The Impact of Agri-environmental Schemes on Farm Performance

1. D4.2: Report on economic performance of existing schemes considering potential trade-offs and synergies when it comes to ecosystem services output. WP 4, T 4.2

Authors: Amer Ait-Sidhoum*; Carolin Canessa*; Johannes Sauer*

*Chair for Production and Resource Economics. Technical University of Munich, 85354 Freising, Germany

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2. List of Tables

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List of Acronyms

ATT	Average Treatment Effect on the Treated
AES	Agri-environmental Schemes
CAP	Common Agricultural Policy
CEM	Coarsened Exact Matching
DiD	Difference-in-Difference
ELS	Entry Level Stewardship
EU	European Union
FADN	Farm Accountancy Data Network
PSM	Propensity Score Matching
RDP	Rural Development Programme
SB	Standardised Bias
TFP	Total Factor Productivity
TF	Type of Farming
UAA	Utilised Agricultural Area
UK	United Kingdom

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1. Summary

The European Union (EU) budget allocated to the agri-environmental schemes (AES) has been increasing constantly in the past 20 years. European citizens are expecting more effective spending of EU budgets. It is therefore of interest to investigate the effectiveness of agri-environmental measures for delivering environmental benefits and improving farms' economic efficiency. Hence, the objective of this study is to examine the effects of agri-environmental schemes (AES) on farm performance in the European Union. We include in the analysis seven diverse European Union (EU) countries (Germany, France, Hungary, Italy, the Netherlands, Spain and the United Kingdom) over 5 years (2006–2011). Our analysis applies a difference-in-difference propensity score matching (DiD-PSM) estimator to reach the objective of this study. Further, the applied models help to address the selection bias issue arising from observed characteristics and time-invariant unobserved factors. The analysis reveals mixed evidence regarding the effects of AES participation on farm-level performance. Specifically, we find a negative association between AES participation and total farm net income in Hungary and France, no significant relationship for Germany, Spain, Italy and a positive relationship for the Netherlands and United kingdom. This difference may suggest that when the share of scheme payments play a marginal role in the farm business, the schemes may not be the best ones for improving economic outcomes. Further, one could expect AES payments to compensate the income foregone, but our results show that this is the case only in three countries. On the other hand, our findings found no clear support that participating farms differ significantly from non-participants with regard to farmers' production decisions that reflect the environmental pressures. The low participation rate in France, Spain and Italy could have introduced some selection bias, which in turn will affect the study findings. The reason for this low participation rate could be attributed to the restrictions some agri-environment measures put on the fertilizers or pesticides use, leading to insufficient uptake rates.

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2. Introduction

Over the last century, a number of factors including price supports, technological developments, changes in profit maximization strategies, etc. have led to agricultural intensification. As a result of changes in farming practices, farmers have been very successful at increasing agricultural yields. This has involved wide social benefits related to increased food production and lower food prices. These achievements, however, have resulted in increased external environmental and health costs. Agricultural practices, especially those used in modern intensive agricultural systems, are increasingly being recognized by their negative environmental impacts.

Public awareness of environmental problems associated with the food production chain has been growing over the last decades. As a response to these growing concerns, agricultural policies have introduced agri-environment schemes (AES) as essential components of the rural development policy in the early 1990s to re-orient agricultural practices towards more sustainable methods. Our analysis focuses on the AES as a core funding instrument of the 2007–2013 EU RDP. The agri-environment measures are subsumed in the categories *organic farming, management of landscape, pastures and High Nature Value farmlands, integrated production and other extensification of farming systems.* After 1993, the EU budget allocated to scheme payments has risen substantially and reached 3026 million Euros in 2010. The overall expenditure for the programme period 2007–2013 was 96.3 billion Euros (about 20% of the total CAP budget), where AES payments accounted for the highest share (23.6%) of the 2007–2013 EU RDP total budget.

AES uptake differs significantly among member states, the European Union (2011) reported that the average share of agricultural area (UAA) for EU-27 under AES represents 22%, with substantial variation from 92% of the UAA in Luxembourg to less than 5% in Bulgaria. In terms of UAA under AES, measures for *management of landscape, pastures and High Nature Value farmland* are the most popular AES (39% of the total UAA under AES in EU-27). From the Total UAA under AES, almost 5 million ha are categorised into *other extensification of farming systems* measures, this involves actions aimed at reducing or the appropriate application of agrochemical and at reducing livestock densities. Organic farming payments are usually part of the rural development programme, where around 8% of the total UAA under AES was committed to organic farming.

As mentioned earlier, the AES budget has been increasing constantly and European citizens are expecting more effective spending of EU budgets. It is therefore of interest to investigate the effectiveness of agri-environmental measures for delivering environmental benefits and improving farms' economic efficiency. This is the objective of the present study. The approach we develop is based on the use of European FADN database for farms located in seven EU countries over the period 2006–2011. Our model is specified as a semi-parametric propensity score matching (PSM) estimator combined with a difference-in-difference estimator to measure the impact of AES participation on farm-level performance indicators. Specifically, we employ a PSM method to address the selection bias issue arising from observed characteristics and DiD approach to address sample selection bias arising time-invariant unobserved factors.

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This deliverable is organised as follows. The next section provides a brief overview of previous studies that have focused on the association between AES and farm performance. We then present the methodology and describes the data. The following section presents the results. A discussion of the major results follows. And the last section concludes.

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3. Background

There is a substantial literature investigating the role of the CAP in promoting sustainable farming across Europe. Several authors try to analyse the factors affecting farmers' participation in agri-environmental contracts (Capitanio et al., 2011; Defrancesco et al., 2007a; Dessart et al., 2019; Giovanopoulou et al., 2011), while others focus on the environmental effectiveness of agri-environmental policies (Richards et al., 2015; Tal, 2009; van Grinsven et al., 2012). The ecological literature focuses on the achievement of the environmental objectives pursued by the measures, but does not take into consideration the effects of AES on farmers' production decisions, such as fertilizers and pesticides use. However, farmers' production decisions are expected to be affected by the participation in AES, as it requires them to change their behaviour and consequently their production choices (Sauer et al., 2012b).

To date, still little is known about whether participation in the AES actually improves farms' environmental performance, and whether there is any economic payoff to be expected from sustainable farming practices. Only a few studies have attempted to measure empirically the impact of European AES participation on farm level structure and economic performance. A literature review on this topic is presented below.

Salhofer & Streicher (2005) studied the effects of AES participation on farm production for ten Austrian agri-environmental measures. They used fixed-effects and difference-in-difference estimations and illustrated their model using FADN data. The impact of AES participation on yield is investigated. They found that only three out of these ten programs have significant negative effects on yields, while one program has a significant positive impact. The results suggest that there are windfall profits associated with some of these programs.

Sauer et al. (2012b) used a directional distance-based matching approach to investigate the effects of different agri-environmental schemes on individual farmers' behaviour for a sample of UK cereal farms. In particular, they considered the effects of participating in voluntary and non-voluntary schemes on farms production intensity, performance and structure. They conclude that farms enrolled in AES are efficiently adjusting their production decisions to the scheme constraints. Farms affected by these schemes tend to adopt a less specialised and more diversified production structure. The use of fertilizers and chemicals decreases, as well as land and capital productivity, while labour productivity increases. They also observed that voluntary agri-environmental measures affect farmers' decisions more strongly than non-voluntary measures.

