

Supplementary materials

Appendix A – Data and Method

1. Data and Sample Used

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.¹

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.²

Following Coderoni and Vanino (2022), farm-level CH₄ emissions from manure management and enteric fermentation are estimated and converted in tonnes of CO_{2eq}.³ One of the main value added of the approach here used to estimate CH₄ emissions is that, for enteric fermentation (that represent the bulk of national CH₄ 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 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.

¹ 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 CH₄ from the same livestock categories in Italy (as reported in the National Inventory Report; ISPRA, 2023).

² 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.

³ Hereafter, when mentioning CO_{2eq} emissions, we mean missions from CH₄ converted into CO_{2eq}

Table A1 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 CH₄ emissions.

Table A1. 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
	<i>n.</i>	<i>Ha</i>	<i>n.</i>	<i>EUR ,000</i>	<i>t¹ CO_{2eq}</i>	<i>t¹ CO_{2eq}</i>	<i>t¹ CO_{2eq}</i>
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 CH₄ 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 are produced by mixed farms, while beef farms are intermediate (Table A1). 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.

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

The mathematical structure of the model for each farm is specified is presented in the supplementary materials in the following equations (1–6)⁴.

$$\max_X = C X - T L \Delta E^+ + S L \Delta E^- \quad (1)$$

$$s. to A X \leq B \quad [\lambda] \quad (2)$$

$$L E = U E X \quad (3)$$

$$L E B = U E X^0 \quad (4)$$

⁴ 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).

$$LER = LEB \text{ tel}\% \quad (5)$$

$$LE - \Delta E^+ + \Delta E^- = LER \quad (6)$$

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.⁵

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 ($\text{tel}\%$; 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 ΔE^+ and ΔE^- are both non-negative variables, 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 ΔE^+ and ΔE^- 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.

⁵ 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.

2.1 Mathematical representation and calibration of the AGRITALIM model including CH₄ emissions

The model is structured as follows:

Objective function

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

$$\text{Operating income} = Z$$

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

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

$$\text{Revenues from Complementary Activities} = \text{RCA}$$

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

$$\text{Quadratic Costs} = \text{QC} = \frac{1}{2} XC' Q XC + \frac{1}{2} XA' Q XA^6$$

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

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

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

$$\text{Depreciation Rates Observed} = \text{DRO}$$

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

Variables

XC = hectares of crops

XA = number of animals

XH = hours of labour

XF = quantity of feed

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)

⁶ 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.

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)

Constraints

$$\sum_j XC_{j,n} \leq ald_n \quad \forall n$$

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

$$\sum_j mw_{j,n} * XC_{j,n} \leq awt_n \quad \forall n$$

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

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

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

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

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; Heckeley 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.

2.2 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 A1.

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 CH₄ 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–like⁷) 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)⁸; 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.

For other emissions sources, we instead adopted a Tier 1-like approach⁹, 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.¹⁰

Finally, emissions are expressed in total CO_{2eq} by multiplying CH₄ emissions by their Global Warming Potential (25) in accordance with the IPCC Fourth Assessment Report (IPCC, 2007).¹¹

References

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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>

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⁷ As the reference unit is here the farm, using farm-specific EF can be considered a Tier 2-like approach.

⁸ 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 CH₄ emissions at the national level in 2021 (ISPRA, 2023).

⁹ As the reference unit is here the farm, using country-specific EF can be considered a Tier 1-like approach.

¹⁰ 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).

¹¹ We chose to refer to the IPCC Fourth Assessment Report (AR4) guidelines rather than the fifth (AR5) to derive CH₄ 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.

