CAP payments and agricultural GHG emissions in Italy.
A farm-level assessment

Abstract

This paper investigates the possible role played by the Common Agricultural Policy (CAP) Fischler Reform on the agricultural GHG emissions at the farm level. The empirical analysis concerns a balanced panel of Italian Farm Accountancy Data Network farms observed over years 2003-2007. Multinomial Logit models are estimated in sequence to express how the farm level emissions (and the respective production choices) vary over time also in response to CAP expenditure. Results suggest that CAP expenditure had a role in the evolution of the farm-level emissions, though the direction of this effect may differ across farms and deserves further investigation.

Keywords: Agricultural Greenhouse Gases Emissions, Farm-level Carbon Footprint, Common Agricultural Policy, Multinomial Choice Models

1. Introduction

The Common Agricultural Policy (CAP) is an important external driver of European agricultural production, together with other relevant external (consumer preferences, trends of international trade, the availability of natural resources and climatic conditions) and internal forces (economic developments in the sector, training for farmers and innovation, etc.). The first CAP objectives were mainly linked to the need to deliver food security across Europe. This policy goal created many criticism to the CAP that was indicated as the main cause of environmental pressures from intensive agriculture. Thus, subsequent CAP reforms have increasingly supported methods of agricultural production more environmentally sustainable. This "greening of the CAP" started with the McSharry reform (Council Regulation (EEC) N. 2078/92), through the introduction of semi-decoupled direct payment, of the agro-environmental programmes and of changes in some Common Market Organisations.

Additional environmental support was provided by the Agenda 2000, with the formal setting of the second pillar of the CAP, the Rural Development Policy (Council Regulation (EC) 1257/1999) and the voluntary eco-conditionality. Moreover, agri-environmental measures, i.e. voluntary measures to support farming practices good for the environment, became the only compulsory component of the Member States' Rural Development Programmes (RDP). But is with the Fischler Reform (FR; COM (2002)394 final), in 2003, that the greening process develops further, through a higher level of decoupling (i.e. the single farm payment decoupled from production), which is considered to generate less pressure on the environment and natural resources (Zezza *et al.*, 2017); a mandatory cross-compliance; a portion of coupled payments tackling specific environmental systems; a mandatory transfer of financial resources from the first pillar to the second (i.e. the so-called modulation). Thus, the FR was expected to have a relevant impact on environmental externalities associated to agricultural production.

Among these different environmental externalities, greenhouse gases (GHG) emissions are a major concern for both international and European policy arena. During its history, the CAP initially favoured activities with higher GHG emission intensity, while, successive reforms helped to mitigated the emission potential of agriculture, especially reorienting production to market and favouring more environmental-friendly practices and technologies (Coderoni and Esposti 2014). Hence, analysing the link between the FR and specific second pillar's measure with farm-level GHG emissions is crucial to understand to what extent the CAP may affect and possibly improve the

emission performance and, thus, contribute to reach the European ambitious mitigation targets also at the sectoral level.
Although there are some studies that have evaluated the ex-ante impact of the Fischler Reform on agricultural GHG emissions at European level, or for some specific countries (Behan *et al.* 2003; Dixon and Matthews 2006), there is almost no empirical literature on the ex-post evaluation of these impacts, especially for Italian agriculture.
However, it is worth analysing ex-post these impact, mainly in the light of the emphasis on agricultural GHG emission performance in the programming period 2014-2020.
The objective of the present study is to assess whether there is any evidence of a correlation between CAP support and farm choices concerning greenhouse gases (GHG) emission. The paper does not aim to investigate the causal relationships, that is, how CAP expenditure affects GHG emissions, but only whether CAP expenditure reform affected production choices that then implied a change of GHG emissions. Therefore, the hypothesis here is that CAP expenditure affects emissions indirectly and we aim to assess whether there is any robust evidence on the fact that, statistically, this relationship occurs. The main assumption behind this model is that the farmer is not directly intended to modify is GHG emissions, but he changes his input or output mixes in response to a change in the policy framework, and this reflects in a variation (positive or negative) in the level on GHG emissions.
The paper is structured as follows: section 2 presents the main issues regarding the estimation of agricultural GHG emission at the farm level and the approach here adopted; section 3 briefly comments on the rationale of the work; section 4 describes the sample analysed; section 5 presents the empirical estimations, together with some policy implications and section 6 the concluding remarks.

2. Agricultural GHG Emissions at the Farm Level

Monitoring, reporting and verification of GHG emission, is a fundamental step of every policy framework for GHG abatement. To fulfil the commitments made under the UNFCCC (United Nation Framework Convention on Climate Change) and the European Union's Greenhouse Gas Monitoring Mechanism, every Member State should prepare the annual National Inventory of emissions and removals of GHG, which is the official tool for monitoring commitments (ISPRA 2016). Within the UNFCCC, the IPCC (Intergovernmental Panel on Climate Change), that is the scientific and technical body of the Convention, has given the role to establish a common methodology to estimate emissions and removals from all sectors, using simple and available data, because they must be adopted all over the world for reporting purposes. According to the estimation made with this methodology, IPCC (2014) finds that the agriculture, forestry and other land uses (AFOLU) sector represents the 24% of global GHG emission in 2010.
Despite their relevance, the calculations of agricultural GHG emissions remains one of the most challenging issues in this field. In fact, agricultural GHG emissions are a typical example of non-point source pollution, so this kind of emissions must be computed indirectly. The common methodology to perform this indirect computation is provided by the IPCC (2006) guidelines that, as already mentioned, represent a widely applicable and, above all, internationally recognized standard. Nonetheless, this standard, and the consequent protocols and applications, refer to aggregate data. The novelty in the present paper, is that the IPCC methodology is not applied to aggregate data to compute macro level (i.e. regional or national) emissions, as typically done in previous works (Coderoni and Esposti 2013 and 2014), but it is adapted and applied at the farm (i.e. micro) level.[1]

[1] The choice of adapting the IPCC methodology at farm level could be questioned, however, not only they represent an internationally recognized standard, but they also provide a widely applicable default methodology used also by relevant empirical literature on this field (De Cara *et al*., 2005; Dick *et al*, 2008; Perez *et al*., 2009. See Colomb *et al*., 2013 for a review of calculators for landscape scale GHG assessment for agriculture)