Mary (2013) analysed the impact of the Common Agricultural Policy (CAP) on total factor productivity. He estimated a Cobb–Douglas production function using panel data covering a large FADN sample of French crop farms observed between 1996 and 2003. He analysed the impact of Pillar 1 and 2 subsidies on total factor productivity (TFP) and showed that the payments had a negative impact on productivity during the period of the study.

Laukkanen & Nauges (2012) evaluated through a structural econometric model the effect of an agri-environmental programme to reduce nutrient pollution on farms production in Finland. In

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particular, they investigated the impact of the scheme on land allocation and on the application of fertilizers and pesticides. Results demonstrated that payments have a small effect on fertilzers use.

In recent years, there is an increasing body of work investigating the causal effect of some measures of rural development programs that are applying propensity score matching (PSM) with a difference-in-differences (DID) estimator. Since AES are voluntary, the adoption might be driven by environmental preferences or pro-environmental behaviour of the farmers. In presence of this selection bias, a direct comparison of participating with non-participating farms will not represent the true causal impact of the policy. To overcome this problem, PSM-DiD techniques allow to robustly handle the selection bias problem arising from observed characteristics as well as the selection bias arising from time-invariant unobserved factors (Heckman et al., 1997).

Pufahl & Weiss (2009) applied a semi-parametric propensity score matching approach to evaluate the effects of AES on input use and farm output of individual farms in Germany. The analysis revealed a positive and significant treatment effect of AES on the area under cultivation. In particular, for the case of grassland, participation in AES results in a decrease in cattle livestock densities. They also observed that AES participation significantly reduces the purchase of farm chemicals (eg. fertilizers and pesticides).

Chabé-Ferret & Subervie (2013) estimated and compared the additional and windfall effects of five AES in France. They used a difference-in-difference matching and a structural household model and observed that AES participation delivers desired impacts but suffer from windfall effects. For example, they found that agri-environmental measures that promote crop diversity resulted in an additional crop in the rotation but with a reduction of the cropped area. Their findings suggest that AES may not be cost-effective. However, the comparison between schemes showed that measures which impose strong requirements, such as the ones aiming to subsidize conversion to organic farming, have large additional effects and almost non-existent windfall effects.

Udagawa et al. (2014) applied a difference-in-difference approach with propensity score matching, to examine the impact of participation on income among farmers participating in the Entry Level Stewardship (ELS) scheme in eastern England. They found that participation in ELS scheme could negatively affect cereal farm incomes – in particular, the total business income. The results also indicate that the ELS payment compensated for much of the cost of joining the scheme, although not sufficient to fully compensate for costs incurred the first year of participation.

Mennig & Sauer (2020) applied a difference-in-difference propensity score matching estimator to test if AES have an unintended effect on dairy and arable crop farms productivity in Bavaria. Their results suggest that schemes designed for arable land overcompensate farmers. For dairy farms, they found that AES participation reduces farm productivity, implying that action-based scheme design not considering changing market and production situations might be too restrictive, potentially preventing farmers from participating.

Cisilino et al. (2019) compared the environmental and economic performance of organic and conventional farms to estimate the impacts of organic farming measures in the Marche Region in Italy. They applied a non-parametric matching model and the difference-in-difference estimator to

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observe specific variables as the level of nitrogen and phosphorus used per hectare. Their analysis suggests that the environmental performance of organic farms is statistically higher than conventional ones, while the findings on the economic performance do not confirm that organic agriculture is as competitive as conventional.

Baráth et al. (2020) propose to use a difference-in-difference and a matching estimator to examine the effect of different types of subsidies, including agri-environmental measures, on the different components of Total Factor Productivity. Their proposal is applied to farm-level data for a sample of Slovenian FADN farms. Their results show that AES measures are less likely to contribute to TFP improvements than other farm subsidies.

Recently, Bertoni et al. (2020) applied the coarsened exact matching (CEM) to analyse the effect of three AES implemented in the Lombardy Region (Italy). Their results suggest that AES are effective in improving the farms' environmental performances. However, their preliminary cost-benefit analysis highlights that the costs of implementing this policy tend to be high compared to the additional environmental results obtained.

D'Alberto et al. (2018) conducted an impact evaluation of AES for the Emilia-Romagna Region in Italy, combining statistical matching and propensity score matching. Results of the PSM estimator applied to the synthetic (complete) data set indicated that there is a statistically significant impact of the AES on the decision of farmers to decrease both the rent-in land and the crop diversity of farms.

To the best of our knowledge, Arata & Sckokai (2016) is the only study that have used the difference-in-difference propensity score matching estimator to perform a comparative analysis of the effects of AES on farmers' environmental and economic performance across different EU countries. Using a balanced panel from the European Farm Accountancy Data Network (FADN) observed between 2003 and 2006, they compared the effects of AES participation on farmers' income and production choices over five EU-countries. Their results suggest that AESs adoption does not affect only the farmer's production choices but also the economic results of the farm, although with strong differences between countries. For example, the fertilizer per hectare expenditure decreases in Germany, the United Kingdom, and Italy as a result of participation. Crop protection per hectare expenditure decreases in France, the United Kingdom, and Italy, the share of grassland increases in France, and the number of crops grown on a farm increases in the United Kingdom and Italy. They also observed that the effects of the AES adoption largely depend on the share of the agri-environmental payment on farm revenue. Indeed, when the share of agri-environmental payments on farm income is smaller than 5%, farmers' practices change only marginally.

This study builds on earlier work by Arata & Sckokai (2016) in evaluating the impact of agri-environmental schemes on farm-level performance indicators. We extend this line of investigation by allowing for a larger period of time, from 2007 to 2011, because AES participation in Europe is typically associated with at least a period of 5 years. Such prolonged periods are likely to help to fulfil the environmental performance objectives. Further, the Fixed-effects regression used in this analysis is well-suited to control for unobserved time-invariant individual heterogeneity that may influence farm performance change as well.

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4. Methodological Framework

This analysis employs the propensity score matching (PSM) model combined with the difference-in-difference (DID) estimation to control for selection bias and unobserved variables.

In non-experimental research, Matching is widely used to measure the average effect of a treatment. When evaluating the effect of a non-randomized program, the key challenge is to be able to observe the counterfactual state, that is, what would have happened to the participants if this program did not exist. Since only one state is observed for each individual, there is a lack of necessary information to carry out the impact analysis. Randomization can be suggested to measure the impact program more precisely, however, in the case of policy programs, however, it could be unethical to withhold a specific treatment from a random group of individuals to give access to another random group of individuals. Moreover, participation in voluntary policy measures such as agri-environment schemes will depend on the implementation costs and the expected benefits, which makes the treatment assignment non-random and related to observed factors. In order to avoid this selection bias, it is necessary to define appropriate methods to construct a statistical comparison group. In this context, matching can be used to control for selection bias and construct a suitable counterfactual or control group. It identifies comparable non-participants who have similar observed characteristics to those of the treatment group.

As mentioned, the idea of matching is to make non-participants similar to those in the treatment group in terms of a set of Covariates X, but instead of conditioning on a large set of observable covariates X, Rosenbaum & Rubin (1983) suggested matching on the propensity score, $\pi(X) = P(T = 1|X)$. The propensity score is defined as the individual's probability of treatment selection, conditional on observed covariates X.

