P., García-Laureano R., Rodríguez-Estévez V. (2021). Greenhouse gas emissions from Mediterranean agriculture: Evidence of unbalanced research efforts and knowledge gaps, Global Environmental Change (69) 102319, https://doi.org/10.1016/j.gloenvcha.2021.102319

Ancev, T. (2008), All Cost Considered: Should Agriculture Be a Part of a National ETS?, Farm Policy Journal: 5 (4): 21-29

Arvanitopoulos, T., Garsous, G. and Agnolucci, P. (2021). Carbon leakage and agriculture: A literature review on emissions mitigation policies. OECD Food, Agriculture and Fisheries Papers 169, OECD Publishing: Paris, France.

Auld G., Mallett A., Burlica B., Nolan-Poupart F., Slater R. (2014). Evaluating the effects of policy innovations: Lessons from a systematic review of policies promoting low-carbon technology, Global Environmental Change, 29: 444-458, https://doi.org/10.1016/j.gloenvcha.2014.03.002

Baldi, L., Calzolai, S., Arfini, F., Donati, M. (2024). Predicting the effect of the Common Agricultural Policy post-2020 using an agent-based model based on PMP methodology. Bio-based and Applied Economics 13(4):333-351. doi: 10.36253/bae-14592

Baldoni E., Coderoni S., Esposti R. (2017). The productivity and environment nexus through farm-level data. The Case of Carbon Footprint applied to Italian FADN farms. Bio-based and Applied Economics 6(2): 119-137, 2017, DOI: 10.13128/BAE-19112

Bakam I., Balana B.B. and Matthews R. (2012). Cost-effectiveness analysis of policy instruments for greenhouse gas emission mitigation in the agricultural sector. Journal of Environmental Management 112 (2012) 33-44, http://dx.doi.org/10.1016/j.jenvman.2012.07.001

Bellassen, V., Stephan, N., Afriat, M. et al. (2015). Monitoring, reporting and verifying emissions in the climate economy. Nature Clim Change 5, 319–328. https://doi.org/10.1038/nclimate2544

Blandford, D. and Hassapoyannes K. (2018), The role of agriculture in global GHG mitigation, OECD Food, Agriculture and Fisheries Papers, No. 112, OECD Publishing, Paris. http://dx.doi.org/10.1787/da017ae2-en

Cai B., Bo X, Zhang L., Boyce J., Zhang Y., Lei Y. (2016). Gearing carbon trading towards environmental co-benefits in China: Measurement model and policy implications, Global Environmental Change, (39): 275-284, https://doi.org/10.1016/j.gloenvcha.2016.05.013

Carl J., Fedor D. (2016). Tracking global carbon revenues: A survey of carbon taxes versus cap-and-trade in the real world, Energy Policy96(2016)50–77, http://dx.doi.org/10.1016/j.enpol.2016.05.023

Caro, D., Frederiksen, P., Thomsen, M., Branth Pedersen, A. (2017). Toward a more consistent combined approach of reduction targets and climate policy regulations: The illustrative case of a meat tax in Denmark, Environmental Science & Policy, 76: 78-81, https://doi.org/10.1016/j.envsci.2017.06.013

Cerutti, N., Lamb, W.F., Crippa, M., Leip, A., Solazzo, E., Tubiello, F.N., Minx, J.C. (2023). Food system emissions: a review of trends, drivers, and policy approaches, 1990–2018, Environ. Res. Lett. 18 (2023) 074030, DOI 10.1088/1748-9326/acddfd

Coderoni S. (2023). Key policy objectives for European agricultural policies: Some reflections on policy coherence and governance issues, Bio-based and applied economics, DOI: 10.36253/bae-13971

Coderoni S., Dell'Unto D., Cortignani R. (2024a). Curbing methane emissions from Italian cattle farms. An agroeconomic modelling simulation of alternative policy tools, Journal of Environmental Management, 351 (2024) 119880, https://doi.org/10.1016/j.jenvman.2023.119880

Coderoni S., Esposti R., Varacca A. (2024b). How differ-ently do farms respond to agri-environmental poli-cies? A probabilistic machine-learning approach. Land Economics, May 2024, 100 (2): 370–397, https://doi.org/10.3368/le.100.2.060622-0043R1

Coderoni S., Vanino S. (2022). The farm-by-farm relationship among carbon productivity and economic performance of agriculture, *Science of the Total Environment*, 819, 153103.

Cortignani, R., Buttinelli, R. and Dono, G. (2022). Farm to Fork strategy and restrictions on the use of chemical inputs: Impacts on the various types of farming and territories of Italy. *Science of the Total Environment*, 810, 152259.

Cortignani, R. and Coderoni, S. (2022). The impacts of environmental and climate targets on agriculture: Policy options in Italy. *Journal of Policy Modeling*, 44(6), 1095-1112.

Cortignani R., Severini S. (2012). A constrained optimization model based on generalized maximum entropy to assess the impact of reforming agricultural policy on the sustainability of irrigated areas. *Agricultural Economics*, 43(6), 621–633.

Dabkienė, V., Baležentis, T. and Štreimikienė, D. (2020). Calculation of the carbon footprint for family farms using the Farm Accountancy Data Network: A case from Lithuania. Journal of Cleaner Production, 262, 121509.