The basic IPCC approach obtains GHG emissions by multiplying activity data (AD) for an Emission Factor (EF), whether default, country specific or region specific. For this study, we have used Farm Accountancy Data Network (FADN) as AD and default or country specific EF (ISPRA 2011) to reconstruct methane (CH_4), nitrous oxide (N_2O) and carbon dioxide (CO_2) emissions for all the emission sources listed in table 1 and grouped in the following five emission categories: livestock production, crops, land use, fuel and fertilizers use.[2] The sum of all these emission sources gives what we have defined, for the purposes of this study, the Carbon Footprint (CF) (see Coderoni *et al*. 2013, for further details on the methodology used).
The farm-by-farm reconstruction of the emission levels across a balanced panel dataset allows observing the variation of emission performance across space, i.e. across the heterogeneous farming types (in terms of farms' characteristics and specialization, geographical localization, economic dimension, etc.) and over time. Evidently, the extreme variety of environmental and management systems in Italian farming represent the main problem when computing these farm-level emissions. Thus, the developed methods are expected to be strongly connected to the different production processes and to use activity data that are strictly and properly linked to emission production.
An important characteristic of the IPCC approach to agricultural emission estimation is that it refers to the production stage while disregarding the consumption one. This means that is the "process level", and not the "product level", emission that counts. This approach seemed to be adapt to the purpose of this study to carry out a sectoral analysis and inform sectoral policies. In fact, it estimates the emissions that occur within the "farm gate" and on which the farmer has a "direct" control, with a focus on the production processes associated to the farm characteristics (specializations, natural processes, methods of production, resource management, etc.) and not on subsequent supply chain and consumption of the respective agricultural products.
As the FADN survey is not designed to collect all the information needed for the estimation of farm-level GHG emission, some assumptions have been made to overcome the information gap to compute the farm-level CF. Major assumption regard the following CF categories. For what concerns rice emission, as at present FADN information does not include data on rice cultivation methods and it is not possible to distinguish between single and multiple aeration, the multiple aeration EF is used; this assumption might evidently represent a slight overestimate of the respective emissions.
The CF deriving from fertilizers consumption has been estimated using total fertilizers expenditure at farm level. Both direct and indirect emission (due to nitrogen leaching and run-off) are accounted for. The estimation assumes that 1 euro of expenditure in fertilizers (N, P or K) at constant 1995 prices, corresponds to the same amount of N input as derived from the Agrefit dataset (Rizzi and Pierani 2006). According to this assumption, every euro spent on fertilizers corresponds to 0.54 Kg of nutrients (N, P or K).[3] The CF of fuel consumption has been estimated using total agricultural fuel expenditure at farm level, by dividing for the average price of agricultural diesel observed over time and across different Italian provinces (available online).
The CF of land use has been calculated in two alternative ways, to reflect different assumption made on the underling methodology. The firs approach (CF Land Use A) has been obtained adapting ISPRA (2016) Implied Emission Factors multiplied by the UAA cultivated with respective crops. More in detail, land uses have been distinguished in: forest, other wooded land, perennial woody crops, plantation and coppices.[4]

[2] To express all these emissions in a unique unit of measure, i.e., total CO_2 equivalent (CO_{2e}), any different GHG is multiplied by its Global Warming Potential (GWP). In this work, we refer to GWP as defined in the Second assessment report by the IPCC (i.e. 21 for CH_4 and 310 for N_2O).
[3] Baldoni *et al.* (2017), using the quantity of N applied provided by FADN dataset from 2008 to 2013, find a very similar value (0.5).
[4] Land use changes have not been considered in at this stage of the methodology, if not because of changed UUA surface. Following ISPRA (2016: 228) "the change in biomass has been estimated only for perennial crops, since, for annual crops, the increase in biomass stocks in a single year is assumed equal to biomass losses from harvest and mortality in that same year", coherently with the IPCC Good Practice Guidance (GPG) for LULUCF.

However, since the value obtained with this approach for perennial wood crops is negative (thus, represent a source of emissions)-for the value of this carbon (C) stocks at maturity-a different EF has been used to consider that perennial crops give both with soils and biomasses a higher contribution in C sink than annual crops. This second approach (CF Land Use B) considers a positive value for perennial wood crops using, in the absence of country specific values, an average value of 10 t C ha-1 (for carbon stock at maturity), deduced by the values adopted in Spain, suggested by JRC (2013) experts to ISPRA considering a cycle of 20 years (ISPRA, 2016: 228).

3. The CAP and GHG emissions: a brief comment on the rationale of the work

In Europe, and in Italy, the agricultural sector is the second largest source of GHG emissions in 2014 (with respectively 10.2% and 7.2% of total emissions), after the energy sector (76.8% and 81.2%) (ISPRA 2016; EEA 2016), though they have already achieved a significant reduction since 1990 at both EU (-20.6%; EEA 2016) and Italian level (-16.2%; ISPRA 2016). However, mitigation of agricultural sector contribution to climate change, still remains a relevant issue for three different kind of policy objectives: the increasing long term trend in emissions (mostly in developing countries), the need for resource efficiency in the sector (mostly in developed countries) and, finally the burden sharing of the emission reduction effort among economic sectors within (EU) countries.

The European strategy to tackle climate change, for the agricultural sector, is represented by the Effort Sharing Decision (ESD. Dec. n. 406/2009/EC) that establishes annual binding GHG emission targets for sectors[5]-like agriculture-not included in the EU Emissions Trading System (ETS) for the Member States for the period 2013-2020.[6]

Policies that were expected and had a role in the achievement of these emission reduction targets are various. On the one hand, several EU environmental policies, e.g., the Nitrates Directives and the Renewable Energy Directive, may have a direct influence on agricultural activities. On the other hand, the CAP itself plays a critical role. In fact, most CAP measures have the potential to influence greenhouse gas emissions from agriculture, even if they are not directly aimed to GHG mitigation. Doorn *et al*. (2012) in analysing the European Environment Agency (EEA) database on climate change policies and measures[7] acknowledge that, within the agricultural sector, most EU or Member States policies are generally RDP measures not specifically aimed at climate change mitigation, but they are still relevant. For instance, they are likely to have a significant positive effect on agricultural GHG emissions by introducing anaerobic digesters or reducing the amount of nitrogen inputs.

The impact of the CAP, and of its reforms, on agricultural GHG emissions over time is the combination of measures supporting production and income, on the one hand, and of more recent environmentally targeted interventions, on the other hand. Thus, the CAP is one of the main drivers of emission trend in the agricultural sector, even it has not a climatic objective *strictu sensu*. In the last two decades, a major role in this respect, can be attributed to the gradual shift of support from coupled to decoupled payments, and to the progressive introduction of measures providing incentives, or obligations, towards sustainable and low-impact practices and activities (EEA, 2012: 439 and 2016; Baldock *et al*. 2007). The 2003 reform of the first pillar of the CAP (also known as the Fischler Reform; henceforth, FR) besides the decoupling of payments, includes a series of measures that are likely to have contribute to the protection of the environment and nature conservation. In the first pillar, the combination of decoupling of support and of the mandatory cross-compliance[8], was expected to provide a stimulus towards better emission performance. More importantly, several second pillar measures might have been associated to a reduction of GHG agricultural emission:

[5] These sectors are: transport, buildings, agriculture and waste

[6] The EU-level reduction target is -10% in 2020 from the 2005 baseline and each Member State is expected to contribute to this effort in different percentages, according to its GDP per capita. Italian target is -13%.

[7] Available at the following url: http://pam.apps.eea.europa.eu/ (accessed on May 2017).