Then, based on the estimated propensity score, each participant is matched with a similar non-participant. The average treatment effect on the treated (ATT) is thus estimated by comparing the average difference in outcomes between the two groups as follow:

$$\text{ATT} = E[Y^1|P = 1, \pi(X)] - E[Y^0|P = 0, \pi(X)] \quad (1)$$

The ATT measures the average effect of the treatment in the subpopulation that participates in the program, where Y^1 is the outcome conditional on participation and Y^0 the outcome conditional on nonparticipation.

Matching techniques control for the selection bias on observables, however, and as rightly reported by Heckman et al. (1997), may be systematic differences between the outcomes of participants and non-participants, even after conditioning on observables. Thus it can be very restrictive to assume that unobservable characteristics play no role in selection. One way to overcome this problem is to combine matching with the difference-in-differences estimator (Smith

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& Todd, 2005). The availability of panel data is essential to the implementation of a DiD approach. The conditional DiD estimator compares the non-participating and participating individuals in terms of outcome changes over time relative to the outcomes observed for a pre-treatment period. Suppose evaluating the impact of policy measures over two time periods, where t represents a time period before the start of the program and t' a time period after program implementtaion, the DiD estimator will estimate the average program impact as follows:

$$\mathrm{ATT} = \mathrm{E}\left[Y_{t'}^{1} - Y_{t}^{0} \middle| P = 1, \pi(X_t)\right] - E\left[Y_{t'}^{0} - Y_{t'}^{0} | P = 0, \pi(X_t)\right] \quad (2)$$

The equation above relies on a comparison of participants and nonparticipants before and after the program implementation. However, a DiD estimation can be implemented within a regression procedure as follows:

$$Y_{it} = \alpha + \beta T_i + \delta t_i + (DiD) T_i t_i + \eta_i + \varepsilon_{it} \quad (3)$$

Where T is the treatment variable, t is the time dummy and the coefficient of the interaction of T and t (DiD) gives the estimate for the impact of treatment on outcome Y, in our case a set of farm-level performance indicators. A critical assumption with a basic DiD estimator, is that unobserved characteristics do not vary over time. The Fixed-effects regression used in this study (equation 3) can control for unobserved time-invariant individual heterogeneity (η_i) that may influence farm performance change as well.

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5. Data

The impact of AES participation on farms' performance is evaluated separately for each country, we concentrated on two types of farming (TF), farms specialised in field crops (TF1) and farms specialised in conventional dairy production (TF5). Our approach helps us to account for heterogeneous effects of AES across different EU member states and farming systems. In our empirical analysis, we rely on a balanced panel data covering the period 2006-2011, we used a difference-in-difference propensity score matching estimator to investigate the effect of AES on a set of economic and environmental indicators that reflect farm performance in integrating sustainability practices into their production strategy.

For the purpose of performing propensity score matching, the year 2006 was considered to identify comparable treated farms and untreated farms based on observable variables before the programme implementation. In our empirical analysis, we are interested in estimating the impact of environmental subsidies on farm-level performance over the period 2007-2011. Consequently, the year 2006 -which is the year before the starting of the 2007-2013 EU budget and rural development program period- is considered to be the pre-treatment period while the year 2011 is considered to be the post-treatment period. An observation is considered untreated during the pre-treatment phase if its participation in the program occurs between the two phases. We, therefore focus on those farms that did not participate in any agri-environment schemes in the initial time period to assess the impact of environmental subsidies. As a result, farms that did not receive environmental subsidies in 2006 were assigned to the control group, while only farms that did receive a payment before the program implementation were assigned to the treated group.

Tables 1 and 2 present descriptive statistics for some of the variables[1] used in our empirical analysis for field crops and dairy farms. The values of agri-environmental payments included in the FADN system are aggregated into a single environmental subsidy variable measured in euros. Unfortunately, no data is available either on the individual scheme implemented by each farm or on the share of the utilized agricultural under agri-environment programmes. The average value of agri-environmental payments received by farmers in our samples fluctuates from around 650 euros in France to 7922 euros in the UK for crops farms, while in dairy farms this range varies between 1,524 euros in Italy and 5,579 euros in Germany. If we consider the average AES payment per hectare, we find that dairy farms receive a higher rate than field crops farms with an average of 44 and 38 euros per hectare for Italian and German dairy farmers respectively, while field crops farmers for both countries received an average of 13 and 23 euros per hectare respectively. Also, it should be noted that French crops farmers received an average AES payment of only 4 euros per hectare during the period 2006-2011, however, this can be explained by the low number of participants (711) compared to the non-participants (4857).

[1] All money valued variables were deflated to the base year 2010 by using price indices provided by Eurostat

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The farm-level data used in this analysis have been obtained from the Farm Accountancy Data Network (FADN) database and covered the period 2006-2011, the FADN database is the most elaborated data source and the only source of microeconomic data that is harmonised and comparable at the EU level. The FADN data include structural and accountancy data of a large sample of farms and is often used to monitor income development and business activities of agricultural holdings in EU member states and allow evaluating the impact of the Common Agricultural Policy. Farms that are monitored in the FADN sample are representative of the whole population of EU commercial farms according to the FADN regions, economic size and type of farming systems.

For the crop farms, six EU countries are considered: Germany, France, Italy, Hungary, Spain and UK, while for dairy farms, four countries (Germany, France, Italy and Netherlands) are analysed in this study. For each country, the empirical analysis was conducted using balanced samples for field crops and dairy farms separately.

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Table 1: Summary statistics (average and standard deviation) for the main variables used in this study (Filed crop farms)

	Germany		France		Spain	
	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.
Land (ha)	189.01	362.51	147.22	85.30	82.54	79.13
Labor (hours)	5983.30	10591.68	3,164.39	2,959.48	2,718.46	1,613.69
Farm net income (euros)	64967.89	111763.69	60,656.07	63,991.33	32,204.17	34,898.21
Environmental subsidies (euros)	3511.76	10789.57	659.73	2,283.83	811.34	2,647.68
Crops output (euros)	249802.77	397589.88	189,146.43	158,206.50	50,718.05	49,295.43
Fertilizers (euros)	33722.98	58167.49	28,108.51	19,083.58	6,837.47	7,506.46
Pesticides (euros)	27223.56	49390.75	22,592.87	16,187.17	2,605.69	4,811.30
Energy (euros)	25584.45	51280.90	11,596.08	12,896.43	4,419.54	4,441.64
Sample size	3336		5568		6390	

	Hungary		United Kingdom		Italy	
	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.
Land (ha)	247.84	415.21	201.46	201.07	45.04	62.66
Labor (hours)	8,342.67	16,678.92	5,208.94	5,973.22	3,495.77	3,701.91
Farm net income (euros)	50,392.03	121,808.31	84,359.32	124,634.14	43,287.39	100,153.35
Environmental subsidies (euros)	6,267.85	21,909.96	7,922.24	13,691.09	874.57	4,775.12
Crops output (euros)	176,215.77	337,884.61	251,465.33	373,490.74	79,571.71	161,659.42
Fertilizers (euros)	25,800.98	49,828.86	32,509.23	33,870.67	6,834.06	10,964.17
Pesticides (euros)	17,801.95	38,027.97	28,763.79	39,190.95	4,502.80	9,744.96
Energy (euros)	30,952.21	60,150.40	22,069.60	33,028.08	7,270.07	12,860.45
Sample size	3708		1200		5742	