Richard E. Howitt (pp. 11-36). Cham: Springer International Publishing, https://doi.org/10.1007/978-3-030-13487-7_2

Heckeles, 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>

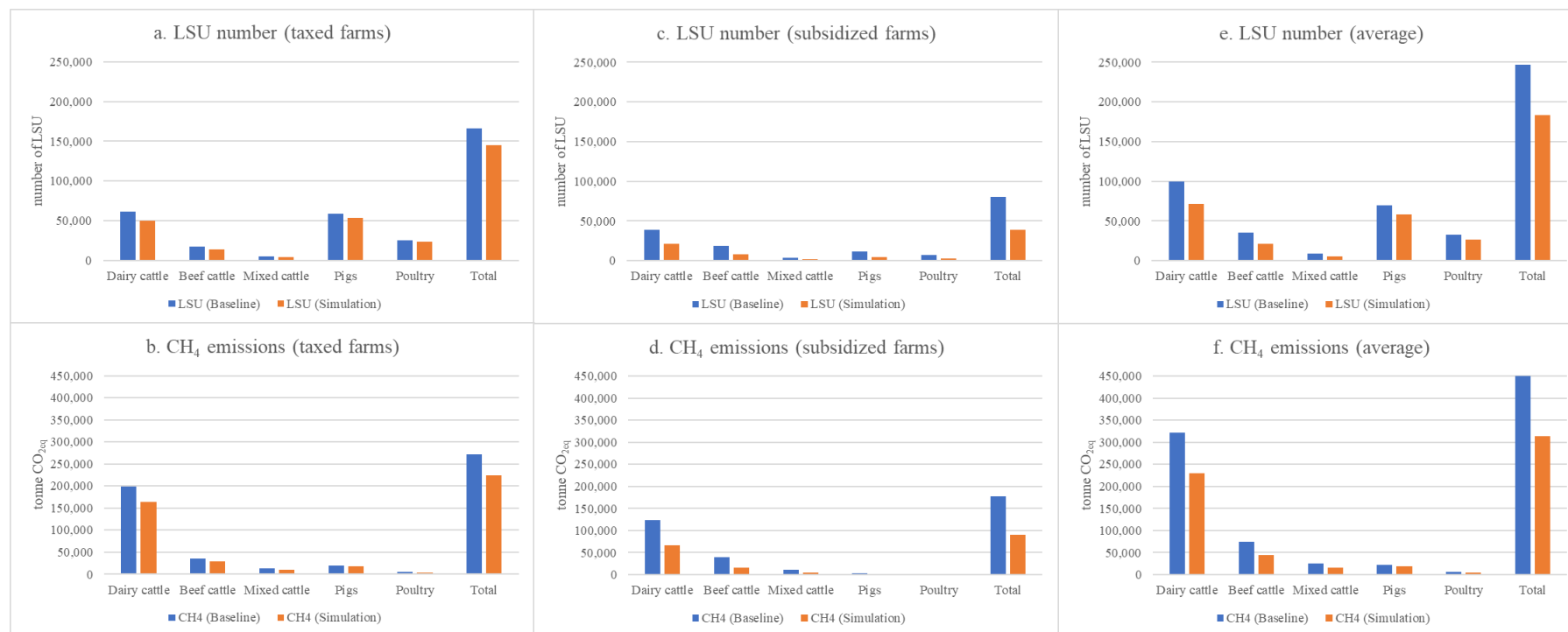
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Appendix B - Figure A.1. Graphical representation of absolute values originating the percentage variations reported in Table 2



FigureA.2. Graphical representation of data reported in Table 3.