Dales, J. H. (1968). *Pollution, Property and Prices*. Toronto, University of Toronto Press.

Dell'Unto D., Dono G., Cortignani R. (2023). Impacts of Environmental Targets on the Livestock Sector: An Assessment Tool Applied to Italy, *Agriculture*, 13, 742.

Dell'Unto, D., Selvaggi, R., Pappalardo, G. and Cortignani, R. (2025). Adoption of precision livestock farming devices in the dairy cattle sector: An assessment based on agroeconomic modelling. *Science of The Total Environment*, *1002*, 180555.

Dumortier, J., Hayes, D. J., Carriquiry, M., Dong, F., Du, X., Elobeid, A., Fabiosa, J.F., Martin, P.A., Mulik, K. (2012). The effects of potential changes in United States beef production on global grazing systems and greenhouse gas emissions. Environmental Research Letters, 7(2), 024023.

Ehlers, M. H., Huber, R., & Finger, R. (2021). Agricultural policy in the era of digitalisation. Food Policy, 100, 102019.

Erjavec, K., Erjavec, E. (2015). Greening the CAP – Just a fashionable justification? A discourse analysis of the 2014–2020 CAP reform documents. Food Policy 51: 53–62.

Esposti, R. (2022). The Coevolution of Policy Support and Farmers Behaviour and Performance. An investigation on Italian agriculture over the 2008-2019 period. Bio-Based and Applied Economics 11(3): 49-82. https://doi.org/10.36253/bae-12912

European Commission: Directorate-General for Climate Action, Trinomics, Bognar, J., Lam, L., Forestier, O., Finesso, A., Bolscher, H., Springer, K., Nesbit, M., Nadeu, E., Hiller, N., Dijk, R. v., Jakob, M., Tarpey, J., McDonald, H., Zakkour, P., Heller, C., Görlach, B., Scheid, A., & Tremblay, L.-L., (2023). Pricing agricultural emissions and rewarding climate action in the agri-food value chain, Publications Office of the European Union. https://data.europa.eu/doi/10.2834/200

European Commission (2022). Proposal for amending Directive 2010/75/EU of the European Parliament and of the Council of 24 November 2010 on industrial emissions and Council Directive 1999/31/EC of 26 April 1999 on the landfill of waste, COM(2022) 156 final/3, Strasbourg, 5.4.2022.

European Commission (2020). An EU strategy to reduce methane emissions COM(2020) 663 final, Brussels.

European Commission (2019). The European Green Deal. COM(2019) 640 final, Brussels.

European Council (2009). Council Regulation (EC) No 1217/2009 of 30 November 2009 setting up a network for the collection of accountancy data on the incomes and business operation of agricultural holdings in the European Community. OJ L 328, 15.12.2009.

European Court of Auditors (2021). Special Report: The Polluter Pays Principle: Inconsistent application across EU environmental policies and actions.

European Scientific Advisory Board on Climate Change (2024). Towards EU climate neutrality.

European Union (2022). European Union Methane Action Plan, available at the following url: https://energy.ec.europa.eu/topics/carbon-management-and-fossil-fuels/methane-emissions_en, accessed on 10/10/2024. Progress, policy gaps and opportunities. Assessment Report 2024, Luxembourg: Publications Office of the European Union, 2024, ISBN 978-92-9480-612-3, doi:10.2800/216446

FAO (2023). Pathways towards lower emissions – A global assessment of the greenhouse gas emissions and mitigation options from livestock agrifood systems. Rome https://doi.org/10.4060/cc9029en

Fellmann, T., Witzke, P., Weiss, F., Van Doorslaer, B., Drabik, D., Huck, I., ... and Leip, A. (2018). Major challenges of integrating agriculture into climate change mitigation policy frameworks. Mitigation and Adaptation Strategies for Global Change, 23, 451-468.

Fredriksson, P. (1997). The Political Economy of Pollution Taxes in a Small Open Economy. Journal of Environmental Economics and Management, 33 (1): 44-58.

Frontuto V., Felici T., Andreoli V., Bagliani MM., CorsiA. (2025).Is there an Animal Food Kuznets Curve, and does it matter? Bio-Based and Applied Economics, Just Accepted. DOI: 10.36253/bae-16172

Gernaat D.E.H.J., Calvin K., Lucas P.L., Luderer G., Otto S.A.C., Rao S., Strefler J., van Vuuren D.P. (2015). Understanding the contribution of non-carbon dioxide gases in deep mitigation scenarios, Global Environmental Change, (33): 142-153, https://doi.org/10.1016/j.gloenvcha.2015.04.010

Henderson B., Frezal C., Flynn E. (2020). A survey of GHG mitigation policies for the agriculture, forestry and other land use sector, OECD Food, Agriculture and Fisheries Papers, No. 145, OECD Publishing, Paris. http://dx.doi.org/10.1787/59ff2738-en

Heckelei, T., Britz, W. and Zhang, Y. (2012). Positive mathematical programming approaches–recent developments in literature and applied modelling. Bio-based and Applied Economics Journal, 1(1050-2016-85729), 109-124.