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Table 2: Summary statistics (average and standard deviation) for the main variables used in this study (Dairy farms)

	Germany		Netherlands	
	Mean	St. dev.	Mean	St. dev.
Land (ha)	174.11	372.16	55.87	32.89
Labor (hours)	10,210.87	23,427.78	4,304.18	1,865.17
Farm net income (euros)	52,668.74	116,547.04	64,291.69	93,824.15
Environmental subsidies (euros)	5,579.92	17,835.69	2,498.28	5,413.56
Milk (euros)	7,201.16	1,689.85	7,817.96	1,317.85
Cows (number)	109.62	189.66	92.08	59.63
Fertilizers (euros)	17,893.36	39,504.79	6,505.48	5,684.68
Pesticides (euros)	9,419.39	27,638.89	1,905.23	3,341.90
Energy (euros)	36,483.46	79,882.01	12,410.03	8,524.38
Sample size	3096		1518	

	France		Italy	
	Mean	St. dev.	Mean	St. dev.
Land (ha)	97.06	50.77	39.87	47.78
Labor (hours)	3,132.96	1,400.02	5,311.70	3,239.72
Farm net income (euros)	38,555.38	37,965.38	98,581.42	143,685.89
Environmental subsidies (euros)	2,132.60	3,820.07	1,524.47	4,703.77
Milk (euros)	6,486.37	1,492.76	5,810.04	2,267.40
Cows (number)	55.19	24.29	58.83	64.43
Fertilizers (euros)	9,342.98	7,422.18	2,138.04	4,322.52
Pesticides (euros)	4,426.86	4,497.70	952.87	2,338.42
Energy (euros)	8,769.55	5,395.77	10,119.32	14,233.69
Sample size	2766		2166	

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6. Propensity Score Matching

In order to balance farms characteristics between farms that participated and did not participate in agri-environmental schemes, propensity score matching was carried out. Identifying which variables to use within the PSM model is a crucial decision when performing matching techniques PSM. Although the literature has extensively explored the problems associated with which variables can be used in the propensity score model, there is still no agreed consensus about the choice of variables in the PSM model. (Austin et al., 2007). Our variable selection differ slightly from one sample to another, however, in spite of the differences, our selection is based on theoretical economic arguments and empirical evidence (Arata & Sckokai, 2016; Chabé-Ferret & Subervie, 2013; Defrancesco et al., 2007b; Matzdorf & Lorenz, 2010; Mennig & Sauer, 2020). Overall, the groups of covariates that were predicted to be useful in matching participants and non-participants include both economic and regional aspects. The main variables are farm UAA, farm labor (working hours per hectare), farm net income, crops and milk (for dairy farms) production intensity (sales per hectare), total assets per hectare, the intensity in fertilizers and pesticides use (costs per hectare), stocking density in the case of dairy farms and share of rented land. In order to take into account regional differences, dummy variables are used to represent the different FADN regions, which makes it possible to take into account the different growing and climatic conditions.

After having defined control and treated groups and the relevant variables for the matching process, for each country and for both field crop and dairy farms, the propensity score[2] is calculated using a logit regression as a measure of the probability that a farm will be classified as a programme participant. Logit model results for the propensity score matching are available from the authors on request. The likelihood ratio tests for each sample are statistically significant at the 1% level, indicating that all farm characteristics considered are jointly significant in explaining programme participation. Propensity scores were calculated for each observation based on the parameter estimates of the logit model, which were then used to match participant and non-participant farms.

Different matching algorithms[3] were tested prior to selecting the specification that presents the best covariates balancing property. Before matching, significant differences are assumed to be found between control and treated groups and therefore, the resultant balance of the relevant covariates assesses the success of propensity score estimation. Tables 3 to 7 show the main covariates mean values before and after matching among non-participants and participants of AES for the pre-treatment period (2006) for both field crop and dairy farms. These results suggest that

[2] The propensity score represents the conditional probability of participation for farm i given a set $X = x_i$ of observed characteristics $p(X) = \Pr(P = 1 | X = x_i$. The propensity score is estimated from a logit model with the binary treatment variable (AES) serves as the dependent variable conditional upon the observed variables (covariates).

[3] We tested the most common matching algorithms: kernel matching, radius matching, and nearest neighbour matching without and with replacement from 1 to 10 neighbours. For each sample farms, we have compared different matching algorithms and selected the model that presents the smallest standardised bias.

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no significant differences[4] between participating and non-participating farms after matching. We can therefore conclude that the applied matching algorithm worked well, as the existing observable differences have been controlled for.

Once the propensity score matching was performed on the pre-treatment year (2006), the average effect of AES participation on different farm performance indicators is calculated using difference-in-difference (DiD) models. The difference-in-difference framework compares changes over time (before and after) of the average outcome differences between participating farmers and the matched nonparticipants. The farm performance indicators examined as potentially affected by the participation in the agri-environment programme concern the farmers' input decisions and economic performance. Among farmers' production decisions, the ones that reflect the environmental pressures, measured by expenditure on environmentally detrimental inputs (fertilizers, pesticides and energy) per hectare and stocking density in the case of dairy farms. The economic performance indicators examined are the total farm income including and excluding AES and the total output per hectare. The results indicate for each performance indicator the average difference in the 2006–2011 growth between participating and non-participating farms over the period 2006-2011. The DiD analysis has been applied for both farm types and on each country treated sample and its matched controls; thus the analysis was conducted 10 times.

[4] Rosenbaum and Rubin (1985) propose the use of standardised bias (SB) to compare between treated unit means and untreated unit means before and after matching as a measure of covariate balance. As noted by Oakes & Kaufman (2017), a standardized bias below 10% after matching would be seen as sufficient. Our findings indicate that the overall SB was reduced significantly for each sample by the matching technique.

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Table 3: Mean and Standardised bias reduction of relevant covariates before and after matching the pre-treatment year 2006 (field crop farms in Germany and Spain).

Variables	Germany						Spain					
	Before matching		After matching		Standardised Bias		Before matching		After matching		Standardised Bias	
	Treated mean	Control mean	Treated mean	Control mean	Before matching	After matching	Treated mean	Control mean	Treated mean	Control mean	Before matching	After matching
UAA (ha)	247.34	149.52	164.84	164.77	25.3	0.0	64.251	76.165	77.518	77.482	-16.1	0.0
Farm net income (€)	57321	49511	52507	52768	7.8	-0.3	48695.07	61290.74	64938.38	55968.35	-3.5	8.5
Labor (hours/ha)	63.75	63.76	64.03	59.26	0	4.6	90.363	102.37	88.439	88.648	-7.3	-0.1
Capital depreciation (€/ha)	10497	12433	12241	12477	-13.6	-1.7	14951	9623.5	12897	12759	38.8	1.0
Crops (€/ha)	1451.2	1787.7	1645.7	1696	-17.9	-2.7	1246.2	1254.1	1183.6	1304.4	-0.4	-6.8
Fertilizers (€/ha)	143.23	156.27	155.06	153.6	-18.3	2	151.79	107.08	135.52	123.93	37.7	9.8
Pesticides (€/ha)	149.59	164.43	171.87	162.66	-13.3	8.2	120.84	68.951	109.66	91.197	40.5	14.4
Share rented land (%)	0.67	0.62	0.61	0.61	16.7	-2.6	0.36	0.35	0.39	0.36	3.2	8.2
Number of observations	235	319	150	151			124	941	98	98		

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Table 4: Mean and Standardised bias reduction of relevant covariates before and after matching the pre-treatment year 2006 (field crop farms in Hungary and France).

