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Research article

Exploring the Linkages between farm efficiency, farm environmental performance, and agri-environmental scheme adoption: Lessons from France☆

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ABSTRACT

The agricultural detrimental effects on the environment are a source of concern. Public mea-sures, such as agri-environmental schemes (AES), have been designed to incentivize farmers to adopt more sound environmental practices on the farm. In this study, we examine the effects of past initial economic and environmental performances on AES adoption by focusing on crop farms. Using Firth's logistic regression to address small sample bias with French FADN data from 1997 to 2007, we mainly find that technical efficiency has heterogeneous effects on AES adoption, depending on environmental indexes. This result suggests the presence of windfall effects. We also show complex interactions (antagonism or synergy) between economic and environmental performances in adoption decisions, and heterogeneous effects depending on the type of farming.

The agricultural detrimental effects on the environment are a source of concern. Public mea-sures, such as agri-environmental schemes (AES), have been designed to incentivize farmers to adopt more sound environmental practices on the farm. In this study, we examine the effects of past initial economic and environmental performances on AES adoption by focusing on crop farms. Using Firth's logistic regression to address small sample bias with French FADN data from 1997 to 2007, we mainly find that technical efficiency has heterogeneous effects on AES adoption, depending on environmental indexes. This result suggests the presence of windfall effects. We also show complex interactions (antagonism or synergy) between economic and environmental performances in adoption decisions, and heterogeneous effects depending on the type of farming.

1. Introduction

Agriculture, through intensive use of pesticides and fertilizers, can have detrimental environmental effects, including increased pollution (Bostian et al., 2019), damage to surface and groundwater (Skinner et al., 1997), and biodiversity deterioration (Tang et al., 2021). Growing environmental concerns and increased social demand for ecosystem protection have underscored the recognition of agricultural externalities as market failures, prompt-ing interventions by public policies to mitigate agriculture's adverse effects while preserving productivity.

In that vein, the European Union (EU) has undertaken reforms since 1985 within the Common Agricultural Policy (CAP) to mitigate agriculture's environmental impact. Agri-environmental schemes (AES) have been implemented to reduce negative externalities and promote environmentally beneficial practices by helping farmers transition from conventional to environmentally friendly farming systems. As a voluntary scheme, they offer pre-miums to offset costs associated with practice changes or income loss and to promote sus-tainable practices with

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positive environmental outcomes (Chabé-Ferret and Subervie, 2013). The environmental impact of AES mainly depends on two factors: the effective application of required changes in management practices (additionality, *e.g.*, Baylis et al. (2008)) and the adoption rate of AES (farmer participation, *e.g.*, Lastra-Bravo et al. (2015)). In this paper, we are interested in the latter, *i.e.*, the enrollment of farmers into AES. Factors influencing AES participation include, among others, the household head's age (Pavlis et al., 2016; Wynn et al., 2001; Defrancesco et al., 2008; Wilson, 1997), farm size (Pavlis et al., 2016; Wynn et al., 2001), education level (Giovanopoulou et al., 2011), subsidies (Wilson, 1997), environmental awareness (Dupraz et al., 2003; Defrancesco et al., 2008, 2018), and financial health (Bostian et al., 2019). However, little is known on the effect of past economic performance on AES enrollment. Our contribution is to address the role of initial economic performance, measured by the estimation of the farm's technical efficiency, on AES adoption.

Technical efficiency (TE hereafter) achieved under conventional farming could indeed influence farmers' adoption of environmentally friendly practices. As AES expand the pro-duction possibility set and create an upward shift in the production frontier by promoting new agricultural practices, farm's managerial practices, *i.e.*, TE, could influence the ability to cope with a shift in the production structure, and consequently the decision to participate in an AES. Latruffe and Nauges (2014) found that larger technically efficient farms in France are more prone to convert to organic farming. Similarly, Was et al., 2021 observed that effi-cient, well-organized farms in Poland are inclined to join AES. AES can also serve as a means to improve efficiency or offset production risks, depending on structure and productivity level (Huang et al., 2024; Lastra-Bravo et al., 2015).

Beyond economic considerations, AES adoption is also influenced by environmental aware-ness. Studies by Dupraz et al. (2003) and Defrancesco et al. (2018, 2008) demonstrate that farmers with greater environmental awareness are more likely to adopt AES, as these schemes aim to promote sustainable agricultural practices.