[8] Cross compliance makes direct payments conditional to the respect of Statutory requirements from 19 Community Acts, including 5 environmental Directives and maintenance of Good Agricultural and Environmental Conditions (GAEC).

measures supporting compliance with environmental legislative requirements (e.g. Water Framework Directive payments); measures supporting the provision of environmental services on a voluntary basis (agri-environmental measures); measures related to animal welfare or to afforestation (Council Regulatiom (EC) 1257/1999).
The emphasis on agricultural GHG emission performance increases in the actual programming period (2014 - 2020) as climate action is one of the three key objectives of the CAP, both in first pillar, with the greening payment linked to the duty of agricultural practices beneficial for the climate and the environment, and in second pillar, with the climate action being a cross cutting objective of the whole rural development policy and of two specific priorities (4 and 5) (Council of the European Union 2013a and 2013b).
In any case, the actual role of the CAP in affecting the agricultural GHG emissions is still questionable.
The rationale of this empirical study, in analysing the role of the CAP in affecting agricultural GHG emissions, is based on two main assumptions: the concept of technical jointness of agricultural production (OECD 2001) and the hypothesis that the farmer is a private agent, that maximises his utility. First, "*Joint production refers to situations where a firm produces two or more outputs that are interlinked so that an increase or decrease of the supply of one output affects the levels of the others"* (OECD 2001: 16). Technical interdependencies or biological characteristics of the production process are the main cause of negative and positive externalities. Among the negative ones, GHG emissions are of interest here. Moving from the concept of technical jointness, many studies (see among others Baldock *et al.* 2007) have shown that even measures not directly aimed at addressing the environmental sustainability of agriculture (e.g. the introduction of milk quota), might have improve it.
The second hypothesis is that farmers are private agents that make their decisions ignoring every consequence not considered within their personal utility function. This is the case for most environmental externalities not directly addressed by the policy (Picazo-Tadeo *et al.*, 2011), like GHG in the time span analysed. In other words, the decision of the farmer whether to reduce or increase use of input or change the output mix, is independent from the consequences on GHG emissions, but as technical jointness of farm activities makes agricultural GHG emission vary intrinsically with farms productions, farmers' choices of production have an impact (even though not intended) on GHG emissions.
To explain the link between farmers' choices and GHG emissions, one clarification on GHG emission estimation is needed. As already stated (see par. 2), agricultural GHG emission cannot be measured directly because they are non-point source of pollution and they must be computed indirectly. IPCC approach is based on a linear relationship between activity data multiplied by an emission factor. AD are the main input used in agriculture (e.g. fertilizers, land, fossil fuel, livestock heads, etc.), while EF can vary depending on production practices and management conditions. The assumption here is that farmers' choices, though not intentionally, affect both AD and EF used to calculate GHG emissions. Indeed, the impact of farmers' choices on AD is expected to be higher than the one the EF as decreasing AD (e.g. reducing heads of livestock), means set to zero its relative GHG emissions, while improving EF means reducing them only of a certain percentage.[9] In fact, Coderoni (2010) concludes that over the period from 1990 to 2007, EU policy interventions and reforms, mostly the CAP, affected more the agricultural GHG emissions concerned dairy and meat (mostly beef) production, as they induced a substantial reduction of the number of animals.
The 2003 Cap Reform was expected to have a major role in decreasing GHG emissions for it provided both negative incentives to the production of environmental externalities by agriculture (i.e.: the cross-compliance) and positive contractual incentives for measures beneficial for the environment (in

[9] E.g. Coderoni *et al.* (2015) for some Italian livestock production chain, find that the greatest mitigation potential for a single action reaches only 15 per cent (for the biogas plant).

the RDPs). Indeed, it would be possible to incorporate some environmental objectives into all measures within the RDP, but for the purposes of this analysis, we choose to analyse only some measures were the sustainability objectives were more explicit. In fact, agri-environmental measures are core instruments to stimulate adoption of action with higher mitigation potential[10]; among these measures we specifically refer to the following: F1-Low environmental impact; F2-Organic Farming; H-Afforestation-costs of planting; H-Afforestation-maintenance; H-Afforestation-loss of revenue; I1-Afforestation non-agricultural areas; E-Less Favourite Area (LFA); I6-Reforestation for natural disturbances.
Following this approach, table 2 presents the expected impact of the different policy instruments introduced (or reinforced by the FR) on the AD of EF used to estimate agricultural GHG emissions.
Decoupling was considered to have an important impact on GHG emissions via reduction of incentives towards intensive productions e.g. extensification, livestock, reduced fertilizers use.

4. The FADN Sample analysed

As the objective here is to assess the evolution of the GHG emission and of the CF in Italian farms with specific attention on the role played by the FR of the CAP, the sample under investigation has to satisfy some specific requisites. Firstly, it must be a balanced panel not just a cross-sectional sample and must contain all the needed information to compute the GHG emission and CF at the farm level as well, as all the other farm-level variables that might significantly affect these performances. Finally, with respect to the time dimension, sample farms have to be observed over the pre and post-treatment periods (i.e. before and after 2005). These conditions can be met by extracting a constant sample of farms yearly observed over the pre and post-2005 period. This balanced panel is pulled out from the FADN (RICA) database. Though FADN database also covers years prior to 2003, the sampling and data collection procedures and criteria do not allow reconstructing a balanced panel backward. Moreover, adding years 2000-2003 in the pre-treatment period can be troublesome as they may still incorporate some effects of the previous CAP reform (namely, Agenda 2000). Thus, a 2001-2007 comparison, for instance, would overlap different CAP reforms and would mix-up different policy treatments. Year 2008 could also be added but some significant changes in FADN data collection would make year-by-year comparison more difficult. Moreover, the huge price turbulence observed in agricultural markets in 2008 (Esposti and Listorti 2013) suggests particular caution in adding this year to the post-treatment period. Farmers' behaviour, as well as farms' performance, might be strongly affected by this price bubble and this year could confound permanent responses due to policy treatment with those temporarily induced by peculiar market conditions.
Table 3 reports the evolution of per farm average CF from 2003 to 2007 distinguishing the total emission performance among its five emission categories. Some major regularities clearly emerge. First, some categories are clearly dominating the total amount of emissions while others are, in fact, negligible. In the former case, we can mention the CF associated to livestock and related activities, representing by large the most important source of emission at the farm level. Fuel and fertilizers' CF also has remarkable role. In the former case, it must be noticed that the CF of fuel is an aspect that it is often disregarded in the empirical studies on the agricultural contribution to the GHG (Coderoni and Esposti 2014) as it is attributed to the transportation (i.e. energy) sector, rather than to agriculture, by the IPCC methodology. In the latter case, we may appreciate how the CF associated to land use and its changes are insignificant compared to all other categories.
It is worth acknowledging that, as detailed in previous sections, the CF associated to land use here only considers the agricultural land use. So forestry and related activities are not investigated due to

[10] E.g. Picazo-Tadeo *et al.* (2011) using a sample of Spanish farmers operating in the rain-fed agricultural found that CAP agri-environmental programs seem to be an effective policy to improve farms' eco-efficiency. Westbury *et al.* (2011) analysing the performance of different type of farming in England (arable, lowland livestock, and upland livestock) found that agri-environment scheme participation was an important factor only for arable farms.

the lack of appropriate and complete information in the FADN dataset in this respect (only data on poplar plantations and few other species are accounted for). Nonetheless, it remains true that these results seem to downsize the emphasis put on land use changes in terms of mitigation of the agricultural contribution to overall GHG emissions, at least in the way that these emissions are accounted following the IPCC methodology revision of this study.[11]

A second major evidence emerging from table 3 consists in the very high cross-farm variability of the computed CF and that can be observed, without significant difference, in all CF categories. On the one hand, this variability can be considered the natural consequence of the large farm heterogeneity that eventually affects also the respective CF performance: indeed both size and production specialization aspects largely affect the CF at the individual farm-level. On the other hand, a large variability prevents from deriving clear-cut conclusions on the evolution of the CF over time since, in fact, confidence intervals built around the observed average values across years, are largely overlapping.