Himics, M., Fellmann, T., Barreiro-Hurlé, J., Witzke, H. P., Domínguez, I. P., Jansson, T. and Weiss, F. (2018). Does the current trade liberalization agenda contribute to greenhouse gas emission mitigation in agriculture? *Food policy*, 76, 120-129.

IPCC (2021). Climate Change 2021 – The Physical Science Basis: Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. First edition. Cambridge University Press. https://doi.org/10.1017/9781009157896

IPCC (2014). AR5. IPCC, 2013: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.

IPCC (2007). Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor and H.L. Miller (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Isbasoiu, A., Jayet, PA, De Cara, S. (2021). Increasing food production and mitigating agricultural greenhouse gas emissions in the European Union: impacts of carbon pricing and calorie production targeting. Environ Econ Policy Stud 23, 409–440 (2021). https://doi.org/10.1007/s10018-020-00293-4

ISPRA, 2023. Italian Greenhouse Gas Inventory 1990-2021. National Inventory Report 2023, ISPRA, Rome.

ISPRA, 2021. Italian Greenhouse Gas Inventory 1990-2019. National Inventory Report 2021, ISPRA, Rome.

Magnapera C., Kazemekaityte A., Raffaelli R., Cerroni S. (2025). Farmers, experts and students' subjective probability distributions on methane emission reductions in livestock farming: An experimental comparison across elicitation methods, Bio-Based and Applied Economics, 2025(2). DOI:10.36253/bae-17310

Mahmoud N., Hutchings, N.J. (2020). The advantages of using field- and farm-scale data to target agri-environmental measures—an example of afforestation, Environmental Science & Policy, 114: 14-21, https://doi.org/10.1016/j.envsci.2020.07.019

McKibbin, W. J., and Wilcoxen. P. J. (2002). The Role of Economics in Climate Change Policy. Journal of Economic Perspectives 16 (2): 107–29

Milich L. (1999). The role of methane in global warming: where might mitigation strategies be focused? Global Environmental Change, 9: 179-201, https://doi.org/10.1016/S0959-3780(98)00037-5

Millock, K. and Nauges C. (2006), Ex Post Evaluation of an Earmarked Tax on Air Pollution, Land Economics, 82(1): 68-84, http://dx.doi.org/10.3368/le.82.1.68

Moran, D., Macleod M., Wall E., Eory V., McVittie A., Barnes A., Rees R., Topp CFE, Moxey A. (2011). Marginal abatement cost curves for UK agricultural greenhouse gas emissions. Journal of Agricultural Economics, 62, 93–118, https://doi.org/10.1111/j.1477-9552.2010.00268.x

NERA (2007). Market Mechanisms for Reducing Greenhouse Gas Emissions from Agriculture, Forestry and Land Management – NERA's Interim conclusions. NERA Economic Consulting, London.

New Zealand Ministry for the Environment (2024), Review of methane science and target, available herehttps://environment.govt.nz/what-government-is-doing/areas-of-work/climate-change/emissions-reductions/emissions-reduction-targets/review-of-methane-science-and-target/ (accessed on 16th October 2024)

Minister of Environment and Climate Change (2023). Reducing Enteric Methane Emissions from Beef Cattle. Federal Offset Protocol Public Consultation Draft, December 2023. His Majesty the King in Right of Canada, ISBN: 978-0-660-69074-2.

OECD (2019), Enhancing Climate Change Mitigation through Agriculture, OECD Publishing, Paris, https://doi.org/10.1787/e9a79226-en

OECD (2022), Agricultural Policy Monitoring and Evaluation 2022: Reforming Agricultural Policies for Climate Change Mitigation, OECD Publishing, Paris.

Ollier M., De Cara S. (2024). Give and take: An analysis of the distributional consequences of emission tax-and-rebate schemes with an application to greenhouse gas emissions from European agriculture, Ecological Economics 219 (2024) 108154, https://doi.org/10.1016/j.ecolecon.2024.108154

Paris, Q. and Howitt, R. (1998). An analysis of Ill-Posed Production Problems Using Maximum Entropy. Journal of Agricultural Economics, Vol. 80(1), pp. 124-138.

Perez Dominguez, I., Fellmann, T., Witzke, P., Weiss, F., Hristov, J., Himics, M., ... and Leip, A. (2020). Economic assessment of GHG mitigation policy options for EU agriculture: A closer look at mitigation options and regional mitigation costs (EcAMPA 3) (No. JRC120355). Joint Research Centre.

Pérez Domínguez, I. P., Fellmann, T., Weiss, F., Witzke, P., Barreiro-Hurlé, J., Himics, M., ... and Leip, A. (2016). An economic assessment of GHG mitigation policy options for EU agriculture. JRC Science for Policy Report, EUR, 27973(10.2791), 843461.

Pezzey, J. (2003), Emission Taxes and Tradeable Permits A Comparison of Views on Long-Run Efficiency, Environmental and Resource Economics, 26(2): 329-342, http://dx.doi.org/10.1023/a:1026393028473.