Our paper differs from existing literature in three ways. First, this study is the first, to the best of our knowledge, to examine the effect of TE on multiple AES. Studies on conven-tional and organic farming have received some attention (*e.g.* Latruffe and Nauges (2014) in France; Kumbhakar et al. (2009) in Finland; and Skolrud (2019) in the USA), but none of these papers examined the link between TE and AES adoption. Secondly, we explore the connection between prior environmental performance and AES adoption, shedding light on windfall effects and potential synergies or antagnisms between economic and environmen-tal factors. Third, we adopt a novel methodology based on Firth-type penalization, which is more convenient for small samples and rare events, and complete separation problems (Puhr et al., 2017) as AES tend to have a small proportion of adopters. Furthermore, we focus our attention on three emblematic AES[1] which encompass significant dimensions of farm practices that impact both the environment and health, and on crop farms (excluding live-stock farming).

Our results indicate that past economic performance measured by TE mainly negatively influences the probability of adopting an AES, except for AES02–Crop Rotation where there is no significant effect. Efficient farms tend to join AES only when they achieve a threshold of environmental performance, implying potential windfall effects across all AES analyzed. Ad-ditionally, higher environmental performance correlates with increased AES participation. Our results underscore the complex interplay between economic and environmental con-siderations in AES adoption choices.

The remainder of this paper is organized as follows: the literature review and characteris-tics that affect AES participation are presented in section 2. The methodology and data follow in section 3. Section 4 presents the results for each AES under study, explores heterogeneity by decomposing our estimations by type of farming (TF), and assesses the robustness of our baseline findings. Section 5 provides a discussion, limitations of the paper and future avenue of research. Section 6 concludes with policy recommendations.

2. Related literature on determinants of AES participation

Farm-level determinants of AES have been extensively studied, given the central role of AES in EU agricultural policies (Uthes and Matzdorf, 2013). Lastra-Bravo et al. (2015) and Pavlis et al. (2016) offer an extensive literature review of the main drivers of AES participation. Various factors influence AES adoption, including household head age and education, farm size and income, expected subsidies, contract design and financial health. Younger farmers, in particular, are more likely to adopt AES due to their greater flexibility and learn-ing aptitude (Pavlis et al., 2016; Wynn et al., 2001), while experienced farmers may find it easier to transition to AES participation due to accumulated knowledge (Wilson, 1997). Ed-ucation also plays a role, with higher education levels generally associated with increased AES adoption (Giovanopoulou et al., 2011; Pavlis et al., 2016) with possible variation due to the level of environmental benefit (Wilson, 1997). Farm size is another determinant, with larger farms more likely to participate in AES (Pavlis et al., 2016; Gailhard and Bojnec, 2015) due to their capacity for extensive farming. Additionally, Defrancesco et al. (2008) showed

that a high dependency on farm income and labor-intensive farming reduce the probability of AES adoption in Italy. Moreover, expected subsidies are crucial, as higher subsidies pos-itively drive AES participation by offsetting costs associated with practice changes (Bostian et al., 2019). Financial health also influences adoption decisions, with farms in better finan-cial standing more likely to adopt AES (Piet and Desjeux, 2021). Other characteristics such as the importance of flexibility in contract design, which allows farmers to select contract terms and related payments, also have an influence (Mettepenningen et al., 2013).

In addition to these factors, this paper aims to explore the roles of economic perfor-mances (TE) and environmental performances (measured by environmental indexes) in AES adoption. Regarding TE, little is known about its effect on AES adoption. TE, defined here as the ability to maximize agricultural output given input levels (output orientation), could play a pivotal role in farmers' decisions to engage in AES as technically adept farmers may readily adopt new production technologies, experiencing minimal efficiency reductions, if any, when participating in AES. Previous research has primarily examined the relationship between TE and organic farming. For instance, Kumbhakar et al. (2009) found that higher TE increases the likelihood of converting to organic farming due to attractive subsidies. Simi-larly, Latruffe and Nauges (2014) showed TE's significant influence on conversion rates, par-ticularly in larger farms specializing in field crops. However, Skolrud (2019) observed a neg-ative association between TE and the shift to organic milk production in the USA because of small amount of subsidies. Unlike previous studies, we focus on various AES rather than just organic farming, allowing for a comprehensive understanding of adoption drivers.

Moreover, we incorporate environmental indexes alongside TE measures. Environmen-tal indicators, measured by attitudes toward sustainability, can drive AES adoption positively or negatively. While some environmentally efficient farms may perceive AES as unnecessary, others see it as a means to improve efficiency and adopt environmentally friendly practices (Defrancesco et al., 2008, 2018). With this in mind, we use three environmental indexes for this study – the crop diversity index (CDI), the crop protection index (CPI), and the fertilizer index (FI) – to partially capture the environmental aspect of the farming system.

Finally, we utilize a methodology to address data challenges inherent in our study, as detailed in the following section.

[1] Namely Cultural Rotation -AES02-, Pesticide Reduction -AES08-, and Fertilization Reduction -AES09- measures.

3. Methodology and data

3.1. Methodology

In this section, we elaborate on our empirical methodology for estimating the effect of TE and environmental performance on AES adoption.