Though inconclusive, however, this evolution indicates that if we exclude the decline of land use, all CF categories experience a growth, on average, over the period under study.. The largest increase can be observed for the CF of cultivations. This evidence might suggest that the decline observed in overall GHG emission observed within the Italian agriculture in the same period (-2.54%) (ISPRA, 2011), should be associated to the generalised decline of agricultural production, rather than to improvements in production processes (EEA 2012).

Table 3 also shows the total CF per group of farms in terms of economic size (ES), physical size (UAA) and production specialization. Size evidently matters: the larger the economic and physical size of the farm, the larger is its expected CF. The correlation coefficient between the farm-level CF and the farm UAA is positive (0.5) and regular over time. Nonetheless, the highest growth over the 2003-2007 period is observed in smaller farms though, once again, the large variability of the computed CF makes such comparison across sub-samples largely inconclusive.

Among the different agricultural specializations, activities associated to livestock show a stabilization of CF over the period under study. This somehow confirms that the largest, if not the only, significant experience of GHG emission reduction within the Italian agricultural of the last decades is essentially related to the decline of livestock activities (ISPRA 2016), rather than to major changes in their organization and management (Coderoni and Esposti 2014).

5. Carbon Footprint and the CAP expenditure

5.1. Some descriptive evidence

The possible linkage between CF evolution over time and the CAP is twofold. On the one hand, we may argue that the reform of the first pillar of the CAP approved in 2003 and implemented (at least in Italy) in 2005, has an impact on farm-level CF, both because the decoupling of support reoriented farm's production choices to market and because of the cross-compliance environmental constraints introduced therein. On the other hand, the second pillar of the CAP (2000-2006 programming period) delivers several measures that directly and indirectly concerns activities and practices that affect the farm-level CF.

Table 4 reports the per farm average CF within sub-samples distinguished in terms of the intensity of the first pillar support. This intensity is expressed as the ratio between the amount of first pillar payments (FPP) received by a given farm and its gross production value (GPV). Both values are taken as the yearly averages of the year 2003 and 2007. This ratio evidently gets rid of the size effects of both FPP and GPV and takes into account the shift from coupled payments (years 2003 and 2004) to

[11] As a consequence, also the relevance of the appropriate procedures to compute this component (Land Use – A vs. Land Use – B, in the present case) seems to be slightly overemphasised, thus in the following analysis, only the Land Use – A will be used to obtain the total CF, as it more coherent with the overall CF estimation methodology adopted.

decoupled payments (or single farm payments) (years 2005, 2006 and 2007). Three sub-samples are compared: farms for which the incidence of FPP on GPV on is almost negligible (<10%) that are almost 3,500 farms; farms for which it is moderate (>10%, <30%) almost 800 farms; farms for which it is high (>30%), almost 700.

Results show that in all sub-samples the CF increases over the period analysed but this growth is higher in farms with a lower incidence of the CAP while, on contrary, farmers depending on first pillar's support show less growing emission performance. The statistical correlation occurring between FPP and CF tends to be negative in the levels and with the variation of the CF, however, when the variation is considered, this correlation is lower.

The lower part of Table 4 shows a preliminary assessment of the linkage between second pillar's payments and the farm-level CF and its evolution. Actually, all 2003-2007 second pillar payments (SPP) refer to the 2000-2006 programming period and, therefore, to the respective RDP policy (measures), as even the 2007 payments here considered, still are the finalization of the previous programming period. Two different sub-samples of farms are treated. The "With SPP" group includes farms that received, over the 2003-2007 period, at least one of the agri-environment payments listed in table 2. The "No SPP" group includes all other farms.

Clear difference emerges between farms that received these payments and those that did not. The former tend to have a higher CF in 2003, but a much more virtuous behaviour over time, with a strong decline than makes the CF of the excluded farms, higher than the supported ones in 2007. This also explains why the correlation coefficient between SPP and CF is positive in both 2003 and 2007 but becomes negative when the 2007-2003 variation is considered.

5.2. The empirical model

The aim of this study is to investigate farm-level GHG emission changes because of farm production choices possibly induced by CAP payments. Therefore, the emission changes of interest here, are those that persists in the medium-long term. Thus, the empirical strategy adopted is to disregard those short-term (i.e., yearly) GHG emission variations that are mostly random, temporary, unexpected and therefore, unintended. The idea is that, these short term variations are not linked to permanent farmer' choices so they are hardly linked to CAP expenditure that are expected to affect these choices. To pursue this empirical strategy, we consider the GHG emission variation over a medium-term period instead of year-by-year. Therefore, even though we have a balanced panel dataset, our model specification is a cross-sectional model.

A first "natural" attempt to model such cross-sectional linkage between GHG emission variations-over the period 2003-2007-and CAP expenditure, consists in estimating a linear regression model, where the GHG emission variation is the dependent variable and the explanatory factors included in the regression models are both farm structural features and policy variables (table 5). This model can produce poor statistical results mostly because a quite large part of the GHG emission performance variability may be totally random and temporary, thus unexplained by regressors. The only regressors that seem to explain the dependent performance are typology dummies. However, this kind of data are also highly linked to policy intervention.

The alternative empirical strategy followed is to define discrete variations that are expected to more clearly identify farms that responded to CAP expenditure with production choices really affecting GHG emission. Therefore, alternative multinomial choice models are specified and estimated to better capture the real linkages between emission variations and CAP expenditure over the period under consideration.

To estimate the potential role of the CAP in influencing farmers' choices and thus GHGs emissions, we have firstly estimated a Multinomial Logit Model (MLM), assuming that the decision of the farmer, whether to reduce or increase use of input or change the output mix, depends on four categories of drivers: geographical information, farm size (both in term of UUA and ES), production mix, and policy variables (both first pillar and second pillar payments).

As already pointed out, the main assumption behind this model is that the farmer is not directly intended to modify is GHG emissions, but he changes his input or output mixes in response to a change in the policy framework, and this reflects in a variation (positive or negative) in the level on GHG emissions, as they are strongly linked to activity data.
The general form of the multinomial logit model is:

$$P(y_i = j) = P_{ij} = \frac{\exp\left(x'_{ij}\ \beta\right)}{\sum_{k=1}^{J} \exp(x'_{iM}\ \beta)},\ for\ j = 0, 1, \dots, M \qquad (1)$$