Povitkina M., Carlsson Jagers S., Matti S., Martinsson J. (2021). Why are carbon taxes unfair? Disentangling public perceptions of fairness, Global Environmental Change (70), https://doi.org/10.1016/j.gloenvcha.2021.102356

Roberts S., Thumin J. (2006). A Rough Guide to Individual Carbon Trading – Report to Defra, Centre for Sustainable Energy, November, London, UK

Slade, P. (2017). The Effects of Pricing Canadian Livestock Emissions. https://doi.org/10.1111/cjag.12157

Stetter, C., Mennig, P., & Sauer, J. (2022). Using Machine Learning to Identify Heterogeneous Impacts of Agri-Environment Schemes in the EU: A Case Study. European Review of Agricultural Economics 49(4): 723-739.

USDA (2004). Agriculture and Forestry Greenhouse Gas Inventory: 1990–2001. Washington, DC: US Department of Agriculture.

Van Doorslaer, B., Witzke, P., Huck, I., Weiss, F., Fellmann, T., Salputra, G., ... and Leip, A. (2015). An economic assessment of GHG mitigation policy options for EU agriculture. EcAMPA vol Report EUR.

Walter, J. M. (2020). Comparing the effectiveness of market-based and choice-based environmental policy. Journal of Policy Modeling, 42(1), 173–191, https://doi.org/10.1016/j.jpolmod.2019.07.006

Wang W., Deng X., Wang Y. (2024). Changes in Non-CO_2 Greenhouse Gas Emissions From Livestock Production, Meat Consumption and Trade in China, Sustainable Production and Consumption, 42 (2023): 281-291, https://doi.org/10.1016/j.spc.2023.09.021.

Weitzman M. L. (1974). Prices vs. Quantities. *Review of Economic Studies*. October, 41:4: 477–491.

Supplementary materials

Appendix A -Mathematical representation and calibration of the AGRITALIM model including CH_4 emissions

The model is structured as follows:

1. Objective function

$$\max Z = \text{GPS} + \text{CAP} + \text{RCA} - \text{VC} - \text{QC} - \text{EXL} - \text{FP} - \text{PW} - \text{DRO} - \text{DRNI}$$

Operating income = Z

Gross Saleable Production = $\text{GPS} = pc * yc * XC + pm * ym * XA + revnm * XA$

CAP payments = $\text{CAP} = dp + cpc * XC + cpa * XA$

Revenues from Complementary Activities = RCA

Variable Costs = $\text{VC} = pfp * qfp * XC + acc * XC + aca * XA$

Quadratic Costs = $\text{QC} = \frac{1}{2} XC' \, Q \, XC + \frac{1}{2} XA' \, Q \, XA$[19]

External Labour = = $\text{EXL} = ph * XH$

Feed Purchased = $\text{FP} = pf * XF$

Pumped Water = $\text{PW} = pw * XW$

Depreciation Rates Observed = DRO

Depreciation Rates New Investments = $\text{DRNI} = drtc * ADTC + drsf * ADSF$

<u>*Variables*</u>

XC = hectares of crops

XA = number of animals

XH = hours of labour

XF = quantity of feed

[19] The specification of multiple constraints allows for an initial calibration and validation of the model. In addition, to achieve a perfect calibration to the observed situation, a Positive Mathematical Programming (PMP) approach was subsequently applied, where linear costs correspond to observed variable production costs from FADN and represent the accounting costs associated with each activity and the quadratic term is introduced within the PMP framework as a calibration device to reproduce the observed production pattern.

XW = quantity of water pumping

ADTC = additional area of tree crops

ADSF = additional area of stables and facilities

Market

pc = prices of crops

pm = prices of milk

pfp = prices of factors of production (fertilizers, pesticides)

ph = prices of external labour

pf = prices of feed purchased

pw = prices of water pumped

drtc = depreciation rates of new investments (tree crops)

drsf = depreciation rates of new investments (animals)

Production function

yc = yields of crops

ym = yields of milk

qfp = quantities of factors of production (fertilizers, pesticides)

Common Agricultural Policy payments

dp = decoupled payments

cpc = coupled payments for crops

cpa = coupled payments for animals

Revenues and average costs

revnm = revenues from other animal products no milk (meat, eggs, honey, etc…)

acc = average costs for crops (per hectare)

aca = average costs for animals (per number)

2. Constraints

$$\sum_{j} XC_{j,n} \le ald_n \quad \forall\, n$$

$$\sum_{j} ml_{j,n} * XC_{j,n} + \sum_{ja} ml_{ja,n} * XA_{ja,n} \le alb_n \quad \forall\, n$$

$$\sum_{j} mw_{j,n} * XC_{j,n} \le awt_n \quad \forall\, n$$

$$\sum_{jt} XC_{jt,n} \le atc_n + ADTC_n \quad \forall\, n$$

$$\sum_{ja} msf_n * XA_{ja,n} \le asf_n + ADSF_n \quad \forall\, n$$

$$\sum_{ja} mf_n * XA_{ja,n} \le afp_n + XF_n \quad \forall\, n$$

$$\sum_{jan} rc_n * XA_{jan,n} \ge \sum_{jap} XC_{jap,n} \quad \forall\, n$$

Sets shown in the mathematical representation

j = types of crops

n = farms

ja = types of animals

jt = tree crops

jan = types of animals non-productive

jap = types of animals productive

Other sets (not shown in the mathematical representation): geographical area [NUTS 2 and NUTS 3], altimetric level, types of cultivation (field, vegetable garden, greenhouse), following crops, main vegetable product, animal production, time

Matrix coefficients

ml = labour (manual and mechanical) needs per each crop and animal

mw = water needs per each irrigated crop

msf = square meter of stables and facilities per each animal

mf = feed needs for each animal

rc = ratio between productive and non-productive animals

Availabilities

ald = land availability per each farm

alb = labour availability per each farm

awt = water availability per each source (e.g. water users' association, well,…) and farm

atc = tree crops area per each farm

asf = total square meter of stables and facilities

afp = quantity of feeds produced in farm.