Variables	Hungary						France					
	Before matching		After matching		Standardised Bias		Before matching		After matching		Standardised Bias	
	Treated mean	Control mean	Treated mean	Control mean	Before matching	After matching	Treated mean	Control mean	Treated mean	Control mean	Before matching	After matching
UAA (ha)	263.56	225.56	263.56	299.93	9.0	-8.7	169.62	134.05	151.61	160.14	41.7	-10
Farm net income (€)	32614	24818	32614	26449	11.8	9.3	55726	41108	44669	48112	31.3	-7.4
Labor (hours/ha)	52.60	54.40	52.60	53.33	-2.4	-1.0	3220.9	3201.2	3027.8	3100.7	0.8	-2.8
Capital depreciation (€/ha)	2170.2	2008	2170.2	2071.9	10.5	6.4	2562.4	3127.2	2616.8	2504.3	-20.8	4.1
Crops (€/ha)	614.63	643.83	614.63	590.17	-5.7	4.8	991.82	1454	1011.5	967.83	-24.3	2.3
Fertilizers (€/ha)	70.60	67.94	70.60	67.55	7.1	8.2	136.73	158.72	139.2	139.88	-32.7	-1
Pesticides (€/ha)	60.28	60.89	60.28	59.04	-1.1	2.2	126.79	146.86	129.84	127.52	-26	3
Share rented land (%)	0.54	0.50	0.54	0.55	9.0	-2.4	0.90	0.89	0.89	0.90	6.7	-6.8
Number of observations	176	442	148	405			172	756	159	159		

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Table 5: Mean and Standardised bias reduction of relevant covariates before and after matching the pre-treatment year 2006 (field crop farms in Italy and the United Kingdom).

	Italy						United Kingdom					
Variables	Before matching		After matching		Standardised Bias		Before matching		After matching		Standardised Bias	
	Treated mean	Control mean	Treated mean	Control mean	Before matching	After matching	Treated mean	Control mean	Treated mean	Control mean	Before matching	After matching
UAA (ha)	74.90	40.75	66.66	72.21	46.9	-7.6	225.64	131.1	186.37	189.13	56.3	-1.6
Farm net income (€)	46002	43779	43998	43295	1.6	0.5	68426	35802	53662	49391	37.2	4.9
Labor (hours/ha)	163.7	330.2	188.01	207.87	-37.1	-4.4	28.80	55.64	29.65	28.93	-55	1.5
Capital depreciation	16218	24107	17862	18670	-34.3	-3.5	9714.4	12305	9932.8	9081.1	-28.7	9.4
Crops (€/ha)	1601.6	3468.3	1867.4	1922.9	-39.7	-1.2	964.28	1483.1	957.48	942.26	-44.2	1.3
Fertilizers (€/ha)	76.34	172.45	90.077	95.91	-63.2	-3.8	126.49	128.43	125.32	124.22	-4.2	2.4
Pesticides (€/ha)	56.82	171.4	67.78	70.29	-53.3	-1.2	124	151.8	123.22	124.36	-41.6	-1.7
Share rented land (%)	0.42	0.37	0.41	0.39	11.1	5.8	0.35	0.36	0.36	0.37	-3.9	-3.8
Number of observations	103	853	88	88			134	66	41	59		

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Table 6: Mean and Standardised bias reduction of relevant covariates before and after matching the pre-treatment year 2006 (dairy farms in Germany and the Netherlands).

Variables	Germany						Netherlands					
	Before matching		After matching		Standardised Bias		Before matching		After matching		Standardised Bias	
	Treated mean	Control mean	Treated mean	Control mean	Before matching	After matching	Treated mean	Control mean	Treated mean	Control mean	Before matching	After matching
UAA (ha)	222.21	134.9	236.29	221.87	22.8	3.8	56.04	53.30	57.53	54.94	9.2	8.7
Farm net income (€)	60370	58707	62418	64732	2.1	-3	58763	63675	68775	65105	-8	6
Labor (hours/ha)	73.993	67.58	73.042	70.09	16.1	7.4	83.25	98.47	87.84	89.54	-35.1	-3.9
Capital depreciation (€/ha)	11363	11383	11090	10579	-0.3	6.6	40947	51273	44178	44389	-66.5	-1.4
Milk (€/ha)	119.89	126.92	118.04	115.64	-7.4	2.5	159.98	209.39	166.06	177.18	-41.2	-9.3
Fertilizers (€/ha)	70.15	100.32	78.60	75.71	-64.5	6.2	62.23	105.08	85.22	86.47	-75.2	-2.2
Pesticides (€/ha)	32.77	39.65	36.45	36.69	-23.2	-0.8	15.34	34.46	21.29	19.23	-67.5	7.3
Share rented land (%)	0.659	0.61	0.65	0.65	13.8	-1.1	0.42	0.32	0.40	0.40	32.6	1.1
Cows per ha	0.76	0.89	0.77	0.77	-35.1	-1.3	1.46	1.70	1.57	1.57	-56.5	-0.1
Number of observations	273	237	102	209			91	162	66	66		

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Table 7: Mean and Standardised bias reduction of relevant covariates before and after matching the pre-treatment year 2006 (dairy farms in France and Italy).

Variables	France						Italy					
	Before matching		After matching		Standardised Bias		Before matching		After matching		Standardised Bias	
	Treated mean	Control mean	Treated mean	Control mean	Before matching	After matching	Treated mean	Control mean	Treated mean	Control mean	Before matching	After matching
UAA (ha)	99.26	91.59	91.36	90.73	16	1.3	49.75	39.12	47.27	43.16	17.9	6.9
Farm net income (€)	35730	33930	32596	33499	5.4	-2.7	54232	88351	66001	73903	-29.5	-6.8
Labor (hours/ha)	34.58	39.53	37.39	37.45	-26.9	-0.4	243.73	263.62	227.14	243.08	-9.4	-7.6
Capital depreciation (€/ha)	4114.60	4457.20	4401.30	4400.70	-19	0.0	27625	38141	29064	28968	-36.1	0.3
Milk (€/ha)	78.47	92.16	89.95	88.00	-27.1	3.9	324.84	302.84	338.10	302.08	7.3	11.9
Fertilizers (€/ha)	65.57	100.60	85.64	87.50	-86.4	-4.6	18.03	61.18	29.41	27.78	-67.8	2.6
Pesticides (€/ha)	25.73	55.75	42.54	42.26	-98.9	0.9	7.84	30.45	13.13	11.90	-65.8	3.6
Share rented land (%)	0.95	0.95	0.95	0.94	-5	7.7	0.59	0.51	0.58	0.56	21.8	6.5
Cows per ha	0.54	0.64	0.60	0.59	-47.8	1.4	1.21	2.16	1.46	1.52	-66.2	-4.1
Number of observations	196	265	110	110			91	270	58	58		

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7. Average treatment effects

In a next step, we will concentrate our attention on the ATT estimator, which measures the gap in the average growth of the performance indicators between the farms participating in AES and non-participating farms. The ATT estimates determine whether there is a significant effect of AES adoption on farm performance. The impact of AES on farm-level performance indicators is calculated using the DiD estimators on the basis of the matched samples from the baseline data.