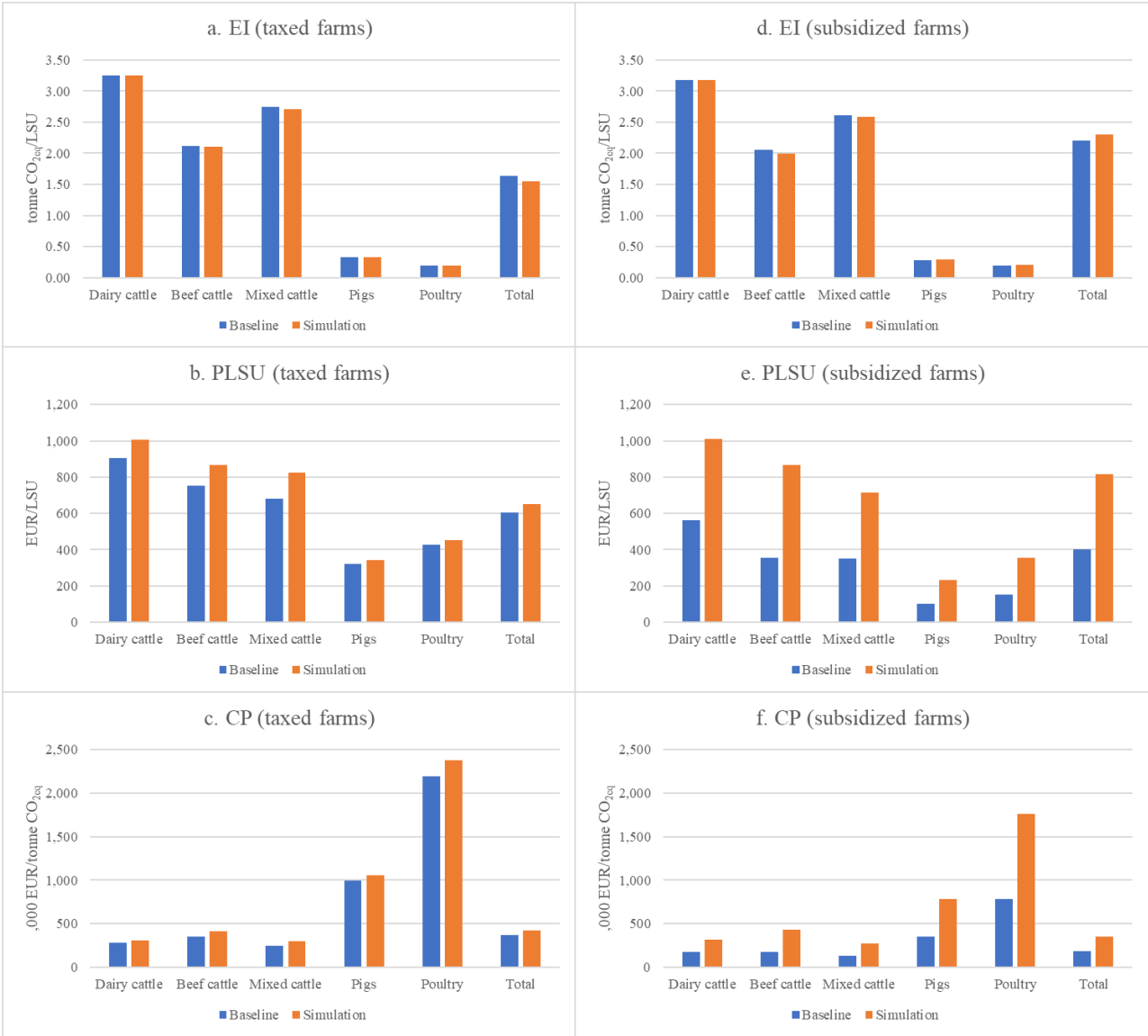


Figure A.3. Graphical representation of absolute values originating the percentage variations reported in Table 5



Appendix C – Baseline and simulation values by geographical location

Table A2. Average value of OI (EUR ,000) and CH₄ (t) at the baseline and $\Delta\%$ under simulation, and respective Coefficients of Variation (CV) by geographic location

	Baseline OI		Baseline CH ₄		$\Delta\%$ OI		$\Delta\%$ 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

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.

Appendix D – Sensitivity analysis with different mitigation targets.

Table A3 displays the results of a sensitivity analysis that considers the percentage variation of OI, LSU and CH₄ 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 A3. Sensitivity analysis performed on OI, LSU and emissions ($\Delta\%$ 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.