The emissions are introduced in the model as follows:

$$\sum_{ja} emisa_{ja,n} * XA_{ja,n} = QE_n^A \quad \forall\, n$$

Matrix coefficients, availabilities and variables

emisa = emissions for animal

QEA = quantity of emissions for animals

XA = number of animals

The calibration is performed with the Positive Mathematical Programming (PMP) approach, that perfectly calibrates the model to baseline (in this study, year 2020) and avoids adding ad-hoc constraints and over-specialised responses of the model in the simulation phase. In general, a PMP model can be built and calibrated using a very simplified farms' database, based only on production levels (e.g., land use and quantities produced) and the main economic information related to production processes (e.g., output prices and variable costs). In fact, even in presence of few data, a PMP model guarantees the reconstruction of the structure of variable costs, of the substitutability relationships between processes as well as of farm productions, used to carry out ex-ante analyses (Paris and Howitt, 1998; de Frahan 2019; Heckelei et al., 2012). However, more data and information used to specify objective function and constraints, as in the case of the AGRITALIM model, determine a more robust model in the simulation phase.

Methane emissions estimation

To estimate GHG emissions, we adapted the IPCC methodology (IPCC, 2006) at the farm/micro level. This methodology represents the established international standard, which has been used in the literature to achieve a farm-level indicator of GHG emissions (e.g., Coderoni and Vanino, 2022). Following this approach, our calculations exclude emissions from input production and food consumption. Computing GHG emissions relies on a linear relationship between emissions factors (EF) and activity data (AD). AD are taken from livestock numbers in the FADN for the livestock sub-categories shown in Table 1.

As regards EF, the IPCC approach foresees three methodological tiers for estimating GHG emissions and removals, that represent increasing levels of methodological complexity and data specificity. The Tier 1 is the default method and uses global default emission factors and simplified activity data provided by the IPCC. The Tier 2 approach uses country-specific or region-specific emission factors and more detailed activity data (e.g., technology types, management practices). The Tier 3 approach employs detailed models, direct measurements, or comprehensive inventories (e.g., process-based models, continuous monitoring systems). In our model, we can reconstruct farm-level GHG emissions of CH_4 from manure management and enteric fermentation. For the latter, we constructed a farm-specific emission factor for the pertinent categories, using the quantity of milk produced at the farm level to estimate a more refined (Tier 2–like[20]) EF. This calculation allows us to consider the impact of increased milk productivity on GHG emissions compared to the use of a national EF (which is identical for all farms)[21]; however, the approach does not allow us to appreciate any differences based on variations in meat productivity (e.g. slaughter ages, etc.) or feeding practices.

[20] As the reference unit is here the farm, using farm-specific EF can be considered a Tier 2-like approach.

[21] Although this refinement of the methodology is applied only to one emission source (enteric fermentation), it is still relevant, as this source constituted 83% of bovine and 69% of agricultural CH_4 emissions at the national level in 2021 (ISPRA, 2023).

For other emissions sources, we instead adopted a Tier 1-like approach[22], applying a default country-specific EF. As the case study under analysis is the Italian one, we applied an EF derived from the Italian national accounting system (ISPRA 2021). However, the present approach could be easily applied to other EU countries by using their national FADN data and their country-specific EF retrieved from the GHG monitoring system.[23]

Finally, emissions are expressed in total CO_{2eq} by multiplying CH_4 emissions by their Global Warming Potential (25) in accordance with the IPCC Fourth Assessment Report (IPCC, 2007).[24]

References

Coderoni S. and Vanino S. (2022). The farm-by-farm relationship among carbon productivity and economic performance of agriculture. Science of the Total Environment, 819, 153103, https://doi.org/10.1016/j.scitotenv.2022.153103

de Frahan, B.H. (2019). Towards econometric mathematical programming for policy analysis. In Applied Methods for Agriculture and Natural Resource Management: A Festschrift in Honor of Richard E. Howitt (pp. 11-36). Cham: Springer International Publishing, https://doi.org/10.1007/978-3-030-13487-7_2

Heckelei, T., Britz, W., & Zhang, Y. (2012). Positive mathematical programming approaches– recent developments in literature and applied modelling. Bio-based and Applied Economics Journal, 1(1), 109-124, https://doi.org/10.13128/BAE-10567

IPCC, 2006. IPCC Guidelines for National Greenhouse Gas Inventories, Prepared by the National Greenhouse Gas Inventories Programme, Eggleston H.S., Buendia L., Miwa K., Ngara T. and Tanabe K. (eds). Published: IGES, Japan.

ISPRA (2021). Italian Greenhouse Gas Inventory 1990-2019. National Inventory Report 2021, ISPRA, Rome.