3.1.1. Technical efficiency

The stochastic frontiers analysis (SFA) adopted in this paper is based on the (Battese and Coelli, 1992)' models for panel data with the production function of the form:

$$Y_{it} = f(X_{it};\beta)\cdot\exp\{V_{it} - U_{it}\}, \tag{1}$$

where Y_{it} is the output for farm i at the t time period (here the gross agricultural produc-tion), X_{it} is a vector of inputs (fixed assets, utilized agricultural area, annual working hours, environmental inputs, and intermediate consumption),[2] and β is a vector of technology pa-rameters (Kumbhakar and Lovell, 2003). The first error component, V_{it}, measures the effects of statistical noise (weather for instance) and is assumed to be *i.i.d.* of $N(0, \sigma_v^2)$ distribution. The second error component, U_{it}, measures the inefficiency with the most efficient farms have $U_{it} = 0$, meaning that they operate on the frontier of production.

TE can be defined as the ratio between the observed output Y_{it} and the maximum pos-sible output (*i.e.*, without inefficiency U_{it}) conditional on inputs used by farms $Y^*_{i\,t}$ (Battese, 1992). It can be expressed as follows:

$$TE_{i\,t} = \frac{Y_{i\,t}}{Y^*_{i\,t}} = \frac{f(X_{it};\beta)\cdot\exp\{V_{it} - U_{it}\}}{f(X_{it};\beta)\cdot\exp\{V_{it}\}} \tag{2}$$

$$= \exp\{-U_{it}\}$$

In our analysis, we use the transcendental logarithmic (Translog) function for efficiency estimates (Christensen et al., 1971, 1973). Estimations are conducted separately for two pe-riods: before AES implementation (1997–1999) and after implementation (2000–2007). The results are presented in Table C24 and Table C25. A detailed explanation of the model is to be found in AppendixA.[3]

Despite the availability of other methodologies like Data Envelopment Analysis (DEA), we prioritize SFA due to their ability to account for unobserved factors and noise. More-over, while recent developments in environmental efficiency modeling offer promising tech-niques (Murty et al., 2012) and some models distinguishing between transient and persistent TE (Kumbhakar et al., 2014), our dataset lacks undesirable outputs necessary for DEA and Kumbhakar et al. (2014)' model did not converge. Therefore, we rely on SFAs and compute environmental indicators to measure farms' environmental performance.

3.1.2. Definition of the environmental indicators

To investigate the role of environmental performances on AES adoption, we use three environmental indexes: the crop diversity index (CDI), the crop protection index (CPI), and the fertilizer index (FI).

Following Bareille and Dupraz (2020), the Crop Diversity Index (CDI_{it}) is computed as follows:

$$CDI_{it} = -\sum_{j=1}^{J-1} \frac{\frac{n_{ijt}}{N_{it}}}{1 - \frac{n_{iPt}}{N_{it}}} \ln\left(\frac{\frac{n_{ijt}}{N_{it}}}{1 - \frac{n_{iPt}}{N_{it}}}\right) \tag{3}$$

where n_{ijt} is the area dedicated to crop j by farm i in t, n_{iPt} is the area of permanent grass-lands, and N_{it} is the UAA of the farm i in t. This index is based on the Shannon index, while being corrected by the permanent grassland, n_{iPt}, to account for crop diversity instead of land-use diversity (Bareille and Dupraz, 2020). It ranges from 0 (monoculture) to its highest value. Higher values signify greater crop diversity, leading to reduced environmental impact such as input efficiency and resource utilization while safeguarding yields (Bommarco et al., 2013), crop complementarity and protection against weeds, diseases, and pests (Bommarco et al., 2013; Di Falco et al., 2010; Lechenet et al., 2014).

The Crop Protection Index (CPI_{it}) and the Fertilizer Index (FI_{it}) are computed as fol-lows: we divide, respectively, the consumption of crop protection (crop protection expenses deducted from inventory change) and fertilizer, by the utilized agricultural area (UAA) to ob-tain the consumption per ha of farm i (cpi_{it} and fi_{it}). Thereafter, we compute the average consumption per ha for each TF ($\overline{cpi_{it}}$ and $\overline{fi_{it}}$). Therefore, CPI_{it} and FI_{it} equal, respec-tively, the ratio between the two components:

$$CPI_{it} = \frac{cpi_{it}}{\overline{cpi_{it}}} \quad and \quad FI_{it} = \frac{fi_{it}}{\overline{fi_{it}}} \tag{4}$$

Even though the average of the TF might not encompass the entire environmental im-pact, being above 1 implies a higher intensity of input usage, potentially leading to greater environmental damages. For instance, a high level of nitrogen surplus, that increases nitro-gen emission, can be the result of high intensity of fertilizer usage (Ait Sidhoum et al., 2022). However, these measures have limitations as they may not fully reflect the environmental footprint due to factors like alternative harmful substances or limited correlation with toxi-city (Uthes et al., 2019). Nevertheless, we would rather prefer to see these indexes as a proxy of the intensity of fertilizer and pesticide usage and assume that they partially capture the environmental aspect of the farming system.