The results are presented in Tables 8 and 9, where the DiD coefficient (equation 3) indicates the estimate for the impact of AES participation on outcome Y, in our case the different farm-level performance indicators over the period 2006–2011 for both the treated and the matched control groups. A positive (negative) DiD coefficient represents an increase (decrease) in the farm-level indicator of the treated group that is greater than the increase (decrease) of the control group or that the decrease (increase) in the farm-level indicator of the treated is smaller than the decrease (increase) of the controls.

We present the findings which differentiate between the effects of agri-environmental schemes on farmers' production decision as a proxy of environmental pressures and on the farm net income to reflect farm economic performance. Differences and a possible explanation of these results are discussed and compared between the different countries for both field crops and dairy production systems.

1. Results of farmers' economic performance

Although agri-environment measures have been launched initially to combat the negative impacts of intensive agricultural systems on environmental aspects, several studies have highlighted the significant role that economic factors can play in farmers' willingness to adopt agri-environment schemes. Thus, the ecological effectiveness of the agri-environment policies cannot be assessed in isolation, but should always involve the economic efficiency of the schemes. We begin by addressing the findings of field crop farms and later we comment on the results of dairy farms.

When considering the variable of farm net income including scheme payments as a measure of economic performance, we would expect a non-significant effect as the loss of income associated with the adoption of environmentally-friendly practices should be adequately compensated by the AES. The corresponding DiD estimator that capture the impact of the AES on the total farm net income per hectare is indeed not significant for Germany, Spain, United Kingdom and Italy. In Hungary and France, the negative and significant effect on total farm net income per hectare may be explained by the fact that scheme payments seem to be insufficient to compensate farmers for the provision of environmental benefits. While, when excluding AES payments from the total farm net income per hectare, our results show a non-significant impact of AES participation. Which is

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consistent with the notion that agri-environmental measures represent a negligible part in the farm business. In the United Kingdom the participating farms show an increase of farm economic indicators higher compared to the non-participating farms, this positive effect may reflect a selection bias in that farmers will participate only in those agri-environment schemes that do not involve important changes in their production practices. These may suggest that some of these AES programmes are subject to important windfall profits (Chabé-Ferret & Subervie, 2013).

The third variable concerns the total output value per hectare, which is another key determinant indicator of economic performance and reflects farm production intensity. One could expect scheme payments to reduce production intensity, but our results show that this is the case only in two countries. In France, the negative effect on total farm output per hectare may be explained by the drop in fertilizer cost due to AES adoption, while in Hungary, the significant negative effect on total farm output does not seem to be associated with environmentally friendly practices. While in the other four countries a non-significant effect is found. These results may suggest that it is unlikely that farmers would consider any significant management changes that affect farm productivity.

For dairy farms, we find similar inconsistent results across countries as found for field crop farms, which was expected given the significant variability across countries in terms of agricultural practices, soil and climatic conditions and the different payment structures. The DiD parameters for the economic indicators are generally not significant, except for the Netherlands where the effect is positive and statistically significant. The absence of the effect of the schemes on total farm income may reflect on the appropriateness of the AES payments to compensate farmers for income losses. However, when we do not consider AES payments as part of the farm income, the latter does not seem to be affected by agri-environmental participation. This suggests that, on average, the implemented sustainable farm practices do not result in a significant income change.

Only in the Netherlands, a positive and statistically significant effect of AES participation is found for the four economic indicators. This positive impact could be linked to more sustainable farm practices, because of the significant decrease in fertilizer, pesticides and energy expenditures.

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2. Results of farmers' production decisions

AES participation is projected to affect farmers' decisions, as they offer incentives to participant farmers to adopt environmentally sustainable farming practices. As a consequence of variation in the conditions in which production takes place, it is expected that the effects of AES on farm performance indicators differ across countries and farm types.

As expected, all models display a negative sign for the impact of AES participation on fertilizer and pesticides expenditure per hectare; however, these coefficients differ in the magnitude and statistical significance across countries. Moreover, changes in energy expenditure per hectare and stocking density for dairy farms may be considered as indicators of the effectiveness and efficiency of agri-environment schemes in reducing environmental pressures at the farm level (Bava et al., 2014; Gadanakis et al., 2015). Our findings suggest differences in the effects of AES of these indicators across countries.

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Table 8: Average treatment effect on the treated for AES from 2007-2011 (field crop farms).

	Germany			Spain			Hungary		
	Coeff	S. E.	t	Coeff	S. E.	t	Coeff	S. E.	t
Farm net income (euros)	-0.023	2.76	-0.01	-3.85	2.59	-1.49	-5.24	2.31	-2.26**
Farm net income without AES (euros)	0.70	2.82	0.27	-1.93	2.78	-0.69	-0.19	2.48	0.08
Farm net income per ha (euros/ha)	-0.13	0.62	-0.21	-0.62	0.57	-1.08	-1.17	0.41	-2.86***
Farm net income without AES per ha (euros/ha)	0.02	0.63	0.04	-0.06	0.63	-0.10	-0.32	0.43	-0.76
Total output per ha (euros/ha)	0.11	0.15	0.73	0.42	0.26	1.59	-0.25	0.13	-1.91*
Fertilizers per ha (euros/ha)	-0.074	0.11	-0.66	-0.05	0.17	-0.32	-0.08	.085	-0.97
Pesticides per ha (euros/ha)	-0.024	0.10	-0.23	0.005	0.18	0.03	-0.07	.071	-0.37
Energy per ha (euros/ha)	0.10	0.077	1.35	0.30	0.13	2.21**	-0.11	.080	-1.34

	UK			France			Italy		
	Coeff	S. E.	t	Coeff	S. E.	t	Coeff	S. E.	t
Farm net income (euros)	10.21	5.35	1.91*	-3.60	1.80	-2.01**	-2.27	2.70	-0.84
Farm net income without AES (euros)	13.00	5.59	2.33**	-1.05	1.81	-0.58	1.40	3.27	0.43
Farm net income per Ha (euros/ha)	1.70	1.06	1.60	-0.79	0.37	-2.11**	-0.75	0.86	-0.88
Farm net income without AES per ha (euros/ha)	2.20	1.10	2.00**	-0.26	0.37	-0.70	0.16	0.93	0.17
Total output per ha (euros/ha)	0.13	0.29	0.43	-0.07	0.03	-2.38**	-0.02	0.42	-0.05
Fertilizers per ha (euros/ha)	-0.06	0.07	-0.75	-0.10	0.04	-2.48**	-0.33	0.25	-1.33
Pesticides per ha (euros/ha)	-0.08	0.08	-1.05	-0.061	0.05	-1.16	0.15	0.25	0.60
Energy per ha (euros/ha)	0.06	0.08	0.76	-0.01	0.04	-0.21	0.20	0.25	0.81

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Table 9: Average treatment effect on the treated for AES from 2007-2011 (dairy farms).