ISPRA (2023). Italian Greenhouse Gas Inventory 1990-2021. National Inventory Report 2023, ISPRA, Rome.

Paris, Q., & Howitt, R. E. (1998). An analysis of ill-posed production problems using maximum entropy. American journal of agricultural economics, 80(1), 124-138, https://doi.org/10.2307/3180275

[22] As the reference unit is here the farm, using country-specific EF can be considered a Tier 1-like approach.

[23] National emissions reported to the UNFCCC and the EU Greenhouse Gas Monitoring Mechanism can be found here: https://www.eea.europa.eu/en/datahub/datahubitem-view/3b7fe76c-524a-439a-bfd2-a6e4046302a2 (accessed 07/02/24).

[24] We chose to refer to the IPCC Fourth Assessment Report (AR4) guidelines rather than the fifth (AR5) to derive CH_4 GWP due to the selection of 2020 as baseline year. For 2020, the EFs were taken in a 2021 National Inventory report, and the AR5 guidelines were only in use by 2022 in Italy and all EU member states. This change followed the COP27 decision in 2022 on the "Revision of the UNFCCC reporting guidelines on annual inventories for Parties included in Annex I to the Convention". However, it should be noted that this metric should not change results in terms of the relative performances of livestock farms (as the coefficient is the same for all livestock categories). It might impact the final price estimated, which could be higher.

Appendix B - Figure 1. Graphical representation of absolute values originating the percentage variations reported in Table 3

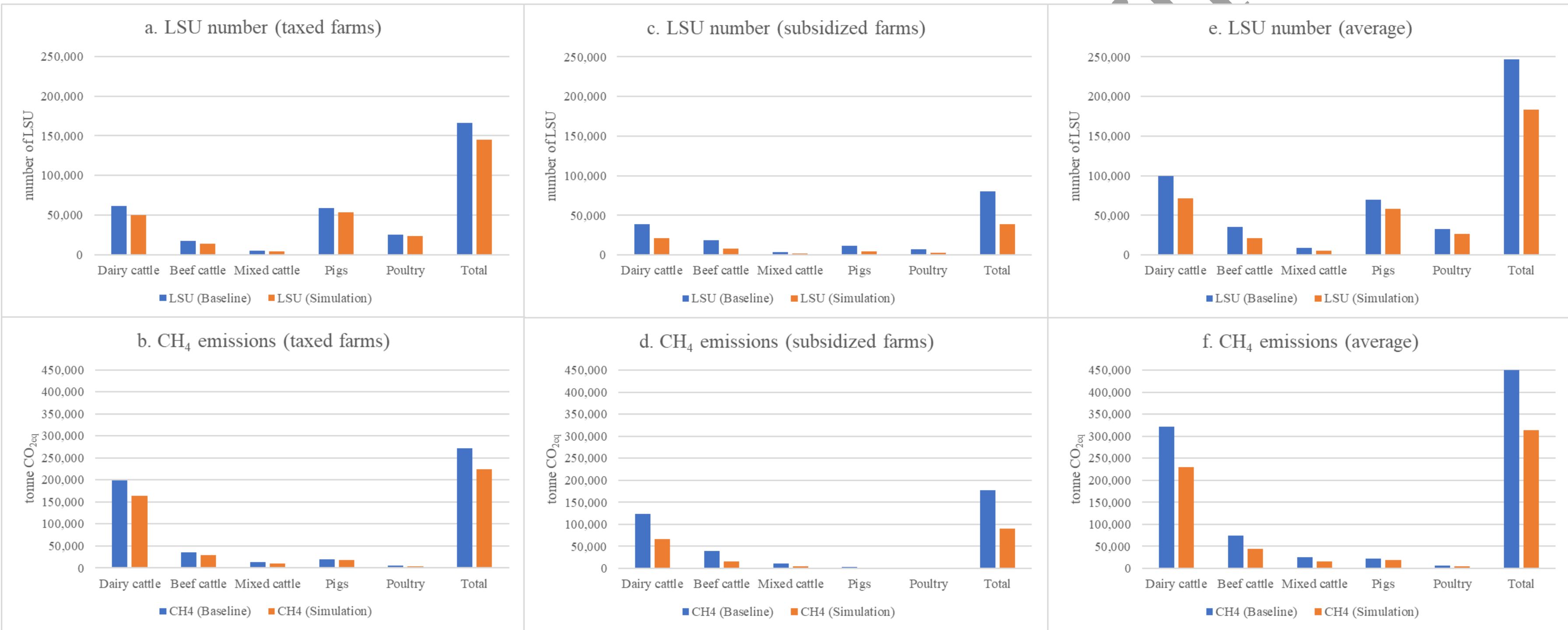


Figure 2. Graphical representation of data reported in Table 4.