3.1.3. Modeling participation to AES

AES are voluntary measures, as farmers decide whether to adopt an AES, and then receive a subsidy, or not. Assuming that farmers are rational and profit maximizers, they will choose the option that gives them a better utility.

In our model, $U_{i0} = X'_{i0}\beta + \varepsilon_{i0}$ represents the utility of not participating, while $U_{i1} = X'_{i1}\beta + \varepsilon_{i1}$ corresponds to participation in an AES. X'_i is the vector of farmer characteristics such as TE and environmental indexes as well as, following the literature, farm size and income, subsidies, the age and the level of education of household head, and the legal status. ε_i is the stochastic component of utility. The decision to adopt is determined by whether U_{i1} exceeds U_{i0}, indicating that the expected net utility of participating in AES is greater than not participating. However, we only observe the chosen outcome (adoption or non-adoption) and not the actual utilities themselves. Thus, our analysis focuses on the farmers' adoption decisions, representing a classic dichotomous choice problem in economics.

Let:

$$V_{it} = X'_{it}\beta + \xi_{it}, \tag{5}$$

be the expected net utility of the farmer i at the time t according to the farmer and farm's characteristics X'_{it}. Therefore, he decides to adopt an AES when $V_{it} > 0$. We will evaluate the probability of adopting an AES by farms based on the following specification:

$$d_{it} = Prob(V_{it} > 0) = F(X'_{it}\beta) + \upsilon_{it}, \tag{6}$$

where $F(.)$ is the cumulative density function of ξ_{it}.

[2] For the estimation, the logarithm of all inputs and output are used. To capture technological change over time, a time trend (T) is introduced into the production function. All variables are deflated using appropriate price indices.

[3] We compute the average four-year TE preceding the adoption as in Latruffe and Nauges (2014). For each farm that adopts an AES in the year t, the average TE for *t-1*, *t-2*, *t-3* and *t-4* will be used to assess past performance.

Limited adoption rate, as it is the case for AES, pose challenges due to small sample sizes, leading to biases in binary outcome models. Small sample bias can result in infinite esti-mates and probabilities fitting to extremes (0 or 1) (Heinze and Schemper, 2002). To miti-gate this, we employ Firth's penalized logistic regression with added covariate (FLAC) (Puhr et al., 2017) which is based on Firth correction of Jeffreys (1946) and adjusts the score func-tion of the logistic regression. It consists of introducing a penalty term derived from an in-variant prior (Jeffreys, 1946) and creates an augmented dataset with original and pseudo-observations, each assigned weights, to refine Firth's estimation. This penalty term accounts for small sample bias and improves parameter estimates and standard errors (Puhr et al., 2017; Firth, 1993). This method outperforms the relogit procedure proposed by King and Zeng (2001), especially in probability estimation (Puhr et al., 2017). Therefore, we employ FLAC in our main estimation, while relogit will serve for robustness checks, and simple logit estimations will act as benchmarks.

3.2. Data and descriptive statistics

Multiple data sources contribute to our analysis, including the French FADN and AES data from the European Rural Development Regulation (RDR).[4] The FADN, provided by the French Ministry of Agriculture and Food, offers detailed information on farm characteristics and income for commercial farms. The dataset employs a rotating and unbalanced panel design, selecting farmers based on strata defined by the agricultural census. Small farmers below a specific threshold (25,000 euros) of Standard Gross Production are not surveyed, result-ing in a database focusing solely on commercial farms.

We integrate farm characteristic data with AES information from the RDR database, part of France's National Rural Development Program (PNDR). The PNDR aims to enhance rural competitiveness, support agriculture and forestry, and preserve the environment. The AES- RDR1 dataset covers 2000–2007, detailing AES adoption timing and subsidies received. By

merging this with the French FADN, our database includes farmer characteristics, AES en-rollment years, and subsidy details. Our analysis focuses on assessing the impact of previous TE on AES adoption, covering 1997–2007 with 38,528 farms. The 1997–2007 period is crucial as it marks the initial implementation of AES in France, providing insights into farmers' behaviors unaffected by previous AES participation. Furthermore, we include only farmers in a single AES studied and account for adopters once to avoid bias, following Latruffe and Nauges (2014).