where i indicates the observation, farms in this case; j indicates the choices (increased, stable or decreased emissions); P_{ji} is the predicted probability of farmers selecting the j^{th} GHG emission trend alternative; β are vectors of unknown parameters and x_i is a vector of explanatory variables, which are characteristics of the observed individual variable, not of the choices. In this model, these variables are the characteristics of the farms listed in table 5. The dependent variable is the three-category variable comprising the three groups obtained dividing the sample according to their emission behaviour during the period analysed.
As there is no natural ordering of the possible three outcomes, what number goes with each category is arbitrary. We decide on the following: j = 1 “decrease”, if a farm decreases its GHG emissions; j = 2 “stable”, if a farm’s emissions are stable; j = 3 “increase”, if a farm’s GHG increase, from 2003 to 2007.
Results of the multinomial logistic regression are not so easy to interpret, as they tell us how a one-unit change in the regressor effects the log of the odds when the other variables in the model are held constant. Therefore, to estimate the effects on the dependent variable for a given change in a particular regressor, while holding the other regressors at their sample means, marginal effects are then estimated (Table 7).
Findings highlight significant and coherent differences between the farmers’ behaviours. Geographic variables give quite clear results: farms located in the north and centre of Italy are less likely to increase emissions and coherently, they are more likely to reduce them, with respect to farms located in the south of Italy.
Looking at farms specialization, being a farm specialized in livestock, negatively affects the probability to increase emission, and consistently, positively affects the probability to decrease them. Farms specialized in crops cultivation are more likely associated with an increase of emissions (and negatively associated with a decrease or a stabilization).
For what concerns the policy variables, that are the focus of our analysis, apparently farms more supported by first pillar are more likely to decrease their emissions over the period analysed. This result is very interesting as it would suggest the idea that the FR, which actually mainly affected the FPP, is positively associated with more virtuous farms in terms of GHG performance.
The opposite holds for SPP: receiving this kind of support is in fact more likely associated with the probability to increase emissions. This aspect, though counterintuitive-as policy instruments that should bring more environmentally sustainable behaviours are associated with less probability to decrease emission-is not so surprising. In fact, this kind of measures are often associated to farms with bigger structure, that are also more likely to increase their dimension over time, and this could partially compensate the eventual increase of farm environmental sustainability.
Thus, what should be evaluated here, is whether the increase or decrease of emission over the period analysed is associated with higher or lower production per unit of emission, i.e. with higher or lower carbon productivity (CP) levels. Hence, though the model gives quite clear results, it also suggests the idea that a more complex structure of choices could exist.
To define a new set of choices, a CP index has been defined as the ratio between GPV and GHG emissions at farm level, considering the carbon (C), i.e. the GHG emissions, as an additional input to the farm’s activities. CP is thus a measure of efficiency: the higher the value, the more efficient is the farm, because a same amount of C (1 unit) produces more GPV. This index should help distinguishing

farms that decrease (or increase) their emission due to a merely scale effect, i.e. also decreasing (or increasing) the value of production. According to this index, each of the three choices (increase, decrease or stable emission), has been divided into two sub-group of choices depending on the different trend of CP index over the period under investigation: those that show a higher level of CP in 2007 than in 2003 (i.e. CP increases) and those that show a lower one (CP decreases).

A new model with six choices, reflecting different behaviors that could probably better fit data, has thus been estimated. Results are shown in table 8; though they are coherent with the previous estimates, still can give more interesting insights to the analysis undertaken.

For what concerns structural characteristics of the farms, statistically significant variables are those related to farm typologies and location. Farm typology results could indicate that livestock farming are the more efficient ones, as even when increase their GHG emissions, show higher CP levels; less efficient farms seem to be the one specialized in crops.

Geographic variables suggest that farms located in the north and centre are more likely to show more efficient behaviour as they are associated with groups showing higher CP both if they increase or decrease GHG emissions.

Looking at policy variables, interestingly, FPP seem to be more likely associated with a decrease in GHG emissions and increase in CP levels, i.e. with the more efficient behaviour, showing a sort of "decoupling" in GHG and production levels. On the opposite, we find no statistical significance of the relationship with a decrease of emissions with lower CP levels.

Receiving SPP is more likely associated with increased or stable emission and lower CP indexes. This could signal a sort of inefficiency of this kind of farms, as CP levels decrease over time and GHG emission increase or remain stable. This inefficiency seems to be reinforced by the negative relationship with SPP and the probability to increase emission, though showing higher CP.

5.3. Results discussion and policy implications

Tackling climate change is one of the main declared objectives of the 2014-2020 CAP reform, thus the role of farms in mitigating GHG emissions is an issue that deserves appropriate farm-level empirical investigation.

Analysis like the present that evaluate GHG performances (or environmental performances in general) at micro level, can help policy-makers to design agricultural policies more effective in reaching environmental sustainability.

Results indicate that farm typologies and localization matter, demonstrating that there are some structural or context specific features that are more likely to be associated with more efficient behaviour. For what concerns policy variables, some positive effect of receiving FPP seems to occur, also if we look at the CP effect, which increases. On the contrary, farms with SPP are more likely to increase (or stabilize) their emissions and to show lower CP indexes.

These counterintuitive behaviours could be linked to extensification processes brought about by SPP, or could actually mean that more inefficient farms are those trying to use RDP funds to allow them to become more sustainable. To this respect, analysing the direction of these relationship, i.e. the causal nexus between variables, is fundamental, but it goes well beyond the scope of this analysis.

The eco-efficiency analysis is very interesting form a policy implication perspective. Firstly, improving eco-efficiency is often the most cost-efficient way of reducing environmental pressures, and secondly, because for policy-makers, it is easier and more acceptable to advocate win-win policies that target improvements in eco-efficiency, than more radical measures that can decrease the level of farming activity. Indeed, this kind of policies can help farms in operating in the frontier of economic efficiency, creating net cost savings in addition to reducing their environmental impacts (Kuosmanen and Kortelainen, 2005; Ekins, 2005; Picazo-Tadeo *et al*., 2011)

It must be noticed that, increasing CP does not necessarily guarantee sustainability because, what this coefficient measures, is only the relative level of economic activity in relation to environmental pressure. Instead, what really counts when dealing with sustainability issues, is absolute (rather than

relative) environmental pressure, which can still exceed the carrying capacity of the ecosystem (Picazo-Tadeo *et al*., 2011). In the case analysed this drawback does not seem to occur, as we are measuring eco-efficiency (i.e. CP) of farms together with their GHG net behaviour (i.e. increase or decrease emissions), but this aspect deserves particular attention.
Further research is still required in several directions. First, it is fundamental to calculate more precise measures of eco-efficiency and also the relative importance of the different drivers that determine eco-inefficiency, to give more rationale for policy intervention. Theses analysis could help also assessing more precisely the costs and benefits of CAP agri-environmental programs (Picazo-Tadeo *et al*., 2011). Secondly, this study disregards farmer features that can be critical in adopting more environmentally sustainable behaviours. Our choice here, was in fact to suppose farmers' behaviour responding to policy intervention just in terms of private utility function, but there can be psychological aspects, such as environmental concerns, that could more appropriately explain eco-efficiency (Huang *et al*. 2015; Picazo-Tadeo *et al*., 2011).

6. Some concluding remarks

This paper represents a first step in the direction of investigating the role of the CAP in affecting the agricultural GHG emission that represent one of the main declared objectives of the 2014-2020 CAP reform. Nonetheless, the empirical literature is still lacking mostly because it requires an appropriate micro-data reconstruction of the emission performance and a careful assessment on how CAP expenditure may affect this performance.
This paper aims to provide a contribution in this direction by computing the farm-level Carbon Footprint and then looking for the statistical relationship between this CF and the CAP payments (both first and second pillar) received by farms during the period of the major (Fischler) reform.
The main assumption of the approach here adopted is that the CAP (and its reform) shaped farming choices that ultimately decide if the farm is moving towards higher or lower emissions (or remains stable).
Results of the MLM estimated in sequence, suggest that FPP are more likely to be associated with more sustainable farms' behaviour, i.e. decreasing of GHG emissions over the period analysed, while SPP are more likely associated with an increase of farm-level emissions.
Moreover, when a more detailed set of choices is expressed, by defining a carbon productivity measure, farm receiving FPP are more likely to show a positive trend, by associating a decrease in GHG with an increase in carbon productivity. Farm supported by SPP show instead less efficient trends, i.e. increased (or stable) emissions and lower CP levels.
Though some interesting results are obtained about the CF-CAP expenditure relationship, further research effort is needed, through more complex farm-level models and empirical estimates, to investigate the causal chains that make this relationship occur. Therefore, this works represents just an initial, though necessary, step in the direction of more advanced investigations on the role of the CAP to mitigate agricultural GHG emission in order to inform the discussion and the decisions about the proper policies to tackle climate change in the agricultural sector.