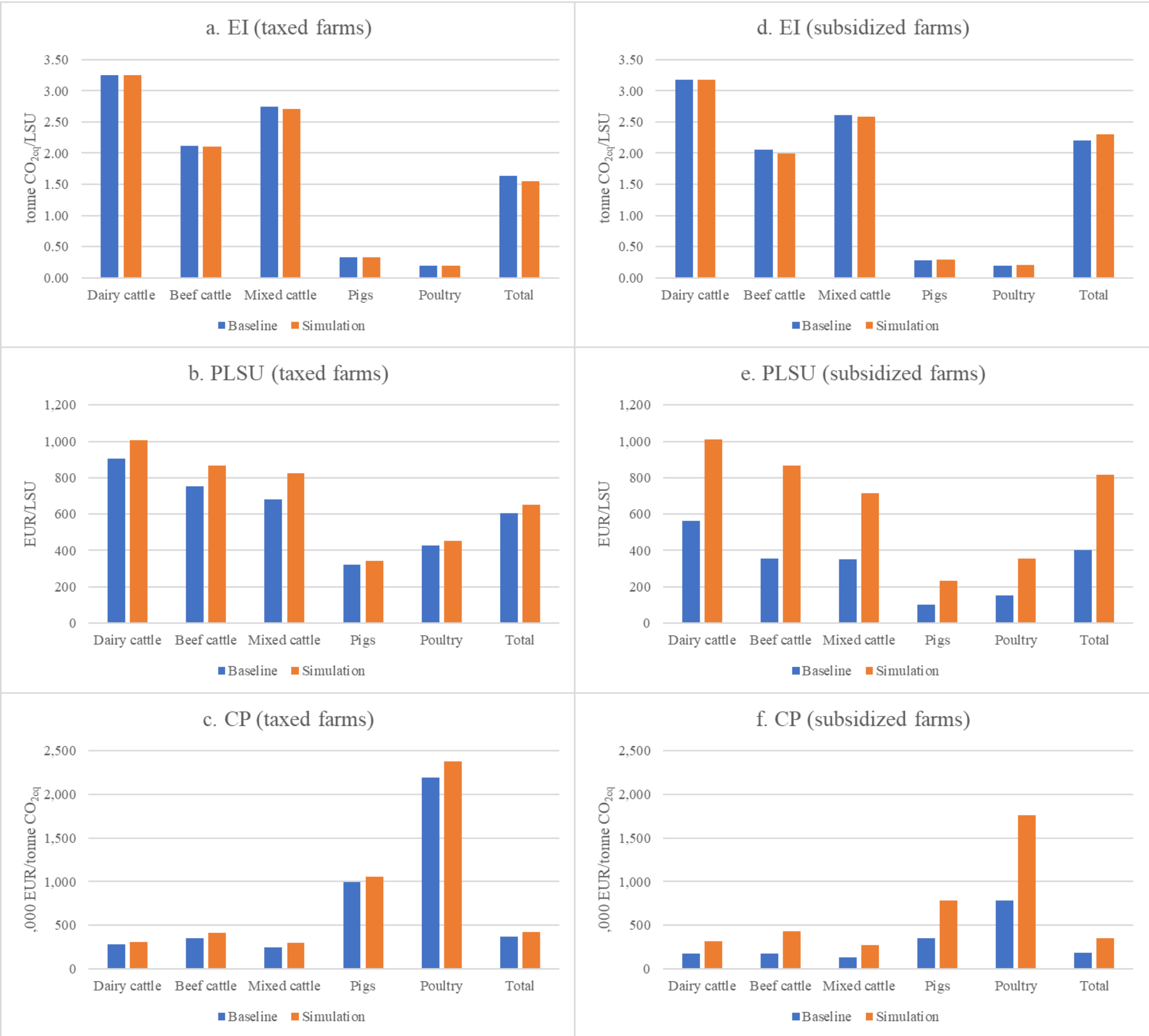
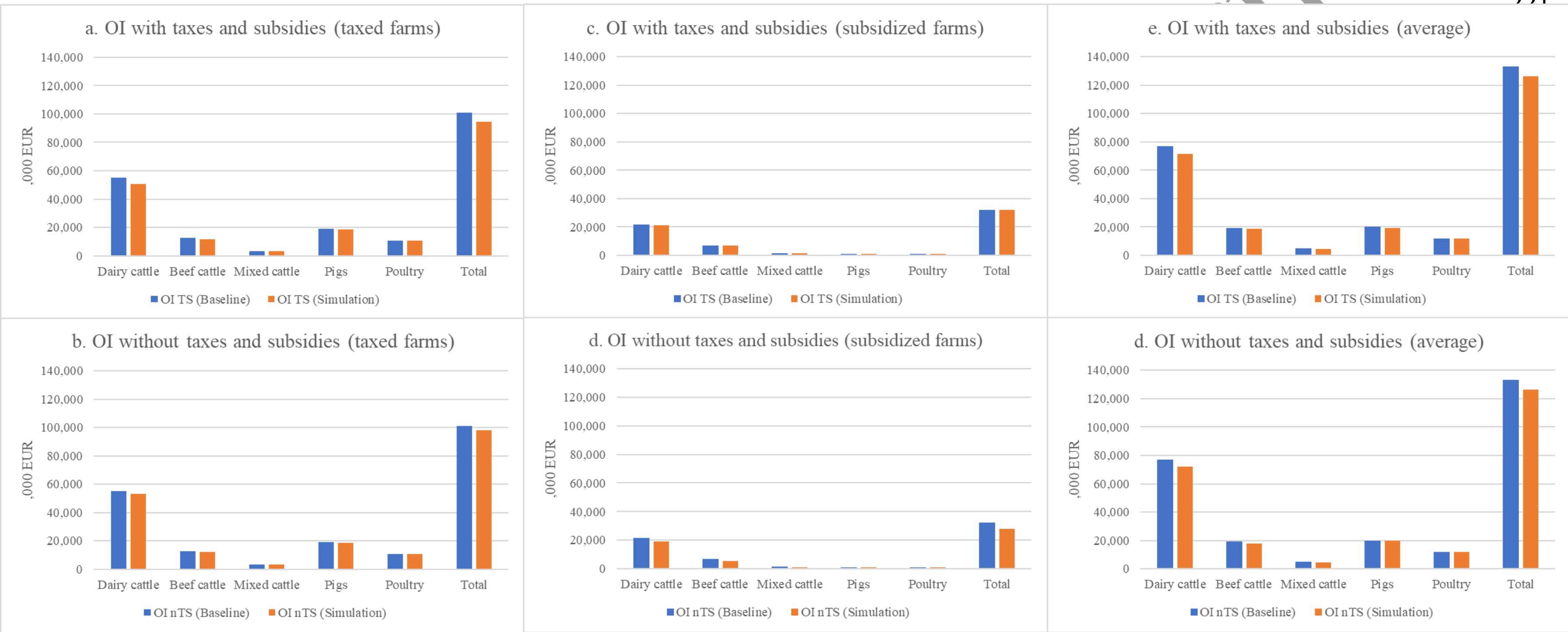