In our sample, we focus only on four specific types of farming (TF) as presented in Fig-ure 1: (1) cereals, oilseeds and protein seeds, and general field cropping (TF–13); (2) wine with designation of origin and other grape production (TF–37)[5]; (3) fruits and permanent crops (TF–39); (4) mixed crop farming (TF–60).

As mentioned, we focus on three emblematic AES[6]: extension of the crop rotation and diversity (AES02–Crop Rotation), modification of the phytosanitary treatments to reduce pollution, or develop organic crop protection (AES08–Pesticide Reduction) and modifica-tion of fertilization (AES09–Fertilization Reduction). AES02–Crop Rotation introduces new crops, diversifies rotations, and includes fallow periods to break mono-cultures, promot-ing soil health and biodiversity. AES08–Pesticide Reduction emphasizes biological control, grass cover under woody crops, and mechanical treatments to reduce chemical pesticide use. AES09–Fertilization Reduction targets nitrogen input reduction, organic fertilization, and rationalized phytosanitary and fertilization practices, aiming to preserve water quality, soil fertility, and biodiversity while combating soil erosion and natural hazards. These AES align with selected TFs, covering diverse farming practices impacting crucial environmental dimensions like water quality, biodiversity, and soil erosion. Figure B1 presents the number and the proportion of AES adopters and non-adopters within each TFs.[7] Farms belonging to TF13 and TF60 have a higher percentage of adoption (6%) and the overall rate of adoption is 6%. It is very small and confirms that only a few farmers tend to adopt at least one AES.

Table 1 presents descriptive statistics for the main variables. The sample comprises 38,528 farm households, with an average output of 447,709.2 euros. There's significant output variation, as indicated by a standard deviation of 707,889 euros. Variability is also observed in classical in-puts like intermediate consumption, UAA, labor, and fixed assets. Table B2 provides descriptive statistics for each TF. Agricultural output averages between 410,518 euros and 480,063 euros, showing significant dispersion within each TF. TF39 - Fruits and permanent crop stands out with the highest production average but is more labor-intensive and less capital-intensive, with an average of 8145 annual working hours and 58,753 euros of fixed assets. While the age of the household head is similar across farming types, environmental indicators vary. TF13 have lower average fertilizer (434) and crop protection (313) ratios, followed by TF60.

4. Results

4.1. Main results

Tables 2–4 present, respectively, the results (marginal effects) of estimations for AES02– Crop Rotation, AES08–Pesticide Reduction and AES08–Fertilizer.[8] The pseudo R^2 (R^2 Mc- Fadden) and the Akaike criterion allow us to assess the goodness of fit of models.

For TE estimations, the average TE is 0.7 (Table 1), suggesting that the average farm can improve its production by 0.3 with the same level of input. More differences can be found when we compared adopters and non-adopters of AES. For all TFs under study, AES adopters have a higher TE than non-adopters, making the former more efficient between 1997 and 2007 as presented in Table C23. From Figure C2, farms specialized in TF37 - Wine with designation of origin and Other grape

Table 1
Descriptive statistics for our sample.

Variables	N	Mean	St. Dev.	Min	Max
Agricultural Output	38,528	447,709	707,889	876.3	18,899,459
Intermediate Consumption	38,528	186,632	286,347.8	1584.8	6,638,055
UAA	38,528	89.2	80.8	0.8	774.4
Labor (hours)	38,528	4020.3	3949.7	1200	76,800
Fixed assets	38,528	82,039.1	218,710.1	0	15,889,689
Technical Efficiency	38,528	0.7	0.2	0.1	1
Fertilizer Index	38,528	467.1	990.3	0	34,841.7
Crop Protection Index	38,528	597.6	1154.1	0	28,385.9
Crop Diversity Index	38,528	0.4	0.6	0	2
Age of the Household Head	38,528	46.9	9.3	16	87

[4] Access to all data is provided by the CASD (Centre d'Accès Sécurisé aux Données), Ref. 10.34724/CASD.

[5] We aggregate different types of farming into one: TF–13 and TF–14 are gathered to form one group and TF–37 and TF–38 are combined as they are all related to vineyards.

[6] These are aggregated AES. Each of these AES encompasses many sub-measures. Therefore, the number of AES adopters is the total number of adopters of all sub-measures.

[7] The proportion of adopters for each AES under study are presented in Table B3, Table B4 and Table B5. Even though the program started in 2000, farms started to adopt AES in 2002 in our sample.

[8] The estimations are done using R 4.3.1 version. This include both TE computation and estimation of different econometric results.

Table 2
Marginal Effects of adopting AES02–Cultural Rotation.