References

Baldock, D., Bartley, J., Framer, M., Hart, K., Lucchesi, V., Silcock, P., Zobbe, H. and Pointereau, P. (2007). *Evaluation of the environmental impacts of CAP (Common Agricultural Policy) measures related to the beef and veal sector and the milk sector*. Report prepared by the Institute for European Environmental Policy for DG Agriculture, December 2007, London.

Baldoni E., Coderoni S., Esposti R., (2017). The productivity and environment nexus with farm-level data. The Case of Carbon Footprint in Lombardy FADN farms. Bio-based and Applied Economics (*in press*).

Behan, J., Binfield, J., Breen, J., Donnellan, T., Hanrahan, K., McQuinn, K., Westhoff, P and Young, R., 2003. *An Analysis of the Effects of Decoupling of Direct Payments from Production in the Beef, Sheep and Cereal Sectors*, Teagasc IE 65.

Coderoni, S. (2010). I principali effetti della Politica Agricola Comune sui dati di attività utilizzati per stimare le emissioni di gas serra del settore agricolo italiano dal 1990 al 2007. Institute for Environmental Protection and Research - ISPRA, Internship Thesis, Rome.

Coderoni, S. and Esposti, R. (2013). Emissioni di metano e crescita della produttività nell'agricoltura italiana. Tendenze di lungo periodo e scenari futuri. *Questione Agraria-Rivista dell'Associazione Rossi-Doria* 3:7-43.

Coderoni, S. and Esposti, R. (2014). Is there a Long-Term Relationship between Agricultural GHG Emissions and Productivity Growth? A Dynamic Panel Data Approach A Dynamic Panel Data Approach, *Environmental and Resource Economics,* 58 (2): 273-302.

Coderoni, S., Bonati, G., D'Angelo, L., Longhitano, D., Mambella, M., Papaleo, A. and Vanino S. (2013). Using FADN data to estimate agricultural greenhouse gases emissions at farm level", in Vrolijk, H. (ed.), Pacioli 20th (eds), *Complex farms and sustainability in farm level data collection,* LEI Proceedings 13-054.

Coderoni S., Valli L., Canavari M. (2015), Climate Change Mitigation Options in the Italian Livestock Sector, *Eurochoices*, Volume 14, Issue 1 Pages 17-24, The Agricultural Economics Society and the European Association of Agricultural Economists, ISSN: 1746-692X, DOI: 10.1111/1746-692X.12077.

Colomb V., Touchemoulin O., Bockel L., Chotte J-L., Martin S., Tinlot M., Bernoux M:, (2013), Selection of appropriate calculators for landscape-scale greenhouse gas assessment for agriculture and forestry, Environmental Research Letters 8 (2013) 015029 (10pp), doi:10.1088/1748-9326/8/1/015029.

Council of the European Union (2013a). Regulation (EU) No 1305/2013 of the European Parliament and of the Council of 17 December 2013 on support for rural development by the European Agricultural Fund for Rural Development (EAFRD) and repealing Council Regulation (EC) No 1698/2005), Brussels, 17 December 2013.

Council of the European Union (2013b). Regulation (EU) No 1307/2013 of the European Parliament and of the Council establishing rules for direct payments to farmers under support schemes within the framework of the common agricultural policy, Brussels, 17 December 2013.

De cara, S., Houzé, M. and Jayet, P-A. (2005). Methane and Nitrous Oxide Emissions from Agriculture in the EU: A Spatial Assessment of Sources and Abatement Costs. Environmental & Resource Economics 32:551–583.

Dick, J., Smith, P., Smith, R., Lilly, A., Moxey, A., Booth, J., Campbell, C. and Coulter, D. (2008). Calculating farm scale greenhouse gas emissions. University of Aberdeen, Carbon Plan, the Macaulay Institute, Pareto consulting, SAOS Ltd, Scotland.

Dixon, J. and Matthews, A., (2006). *Impact of the 2003 Mid-Term Review of the Common Agricultural Policy*. Quarterly Economic Commentary: Special Articles. Economic and Social Research Institute (ESRI) vol. 2006(1-Spring): 1-17.

Doorn A. van, Lesschen j. P., Kuikman P., (2012). *Next phase of the European Climate Change Programme: Analysis of Member States actions to implement the Effort Sharing Decision and options*

for further community wide measures. A report for DG Climate Action. Agriculture sector-Policy case studies report, AEA, Number: 2, UK.
EEA (2012). Annual European Union greenhouse gas inventory 1990–2010 and inventory report 2012. Submission to the UNFCCC Secretariat. EEA Report No 3/2012, EEA, Copenhagen, 2012.
EEA (2016). Annual European Union greenhouse gas inventory 1990–2014 and inventory report 2016. Submission to the UNFCCC Secretariat. Technical report 15/2016, EEA, Copenhagen, 2016.
Ekins, P., (2005). Eco-efficiency. Motives, drivers and economic implications. *Journal of Industrial Ecology* 9, 12e14.
Esposti, R. and Listorti, G. (2013), Agricultural price transmission across space and commodities during price bubbles. *Agricultural Economics* 44: 125–139.
Hausman, J., and D. McFadden (1984). Specification Tests for the Multinomial Logit Model, *Econometrica* , 52(5), 1219–1240
Huang J. Tichit, M., Poulot, M., Darly, S., Li, S., Petit C., Aubry C., (2015). Comparative review of multifunctionality and ecosystem services in sustainable agriculture. *Journal of Environmental Management* 149 (2015) 138e147
IPCC, Intergovernmental Panel on Climate Change, 2006. 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. (ed.). Japan.
IPCC, Intergovernmental Panel on Climate Change, 2014. Summary for Policymakers. In: Climate Change 2014, Mitigation. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (eds Edenhofer O, Pichs-Madruga R, Sokona Y, Farahani E, Kadner S, Seyboth K, Adler A, Baum I, Brunner S, Eickemeier P, Kriemann B, Savolainen J, Schlomer S, von Stechow C, Zwickel T, Minx JC), pp. 5–7. Cambridge University Press, Cambridge, UK and New York, NY, USA.
ISPRA, Institute for Environmental Protection and Research (2016). Italian Greenhouse Gas Inventory 1990-2014. National Inventory Report 2016. Report 239/2016, Rome.
ISPRA, Institute for Environmental Protection and Research, (2011). Italian Greenhouse Gas Inventory 1990-2009. National Inventory Report 2011. Institute for Environmental Protection and Research - ISPRA, Report 139/2011, Rome.
JRC (2013) Personal communication by Giacomo Grassi, Viorel Blujdea and Raul Abad Vinas, Joint Research Center - Institute for Environment and Sustainability, Ispra (Italy).
Kuosmanen, T., Kortelainen, M., (2005). Measuring eco-efficiency of production with Data Envelopment Analysis. *Journal of Industrial Ecology* 9, 59e72.
OECD (2001). Multifunctionality: Towards an Analytical Framework, OECD Publishing, Paris.
Perez Dominguez I., Britz W. and Holm-Muller K. (2009) Trading Schemes for Greenhouse Gas Emissions from European Agriculture: A Comparative Analysis based on different Implementation Options, *Review of Agricultural and Environmental Studies* 90(3), pp.287-308.
Picazo-Tadeo A., Gómez-Limón J- A., Reig-Martínez E., (2011). Assessing farming eco-efficiency: A Data Envelopment Analysis approach, Journal of Environmental Management 92 (2011) 1154-1164, doi:10.1016/j.jenvman.2010.11.025.
Rizzi, P.L., Pierani, P. (2006). AGREFIT. Ricavi, costi e produttività dei fattori nell'agricoltura delle regioni italiane (1951-2002). Milano: Franco Angeli.
Westbury D.B., Park J.R., Mauchline A.L., Crane R.T., Mortimer S.R., (2011). Assessing the environmental performance of English arable and livestock holdings using data from the Farm Accountancy Data Network (FADN) Journal of Environmental Management 92 (2011) 902-909, doi:10.1016/j.jenvman.2010.10.051.
Zezza A., Henke R., Lai M., Petriccione G., Solazzo R., Sturla A., Vagnozzi A., Vanino S, Viganò L., Smit B., van der Meer R. Poppe K., Lana M., Weltin M., Piorr A., (2017). Research for AGRI Committee - Policy support for productivity vs. sustainability in EU agriculture: Towards viable farming and green growth. © European Union, 2017. Print ISBN 978-92-846-0519-4 doi:10.2861/99030 QA-02-17-023-EN-C.