Figure 3. Graphical representation of absolute values originating the percentage variations reported in Table 5



Appendix C – Baseline and simulation values by geographical location

Table A1. Average value of OI (EUR ,000) and CH_4 (t) at the baseline and Δ% under simulation, and respective Coefficients of Variation (CV) by geographic location

	Baseline OI		**Baseline CH_4**		**Δ% OI**		**Δ% CH_4**	
	Average	CV	Average	CV	Average	CV	Average	CV
North-West	72.7	243.6	272.2	167.1	-33.0	-702.2	-31.2	-73.0
North-East	106.0	235.1	284.3	167.9	-32.6	-906.2	-24.1	-75.5
Centre	69.2	302.5	210.9	190.6	-12.7	-651.4	-27.2	-76.3
South	52.1	145.9	245.4	168.2	-7.3	-629.5	-31.4	-63.6
Islands	39.6	232.8	168.4	242.4	-4.3	-625.5	-35.8	-82.2
Total	74.5	250.7	251.8	176.2	-22.1	-926.3	-29.1	-75.1

Source: Authors' elaborations

Appendix D – Sensitivity analisis with different mitigation targets.

Table A1 displays the results of a sensitivity analysis that considers the percentage variation of OI, LSU and CH_4 emissions, as well as the percentage incidence of the subsidy over the tax. These calculations were obtained by imposing increasing targets of reduction of emissions (–25%, –30%, –35% with respect to baseline level of emissions; we include the results of the 30% reduction target for a quicker comparison with other targets).

The overall results indicate that the extent of the impacts on OI, LSU and emissions increase as the mitigation target becomes more ambitious. When considering the percentage incidence of the total amount of the subsidy granted on the tax collected, it is vital to highlight the different behaviour of farm types. Although for dairy and beef cattle farms, the value of this indicator remains nearly unchanged, it increases substantially for mixed cattle farms (from 239.6 to 389.3). Thus, it is less convenient for these farms to maintain the same level of production activities as the level of the tax increases. This is in line with the lowest value of MeP among cattle farms shown in Table 4, under the –30% reduction target.

To a lesser extent, the same is true for poultry farms, while pig farms maintain the value of this indicator as the mitigation target increases (by limiting how many LSUs they must reduce).

Table A2. Sensitivity analysis performed on OI, LSU and emissions (Δ% under the simulations with respect to baseline) and percentage incidence of the subsidy over the tax for different mitigation targets.

25%	OI	LSU	CO_{2eq}	% Subsidy/Tax
Dairy cattle	-4.5	-23.7	-23.6	79.8
Beef cattle	-2.1	-33.5	-34.1	288.9
Mixed cattle	-4.0	-29.1	-29.6	239.6
Pig	-1.8	-13.3	-12.6	20.2
Poultry	-0.8	-15.2	-16.1	34.0
Total	-3.4	-21.3	-25.0	100.4
30%				
Dairy cattle	-6.7	-28.5	-28.4	79.1
Beef cattle	-3.1	-39.4	-40.0	294.2
Mixed cattle	-5.9	-36.2	-36.6	315.6
Pig	-2.7	-15.9	-15.2	19.0
Poultry	-1.2	-18.7	-19.7	36.3
Total	-5.0	-25.5	-30.0	100.2
35%				
Dairy cattle	-9.4	-33.4	-33.2	78.0
Beef cattle	-4.6	-44.9	-45.4	293.9
Mixed cattle	-8.1	-43.2	-43.4	389.3
Pig	-3.7	-18.5	-17.9	18.3
Poultry	-1.6	-29.9	-28.7	64.6
Total	-7.1	-30.8	-35.0	99.6

Source: Authors' elaborations.