Dependent variable:				
	(1)	1 if farm ado (2)	pts AES02 (3)	(4)
Technical Efficiency (TE)	0.005		0.003	−0.029
Crop Diversity Index (CDI)	(0.663)	0.007 ***	(0.674) 0.007 ***	(1.546) −0.015
		(0.167)	(0.168)	(0.988)
TE*CDI				0.034
UAA	3.00e−05 ***	2.00e−05 *	2.00e−05 *	(1.452) 2.00e−05 *
Subsidies	(1.90e−04)	(1.90e−04)	(1.90e−04)	1.90e−04
Age of	2.00e−05 ***	2.00e−05 ***	2.00e−05	2.00e−05 ***
Household	(0.007)	(0.007)	*** (0.007)	(0.007)
Head	−3.60e−04	−3.60e−04	−3.60e−04	−3.70e−04
Income	*** (0.008)	*** (0.008)	*** (0.008)	*** (0.008)
Education	2.00e−08 **	3.60e−08 **	2.00e−08 **	2.00e−08 **
(ref = Prim. Educ)	(1.40e−06)	(1.40e−06)	(1.40e−06)	(1.40e−06)
Sec. Educ	0.005 **	0.005 **	0.005 **	0.005 **
	(0.149)	(0.149)	(0.149)	(0.149)
Higher Educ	0.005	0.006	0.006	0.006
Legal Status (ref = Ind. Enterprise)	(0.406)	(0.407)	(0.407)	(0.407)
GAEC	0.011 ***	0.012 ***	0.011 ***	0.011 ***
EARL	(0.180)	(0.181)	(0.180)	(0.180)
	0.010 ***	0.010 ***	0.010 ***	0.010 ***
	(0.147)	(0.147)	(0.147)	(0.147)
SCEA	0.001	0.002	0.002	0.002
Other	(0.380)	(0.380)	(0.380)	(0.380)
Constant	−0.004	−0.004	−0.004	−0.004
	(0.594)	(0.595)	(0.593)	(0.593)
	−0.166 ***	−0.169 ***	−0.171 ***	−0.150 ***
	(1.114)	(1.011)	(1.129)	(1.422)
AIC	−745.292	−753.803	−751.466	−751.648
Pseudo R2	−0.392	−0.398	−0.397	−0.399
Observations	16,522	16,522	16,522	16,522

Note: 0.10 * 0.05 ** 0.01 ***. The TE variable is four years lagged. The other variables are all 1-year lagged except for the Expected Subsidies. Standard Errors are in parentheses. Dummies' time and TFs are in-troduced in all specifications. Columns (1) to (4) represent different specifications depending on the variables added.
The four columns of specification differ by the number of independent variables. For all the models, the pseudo-R range from −0.399 to −0.392 which represent well-fitted models (McFadden et al., 1977).

Table 3
Marginal effects for AES08–Pesticide reduction.

Dependent variable				
	(1)	1 if farm adop (2)	ts AES08 (3)	(4)
Technical	−0.063 ***	−0.009 ***	−0.059 ***	−0.054 ***
Efficiency	(0.530)		(0.538)	(1.077)
(TE)			−0.007 **	−6e−05
Crop Protection Index (CPI)				
TE*CPI UAA	−1.00e−05	(0.189)	(0.188)	(1.080)
		−3.00e−05 *	−1.00e−05	−0.012
				(1.645)
				−1.00e−05
Subsidies	(0.001)	(0.001)	(0.001)	(0.001)
Age of	1.00e−06	1.00e−06	1.00e−05	1.00e−06
Household	(3.00e−04)	(2.90e−04)	(3.00e−04)	(3.00e−04)
Head Income	−2.60e−04	−2.40e−04 *	−2.40e−04 *	−2.40e−04 *
Education	** (0.006)	(0.006)	(0.006)	(0.006)
(ref = Prim.	−2.01e−08	−3.35e−08	−2.01e−08	−2.01e−08
Educ)	(1.50e−06)	**	(1.50e−06)	(1.50e−06)
		(1.50e−06)		
Sec. Educ	0.004	0.004	0.004	0.004
Higher Educ	(0.117)	(0.117)	(0.117)	(0.117)
Legal Status	−0.008	−0.009	−0.008	−0.008
(ref = Ind.	(0.391)	(0.389)	(0.390)	(0.390)
Enterprise)				
GAEC	0.014 ***	0.014 ***	0.014 ***	0.014 ***
EARL	(0.153)	(0.153)	(0.153)	(0.153)
	0.017 ***	0.016 ***	0.017 ***	0.017 ***
	(0.118)	(0.118)	(0.118)	(0.118)
SCEA	0.002	0.002	0.0022	0.002
Other Constant	(0.269)	(0.268)	(0.268)	(0.268)
	−2.00e−04	−0.001	−3.00e−06	−4.00e−06
	(0.414)	(0.413)	(0.414)	(0.414)
	−0.045 ***	−0.085 ***	−0.044 ***	−0.047 **
	(0.859)	(0.764)	(0.859)	(0.967)
AIC	−486.638	−469.586	−488.8	−486.665
Pseudo R2	−0.160	−0.154	−0.161	−0.161
Observations	17,789	17,789	17,789	17,789