	Germany			Netherlands		
	Coeff	S. E.	t	Coeff	S. E.	t
Farm net income (euros)	-1.07	2.68	-0.40	9.23	3.62	2.55**
Farm net income without AES (euros)	0.50	2.71	0.18	11.06	3.86	2.87***
Farm net income per ha (euros/ha)	-0.002	0.47	-0.00	1.91	0.90	2.12**
Farm net income without AES per ha (euros/ha)	0.20	0.49	0.40	2.38	0.96	2.47**
Total output per ha (euros/ha)	-0.01	0.03	-0.43	-0.30	0.24	-1.21
Fertilizers per ha (euros/ha)	-0.12	0.13	-0.93	-0.41	0.35	-1.17
Pesticides per ha (euros/ha)	-0.15	0.11	-1.35	-0.41	0.21	-1.98*
Energy per ha (euros/ha)	-0.01	0.03	-0.19	-0.28	0.11	-2.52**
Cows per ha (number/ha)	0.002	0.03	0.07	-0.02	0.01	-1.86*

	France			Italy		
	Coeff	S. E.	t	Coeff	S. E.	t
Farm net income (euros)	0.68	1.98	0.35	-1.83	2.83	-0.64
Farm net income without AES (euros)	2.93	2.15	1.36	-1.94	3.10	-0.63
Farm net income per ha (euros/ha)	-0.03	0.45	-0.08	-1.53	1.03	-1.48
Farm net income without AES per ha (euros/ha)	0.47	0.48	0.97	-1.65	1.12	-1.48
Total output per ha (euros/ha)	-0.01	0.11	-0.14	-0.50	0.61	-0.81
Fertilizers per ha (euros/ha)	-0.09	0.11	-0.85	-0.27	0.34	-0.78
Pesticides per ha (euros/ha)	-0.11	0.11	-0.97	-0.10	0.25	-0.40
Energy per ha (euros/ha)	-0.03	0.05	-0.68	-0.17	0.24	-0.72
Cows per ha (number/ha)	0.00	0.01	0.28	-0.03	0.04	-0.79

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Our findings for the German field crop sector suggest that AES payment does not seem to affect significantly any of the above-mentioned indicators, indicating that the mean change in farm performance indicators from 2007 to 2011 does not significantly differ between the subsidised and the non-subsidised farms. The largest share of agri-environmental measures in Germany was related to grassland, arable land and organic farming (Osterburg, 2005), however with more than 100 separate sub-category measures that are available at the state level, this heterogeneity may also be responsible for the absence of a significant impact, this could come from the fact that measures that aim to promote the implementation of diversified crop rotations do not impose restrictions on the use of fertilizers or pesticides, but rather limited the option of which crops to grow in which zone.

In Spain, AES payment does not seem to have a significant impact on reducing the use of fertilizers and pesticides products, suggesting no significant differences between program participants and non-participants. This result is compatible with the argument that most of the agri-environmental program euros spent in Spain were linked to landscape preservation (Peco et al., 2000) and thus not targeting environmentally sustainable practices that require input use reduction. The only exception is energy consumption per hectare, which surprisingly appears to be positively affected by programme participation.

In Hungary, AES have been launched only in 2002 under the name of "National Agri-Environmental Protection Programme", thus the short history of Hungarian AES may explain the lack of effectiveness of these measures. Furthermore, a review of the Hungarian agri-environmental programme criticised its implementation, particularly a failure by policy-makers to engage and involve relevant stakeholders and their views (Nemes & High, 2011). This is consistent with our findings for Hungary that show a non-significant effect of AES adoption on Hungarian farmers' input decisions. Another consideration to keep in mind is that there are some RDPs across the EU which do not seem to have any specific action targeting the reduction of fertilizers and pesticides products (Keenleyside et al., 2011).

For field crop farms in France, mixed results are obtained regarding the effectiveness of the schemes in reducing environmental pressures. For pesticides and energy expenditure per hectare, the sign of the impact is negative as expected, but not significant, while the DiD coefficient on the variable of fertilizers use per hectare has the predicted negative sign, and is robust at the 1% level of significance. These results are consistent with previous findings from Arata & Sckokai (2016). France is one of the EU member states with a long tradition of agri-environment schemes. Two important schemes are implemented at the national level of the programming period 2007-2013 and were related to extensive grazing systems and diversification of arable crop rotations. The latter aims to reduce the need for pesticides inputs with longer intervals before a crop is repeated on the same plot and thus keeping some crop-specific pests under control. However, according to our results, this does not seem to be happening for our French field crop farms.

Given the long history of agri-environment schemes in the UK, and their high participation rate, it would be expected that the schemes perform well and reduce the environmental pressures. However, our results are not consistent with the previously suggested hypotheses and indicate that the adoption of AES does not affect significantly any of the indicators considered in this study. Arata

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& Sckokai (2016) also found a non-significant impact of AES participation for the fertilizers and pesticides inputs for their first subsample. An important point to note is that the rural development programme 2007–2013 in the United Kingdom is among the most complex across the EU with very large agri-environment scheme options and by the fact that our AES payments data are aggregated into a single variable, which may explain the absence of effects on the farmers' production decisions.

In Italy, the share of the agri-environment payments in the RDP 2007-2023 budget is 22.5%, where more than half the AES budget is spent on schemes supporting organic farming and integrated farming (COM, 2008). In addition, some schemes promote also farm crop diversification and reduction of fertilizers use. Our results suggest that AES participating farmers were not able to reduce significantly their energy, fertilizer and pesticides expenditure per hectare during the period of investigation (2007-2011). The absence of the effect could be the result of the interaction between the AES and the cross-compliance instruments – both policies aim at providing environmental benefits from agriculture. (Bartolini et al., 2012) suggest that this linkage could lower the impact of one of the instruments, especially when both mechanisms are not well designed.

Results of the impact of AES participation for dairy farms are presented in table 9. Unfortunately, due to the lack of a sufficient number of observations, only four countries (Germany, Netherlands, France and Italy) are considered to investigate the impact of AES participation on the performance of dairy farms. We observe almost similar patterns as seen for field crop farms, where the effects of the AES appear to differ across countries. In Germany, France and Italy, none of the indicators that reflect environmental pressures was significantly affected by AES participation, this means that the average change in farm performance indicators from 2007 to 2011 does not significantly differ between participating and controls dairy farms. The Netherlands is the only country whose participating dairy farms have a significant decrease in the expenditure for energy use and pesticide products per hectare as well as a significant negative effect is observed with respect to the stocking density. The only exception is fertilizer expenditure per hectare, which coefficient is negative but insignificantly different from zero. By contrast, previous studies on the effectiveness of the agri-environment measures in the Netherlands failed to demonstrate the environmental benefits of the AES (Batáry et al., 2010; D. Kleijn et al., 2006). These ambiguous results have been reported in several other studies as documented by Klaus et al. (2013).

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8. Discussion

Some twenty-five years ago, Professor Michael Porter of Harvard business school suggested that environmental degradation is usually linked with a waste of resources and a reduction in pollution may result in productivity gains: "Pollution is a manifestation of economic waste and involves unnecessary or incomplete utilisation of resources … Reducing pollution is often coincident with improving productivity with which resources are used" (Porter & der Linde, 1995). Furthermore, Porter claimed that "properly designed environmental regulations can trigger innovation that may partially or more than fully offset the costs of complying with them". This claim is now widely known as the Porter Hypothesis. In other words, environmental pollution and production costs can be lowered simultaneously, resulting in "win-win" outcomes.