Tables

Table 1 Summary of GHG emission sources considered and the respective FADN activity data used

Emission sources	CF category	FADN data
N_2O manure management	CF livestock	Animal numbers
CH_4 manure management	CF livestock	Animal numbers
CH_4 enteric fermentation	CF livestock	Animal numbers
CH_4 rice cultivation	CF cultivation	Rice area (UAA)
N_2O agricultural soils:	various	
- *Direct emissions*		
Use of synthetic fertilisers	CF fertilizer	Fertilisers expenditure
Biological N fixation	CF cultivation	N-fixing crop area
Crop residues	CF cultivation	Crop area (UAA)
- *Indirect emissions*[1]		
Atmospheric deposition	CF fertilizer/CF cultivation	Fertilisers and animal numbers
Leaching and run-off	CF fertilizer/CF cultivation	Fertilisers and animal numbers
CO_2 Energy	CF Fuel	Fuel expenditure
CO_2 Forest land	CF Land use	UAA
CO_2 Cropland	CF Land use	UAA
CO_2 Grasslands	CF Land use	UAA

[1] Indirect emissions of N_2O linked to N application to agricultural soils are partly accounted for in fertilizers CF and partly in crops CF.

Table 2 Likely impact of CAP instruments on GHG emissions.

Measures	Actions	Expected impact on GHG mitigation
Decoupling	Reduced incentives for intensive production (less fertilizer use, extensification); Farmers more careful to market signals	+++
Modulation	More resources for rural development (agri-environmental measures, training, etc.)	+
Cross-compliane	Structural measures	+/++
	Soil erosion reduction Better management of soil organic carbon Reduction of fertilizers use	+
Set aside*	Reduction of fertilizers use Potential carbon sequestration improvement	+/++
Energy Crops	Potential fossil fuel replacement, but higher emissions from land conversion	?
Agri-environment	F1-Low environmental impact	+++
	F2-Organic Farming	++
	H-Afforestation-costs of planting	+++
	H-Afforestation-maintenance	+++
	H-Afforestation-loss of revenue	+++
	I1-Afforestation non-agricultural areas	+++
	E-Less Favourite Area (LFA)	+
	I6-Reforestation for natural disturbances	+++

*until 2008.
+/++/+++ = expected impact low/medium/high; ? = uncertain.
Source: authors' elaboration on Coderoni 2010 and Eea 2006.

Table 3 2003-2007 evolution of the farm-level CF distinguished into the five macro categories of emissions and across different farm typologies (ton CO_{2e} per farm avg.; standard deviation in parenthesis)

Emission category:	**2003**	**2004**	**2005**	**2006**	**2007**	**Var. 2007-2003 (%)**
CF Fuel	25,9 (60,0)	27,1 (60,4)	29,8 (67,4)	31,4 (68,7)	32,6 (70,5)	0.9 (10.2)
CF Cultivation	14,1 (137,1)	14,3 (138,9)	14,3 (139,4)	14,8 (140,7)	14,9 (141,3)	53.4 (792.4)
CF Fertilizers	45,0 (157,1)	57,6 (178,2)	58,8 (198,9)	58,3 (179,0)	64,8 (190,5)	2.1 (14.5)
CF Livestock	99,2 (432,3)	100,4 (451,3)	101,0 (474,7)	101,6 (503,8)	100,0 (491,2)	0.1 (2.9)
CF Land Use – A[1]	-3,3E-03 (1,4E-02)	-3,3E-03 (1,5E-02)	-3,1E-03 (1,9E-02)	-3,1E-03 (1,8E-02)	-3,1E-03 (1,8E-02)	0.02 (0.9)
CF Land Use – B[1]	5,8E-03 (1,9E-02)	6,0E-03 (2,1E-02)	6,0E-03 (2,3E-02)	6,0E-03 (2,3E-02)	6,0E-03 (2,3E-02)	0.04 (0.9)
CF Total – A	184,1 (563,7)	199,3 (584,5)	203,9 (623,7)	206,1 (642,9)	212,4 (644,3)	14.3 (1087.5)
CF Total – B	184,1 (563,7)	199,3 (584,5)	203,9 (623,7)	206,1 (642,9)	212,4 (644,3)	14.3 (1087.5)
Farm typology:						
Economic Size:						
ES 3-4	25.2 (25.3)	29.3 (26.3)	30.0 (32.9)	32.1 (41.5)	32.6 (37.2)	33.7 (1697.2)
ES 5-6	120.0 (152.9)	132.7 (154.4)	134.3 (147.2)	120.3 (128.2)	124.8 (129.1)	0.8 (4.0)
ES>=7	887.4 (1304.7) (432,3)	932.8 (1336.5) (451,3)	992.1 (1461.9) (474,7)	965.4 (1473.1) (503,8)	989.2 (1462.1) (491,2)	0.7 (3.1) (2.9)
Utilized Agricultural Area:	0.4	0.4	0.4	0.4	0.4	0.01
UAA < 10 ha	46.6 (140.3)	53.3 (144.0)	54.1 (166.1)	53.7 (142.6)	53.9 (135.0)	29.2 (1576.3)
UAA 10-50 ha	145.2 (254.7)	157.8 (251.5)	157.3 (250.6)	158.1 (252.2)	166.9 (263.6)	0.8 (2.6)
UAA >50 ha	719.0 (1238.4)	762.7 (1282.4)	784.0 (1374.3)	791.7 (1427.2)	804.9 (1416.2)	0.5 (1.6)
Correlation coeff. UAACF	0.5	0.5	0.5	0.5	0.5	0.2
Specialization:						
Crops	149.2 (425.2)	168.4 (425.2)	174.4 (486.8)	175.4 (470.9)	185.1 (485.9)	1.0 (4.3)
Permanent crops	44.4 (121.9)	59.8 (121.9)	62.1 (131.9)	64.2 (144.0)	70.0 (154.5)	1.3 (3.8)
Livestock	425.2 (885.5)	434.5 (885.5)	439.8 (1002.0)	442.8 (1018.8)	442.8 (979.8)	0.1 (0.5)
Mixed crops and livestock	196.2 (651.2)	211.6 (651.2)	216.4 (678.8)	219.9 (767.1)	229.2 (820.0)	83.3 (2696.7)