Note: 0.10 * 0.05 ** 0.01 ***. The TE variable is four years lagged. The other variables are all 1-year lagged except for the Expected Subsidies. Standard Errors are in parentheses. Dummies' time and TFs are introduced in all specifications. Dummies' time and TFs are introduced in all specifications. Columns (1) to (4) represent different specifications depending on the variables added. case here and as was also found by Skolrud (2019). The result of the interaction term from the fourth column might confirm this explanation. We show that the effect of the TE is negative independently of the value of the crop protection index (CPI).

production are closer to 1, meaning that they are more technically efficient, followed by TF13 - cereals, oilseeds and protein seeds, and Gen-eral field cropping. This is confirmed by Table B2. The differences between adopters and non-adopters may stem from various factors beyond this paper's scope. The next subsection presents our estimation results.

4.1.1. Determinants of AES02 adoption

The impact of the TE and the Crop Diversity Index (CDI) on the probability of adopting AES02–Crop Rotation is displayed in Table 2.

On the one hand, we can see that TE has a positive, but non-significant effect on adop-tion probability for AES02–Crop Rotation. This result is consistent across all specifications. Therefore, past economic performance is not a key driver for AES02. On the other hand, the environmental indicator, namely CDI, has a positive and significant effect on the probabil-ity of adopting AES02. To put it differently, farmers who contribute more favorably to the environment are more likely to adopt this AES. An increase of one unit of the CDI increases the probability of AES02 adoption of 0.007. Indeed, farms with more diverse crop rotation might easily comply with the AES02 requirements. Therefore, this AES is attractive for them as they might maintain their environmental footprint while receiving a premium. This result is in line with the one of Defrancesco et al. (2008, 2018) and Dupraz et al. (2003) who found that environmentally sensitive farmers tend to participate more in AES. When it comes to the interaction between TE and the CDI, there is no significant effect.

The expected subsidies increase the probability of joining the AES02–Crop Rotation sug-gesting that subsidies are considered enough to cover the costs related to transition. This is in line with previous results from Wilson (1997) in the case of environmental sensitive area scheme, and Latruffe and Nauges (2014) and Kumbhakar et al. (2009) for organic farming. Likewise, the income tends to increase participation in the AES significantly, even though the magnitude of the effect is small. When farms are better off in terms of finance, they are more resilient to shocks but, also have more capacities to change agricultural practices (Bos-tian et al., 2019). The age of the household head seems to decrease significantly the prob-ability of adopting the AES02. Therefore, AES02 attracts younger farmers more than older ones. This result confirms the ones of Pavlis et al. (2016) and Wynn et al. (2001). It can be re-lated to the idea that older farmers tend to be more conservative and less flexible or they are more driven by economic benefits than environmental ones as shown by Defrancesco et al. (2008). The legal status

Table 4
Marginal effects for AES09 fertilization reduction.

Dependent variable				
	(1)	1 if farm ado (2)	pts AES09 (3)	(4)
Technical	−0.053 ***	3.00e−05	−0.057 ***	−0.080 ***
Efficiency	(0.538)		(0.539)	(0.670)
(TE)			1.00e−04	−0.041 ***
Fertilizer				
Index (FI)				
TE*FI UAA	−1.00e−06	(0.057)	(0.054)	(0.613)
		−1.00e−05	−1.00e−06	0.058 ***
				(0.840)
				−1.00e−06
Subsidies	(7.00e−04)	(7.00e−04)	(7.00e−04)	(7.00e−04)
Age of	−4.00e−05	−3.00e−05	−4.00e−05	−4.00e−05
Household	***	***	***	***
Head Income	(4.70e−04)	(4.70e−04)	(4.70e−04)	(4.70e−04)
Education	−3.90e−04	−3.80e−04	−3.90e−04	−3.90e−04
(ref = Prim.	*** (0.006)	*** (0.006)	*** (0.006)	*** (0.006)
Educ)	−2.00e−08	−3.23e−08 *	−2.00e−08	−2.00e−08
	(1.50e−06)	(1.50e−06)	(1.50e−06)	(1.50e−06)
Sec. Educ	0.008 ***	0.008 ***	0.008 ***	0.008 ***
Higher Educ	(0.125)	(0.124)	(0.125)	(0.125)
Legal Status	−5.00e−04	−0.002	−5.00e−04	−8.00e−04
(ref = Ind.	(0.370)	(0.369)	(0.370)	(0.371)
Enterprise)				
GAEC	0.017 ***	0.016 ***	0.017 ***	0.016 ***
EARL	(0.145)	(0.145)	(0.145)	(0.145)
	0.013 ***	0.012 ***	0.013 ***	0.013 ***
	(0.122)	(0.122)	(0.122)	(0.122)
SCEA	0.006	0.006	0.006	0.006
	(0.254)	(0.254)	(0.255)	(0.255)
Other	0.003	0.002	0.003	0.003
	(0.414)	(0.413)	(0.414)	(0.414)
Constant	0.040	0.003	0.040	0.058 **
	(1.095)	(1.018)	(1.095)	(1.130)
AIC	−337.961	−318.116	−335.798	−343.695
Pseudo R2	−0.112	−0.106	−0.112	−0.115
Observations	17,789	17,789	17,789	17,789