While several studies have tried to test this hypothesis empirically, most of them focus on non-agricultural sectors (Vercammen, 2011). These existing studies on this relationship provide contradictory results. Some studies indicate a positive link (with varying strength) (Ambec et al., 2013), other studies conclude that a negative relationship exists between environmental regulation and business performance (Jaffe et al., 1995; Lanoie et al., 2011). However, Cohen & Tubb's (2018) meta-analysis of 103 studies examining the link between environmental regulation and productivity or competitiveness performance show a more complex picture: the authors claimed that there is no straightforward negative or positive relationship between environmental policy and economic performance. Instead, this linkage is mediated by a variety of different characteristics and has to be evaluated empirically on a case-by-case basis.

The agri-food sector faces unique challenges in the context of these trade-offs between environmental and economic performance, especially for three reasons. First, the agri-food industry has a significant impact on the environment and strongly depends on non-renewable resources (Walder & Kantelhardt, 2018). Second, as agricultural products cover basic human needs, citizens have strong views on what they consume and how it is produced. This results in a diverse set of criteria for the agri-food sector regarding the production process, the quality and safety of products as well as the preservation of ecosystems and biodiversity. Third, the agri-food sector involves different stakeholders (ranging from farmers to policymakers) with different objectives, this could lead to potential conflicts over which objectives should be met first.

Agri-environmental measures represent the highest share of EU funding for rural development programmes and one of the most important instruments for the promotion of environmentally sustainable farming practices. Cost-effectiveness assessments of these interventions are thus important and would help policymakers to design and implement more effective policies and programs and thereby helps to pave the way to reduce negative externalities while simultaneously maximizing intended outputs. This is also consistent with the idea that economic and environmental externalities are interlinked and cannot be evaluated in isolation, but must be considered together.

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The economic efficiency of the agri-environmental policies is an important component of the overall AES performance. But few studies have assessed the impact of agri-environmental schemes on farm performance[5]. Overall, the impact of environmentally sustainable practices participation on economic performance was mixed. There are some studies that find a decrease in the productivity of the participating farms (Kumbhakar et al., 2009; Lansink et al., 2002; Mayen et al., 2010), while others find that the adoption of sustainable farming practices increases firm performance (Flubacher et al., 2015; Piot-Lepetit & Le Moing, 2007; van der Vlist et al., 2007). These inconsistent results are often considered to be the result of lack of information that can adequately support cost-benefit assessments for environmental policies in agriculture (Hardelin & Lankoski, 2018). Our findings underpin the results just above, providing mixed evidence on the success of scheme payments in achieving improved economic performance at farm-level. Specifically, we find a negative association between AES participation and total farm net income in Hungary and France, no significant relationship for Germany, Spain, Italy and a positive relationship for the Netherlands and United kingdom. This disparity may suggest that when the share of scheme payments play a marginal role in the farm business, the schemes may not be the best ones for improving economic outcomes. Further, one could expect AES payments to compensate the income foregone, but our results show that this is the case only in three countries. This is compatible with the argument that the quantification of environmental benefits is difficult to account for and appropriate indicators are not integrated in the FADN database (Latruffe et al, 2017).

As the primary objective of agri-environment schemes is to stimulate environmental enhancement, a significant body of literature examines the impact of AES on environmental effectiveness. Batáry et al. (2015) perform a meta-analysis that covers a wide swath of literature over the last 20 years and concludes that agri-environment measures have been generally successful in improving farmland biodiversity. Similar findings have been reported by; Marconi et al. (2015) for the use of nitrogen-based mineral fertilizers; Poole et al. (2013) for water quality in the UK; Peerlings & Polman (2008) for air/greenhouse gas emissions and Deumlich et al. (2006) for soil erosion. However, in his meta-analysis, Batáry et al. (2015) asserted that the environmental effectiveness of AES depends on the compatibility of the scheme's design with respect to the specific region in which they are implemented. Kleijn & Sutherland (2003) have reached a similar conclusion on the ambiguous pattern of environmental effectiveness of AES aimed at improving farmland biodiversity. Our findings are in agreement with the above- mentioned results and found no clear support that participating farms differ significantly from non-participants with regard to farmers' production decisions that reflect the environmental pressures. The low participation rate in France, Spain and Italy could have introduced some selection bias, which in turn will affect the study findings. The reason for this low participation rate could be attributed to the restrictions some agri-environment measures put on the fertilizers or pesticides use, leading to insufficient uptake rates. Nevertheless, one way to overcome this problem is to use more elaborated performance indicators such as eco-efficiency, where farmers will be asked to achieve improvements in eco-efficiency rather than more radical policies that limit the use of productive inputs (Pérez Urdiales et al., 2016).

[5] But without directly testing the innovation framework as suggested by Porter

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9. Conclusions

The key research questions addressed in this study concerns the link between agri-environment schemes and farm performance in operations specializing in field crops and dairy farms in different EU countries. The first policy-related question examined is whether there is an association between AES payments and environmental cost-effectiveness in field crop and dairy farming systems in different EU countries. The second such question is whether there is a positive or negative impact of AES on farm economic indicators.

The data used are balanced panels from the European FADN database for farms located in seven EU countries for 6 years ranging from 2006 to 2011 (with 2006 being the pre-treatment year). The countries included are Germany, France, Hungary, Italy, the Netherlands, Spain and the United Kingdom. Our model is specified as a semi-parametric propensity score matching estimator combined with a difference-in-difference estimator to measure the impact of AES participation farm-level performance indicators. Specifically, we employ a PSM method to address the selection bias issue arising from observed characteristics and DiD approach to address sample selection bias arising time-invariant unobserved factors.

This study contributes to the literature by using a wide set of EU countries and for two types of farming, farms specialised in field crops and conventional dairy production, while at the same time applying an appropriate methodology to derive results that enable meaningful comparisons across countries to be made. Our research suggests mixed evidence regarding the association between AES and farm performance. It could be expected that AES payments would compensate the income foregone and deliver substantial environmental benefits. However, our results does not confirm this expectation. The disparity in our results across countries and those of Arata & Sckokai (2016) are probably due to the absence of disaggregated variables on AES payments from the FADN database that identify the payments received by farmers for each individual scheme. Such information would help us to obtain more detailed findings, allowing more adjusted policy recommendations. Another limitation of the data sources used in this analysis is the lack of more sophisticated indicators of environmental sustainability (Kelly et al., 2018). It would be interesting to extend this study using the core FADN database in combination with national initiatives that collect additional information. Then, instead of using indicators of farmers' input decisions to examine the environmental effectiveness of AES, one could use non-parametric techniques to measure eco-efficiency such as the ones proposed by Kuosmanen & Kortelainen (2005). Early studies on farm-level performance have considered the use of different assumptions to model an overall performance. Murty et al. (2012), for example, model farm performance as an interaction between an intended-production process and a pollution-generating process. This is another area that deserves attention, particularly in relation to evaluating the environmental effectiveness of policy programs.

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10. Ongoing work:

Considering the objectives and project duration, two scientific papers are being written-up for journal publications.

First scientific paper: This paper will focus on assessing the impact of agri-environmental schemes on the eco-efficiency concept. While previous research has discussed the ecological or economic effectiveness of the schemes, no previous study has evaluated the impact of AES on eco-efficiency, which is a concept that integrates both economic and environmental objectives.

Second scientific paper: This article will also focus on deriving combined efficiency and environmental measures for a sample of Bavarian dairy farms (Murty et al., 2012). We will use the propensity score matching (PSM) model combined with the difference-in-difference (DID) estimation to evaluate the effect of the schemes on farm-level performance.

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