[1]CF of land use reports negative values for emissions and positive values for removals

Table 4 Farm-level total CF (ton CO_{2e}) and first and second pillar payments, FPP and SPP (avg. 2003-2007) (per farm avg.; standard deviation in parenthesis)

Farm groups:	2003 CF	2007 CF	Var. CF 2007-2003 (%)
FPP/GPV <10%	201.5	212.7	364.9
	(588.5)	(664.9)	(19,069.4)
FPP/GPV 10-30%	46.3	48.2	29.8
	(84.7)	(82.9)	(99.9)
FPP/GPV 30%	31.7	35.0	37.1
	(70.4)	(76.1)	(150.9)
Correlation coefficient FPP – CF	-0.10	-0.09	-0.01
With SPP	242.0	141.1	-42.0
	(812.2)	(314.5)	(84.49)
No SPP	145.0	162.0	12.0
	(461.6)	(579.3)	(16.63)
Correlation coefficient SPP – CF[1]	0.4	0.5	-0.1

[1] Only farms with SPP.

Table 5. List of the explanatory factors included in the regression models

Explanatory factors	Type of variable (measure)
Geographical information	Categorical (north; south; islands; centre)
Size - UUA	Categorical (small<10 ha, 10<medium<50 ha, big> 50 ha)
Size - Economic Size	Categorical (small, medium, big)
Production	Categorical (livestock, crops, mixed)
Policy variables – First pillar payments	Continuous (FPP/GPV)
Policy variables – Second pillar payments	Continuous (SPP/GPV)
Altitude	Categorical (1=mountain; 2= hill; 3= lowland)

Table 6. Results of the regression model (standard error in parenthesis)

Variable	Coefficient Estimation (st. err)	
Constant	172.7***	(75.898)
UAA	-15.48	(22.319)
FPP	-0.162	(0.263)
SPP	-0.665	(1.747)
d_crop	-84.59***	(37.942)
d_livestock	-80.90	(45.483)
ES	-3.397	(24.550)
Altitude	-27.76	(20.310)
d_North	-1.631	(43.871)
d_Cetre	-13.01	(52.594)
d_Islands	30.80	(45.978)
R-squared	0.0016	

Table 7. Marginal effects of the MLM with 3 choices

	Increase		**Stable**		**Decrease**	
	Coeff.	*Std.err*	*Coeff.*	*Std.err*	*Coeff.*	*Std.err*
UAA	-0.002	(0.009)	-0.001	(0.005)	0.004	(0.009)
FPP	-7.1E-05	(1.1E-04)	-1.1E-04	(8.5E-05)	1.8E-04*	(1.0E-04)
SPP	0.002**	(0.001)	4.5E-04	(3.4E-04)	-0.002***	(0.001)
d_crop	0.094***	(0.016)	-0.054***	(0.009)	-0.041***	(0.015)
d_livestock	-0.050***	(0.014)	0.025***	(0.008)	0.025	(0.014)
ES	-0.006	(0.010)	0.005	(0.006)	0.001	(0.010)
Altitude	0.012	(0.008)	0.004	(0.005)	-0.016**	(0.008)
d_North	-0.234***	(0.013)	0.028***	(0.008)	0.206***	(0.013)
d_Centre	-0.253***	(0.017)	0.036***	(0.010)	0.217***	(0.016)
d_Islands	0.021	(0.022)	-0.021	(0.013)	3.9E-04	(0.022)

The Independence of Irrelevant Alternatives (IIA) assumption inherent in multinomial logit models is most frequently tested with a Hausman-McFadden test (Hausman and McFadden, 1984). In this case Hausman-McFadden test cannot be used, SUEST test doesn't reject the hypothesis of IIA (10%).
Single, double and triple asterisks (*) denote significance at the 10%, 5% and 1% levels, respectively.

Table 8. Marginal effects of the MLM with 6 choices

Choice:	**GHG increase with higher CP**		**GHG increase with lower CP**		**GHG stable with higher CP**	
	Coeff.	*Std.err*	*Coeff.*	*Std.err*	*Coeff.*	*Std.err*
UAA	0.031	(0.007)	-0.032***	(0.009)	0.003	(0.004)
FPP	-1.5E-05	(9.4E-05)	-5.5E-05	(1.1E-04)	-9.5E-05	(7.6E-05)
SPP	-4E-07**	(2.0E-07)	3.3E-07*	(1.8E-07)	8.5E-08	(6.3E-08)
d_crop	-0.002	(0.013)	0.093***	(0.016)	-0.034***	(0.007)
d_livestock	0.055***	(0.015)	-0.114***	(0.019)	0.015**	(0.008)
ES	-0.021**	(0.008)	0.014	(0.010)	0.002	(0.005)
Altitude	-0.005	(0.007)	0.015	(0.009)	0.003	(0.004)
d_North	0.058***	(0.011)	-0.281***	(0.012)	0.025***	(0.007)
d_Centre	0.069***	(0.014)	-0.315***	(0.017)	0.030***	(0.008)
d_Islands	-0.014	(0.018)	0.050	(0.020)	-0.014	(0.012)
Choice:	**GHG stable with lower CP**		**GHG decrease with higher CP**		**GHG decrease with lower CP**	
	Coeff.	*Std.err*	*Coeff.*	*Std.err*	*Coeff.*	*Std.err*
UAA	-0.004	(0.003)	0.005	(0.008)	-0.003	(0.005)
FPP	-1.3E-05	(4.7E-05)	1.8E-04*	(9.4E-05)	-2.4E-06	(6.0E-05)
SPP	6.4E-08*	(3.9E-08)	-1.1E-07	(1.9E-07)	2.5E-08	(8.4E-08)
d_crop	-0.019***	(0.006)	-0.018	(0.014)	-0.021***	(0.008)
d_livestock	0.011**	(0.006)	0.033**	(0.016)	-0.001	(0.009)
ES	0.002	(0.004)	-0.006	(0.009)	0.008	(0.005)
Altitude	0.001	(0.003)	-0.017**	(0.007)	0.003	(0.004)
d_North	0.002	(0.005)	0.187***	(0.013)	0.008	(0.007)
d_Centre	0.005	(0.006)	0.188***	(0.015)	0.022***	(0.009)
d_Islands	-0.006	(0.008)	-0.028	(0.022)	(0.012)	(0.010)

The Independence of Irrelevant Alternatives (IIA) assumption inherent in multinomial logit models is most frequently tested with a Hausman-McFadden test (Hausman and McFadden, 1984). In this case Hausman-McFadden test cannot be used, SUEST test doesn't reject the hypothesis of IIA (10%).
Single, double and triple asterisks (*) denote significance at the 10%, 5% and 1% levels, respectively.