Note: 0.10 * 0.05 ** 0.01 ***. The TE variable is four years lagged. The other variables are all 1-year lagged except for the Expected Subsidies. Standard Errors are in parentheses. Dummies' time and TFs are intro-duced in all specifications. Dummies' time and TFs are introduced in all specifications. Columns (1) to (4) represent different specifications depending on the variables added.a negative and significant effect on the probability of adopting the scheme. This result is similar to the one found for the AES08 and in Skolrud (2019).

of the farm plays a significant role in partaking in AES02. Farmers who are in a 'groupement agricole d'exploitation en commun' (GAEC) or 'entreprise agri-cole à responsabilité limitée' (EARL) are more likely to adopt AES02 than the reference type of holding ("Entreprise Individuelle" (EI)). Therefore, AES02 seems to be more appealing to farms managed by multiple stakeholders. Likewise, a secondary education level seems to increase the odds of joining the AES02 compared to a primary level of education as found previously in the literature (Pavlis et al., 2016; Giovanopoulou et al., 2011). Indeed, a higher level of education can allow them to be more aware of the environmental benefits of AES and also be more able to adapt themselves to new technologies. The farm size (UAA) seems to influence positively the likelihood of adopting AES02, but the magnitude of the effect is small for all the specifications.

4.1.2. Determinants of AES08 adoption

The results of AES08 - Pesticide Reduction are summarized in Table 3.

We can see that TE has a negative and significant effect on participation in AES08. The more farms are technically efficient, the less likely is to see them joining the AES08. A similar result has been found by Skolrud (2019) in the case of conversion to organic farming. It may be explained by the fact that farmers consider the AES08 as a threat to their efficiency. As the AES mainly targets the reduction of phytosanitary usage, if farmers depend heavily on this to be efficient, they will not be willing to risk joining the AES and reducing their efficiency, especially when subsidies do not cover costs related to production structure change as it the.

As far as the environmental index is concerned, it affects negatively and significantly the probability of adopting AES08. This is a negative index, meaning that farmers with a greater negative impact on the environment tend not to adopt this AES08. In other words, the one with a higher positive impact will be more likely to join AES08. Farmers might consider that the AES08 adoption does not cover enough for the loss they will endure by joining the scheme. Therefore, farmers using more polluting inputs might be reluctant due to financial costs or additional constraints that they will face.

Similarly to AES02, the juridical status also has a significant effect on joining AES08. Farms with GAEC and EARL status are more likely to adopt AES08 than the Individual En-terprise (IE) status. The age of the household head is negatively and significantly related to the probability of joining AES08. Younger farmers seem to be more attracted by AES than their older counterparts. The other variables are not found to be significant.

4.1.3. Determinants of AES09 adoption

Table 4 displays results for the AES09–Fertilization Reduction. We can see that TE has.

The fourth column shows that the effect of TE and Fertilizer Index (FI) depend on each other. Indeed, for values of FI higher than 1.38, an increase in TE improves the probability of participating in AES09. More than 80% of farms have a FI lower than 1.38.[9] Therefore, for the vast majority of our sample, an increase in TE reduces the probability of joining AES09. This result might be explained by the fact this AES can be perceived as a threat to productivity. Therefore, if farms are environmentally efficient, an increase in their productivity will reduce the value of joining the AES. In the case they are not environmentally efficient, farms may be now concerned about their environmental footprint. Therefore, they will try to reduce their negative environmental impact while increasing their productivity.

Reversely, when TE is higher than 0.707 (40% of farms in our sample), an increase in the intensity of fertilizer usage improves the probability of joining AES09. In other terms, farms which exert a greater impact on the environment are willing to adopt the AES only when they have high productivity. Therefore, the windfall effect might not exist if farms have a higher productivity.

The expected subsidies seem to negatively affect the probability of adopting an AES, even though the magnitude is very small. Similar to previous AES, the age of the household head affects negatively and significantly the probability of adopting AES09. The level of secondary education also increases the probability of participating in the AES. This result is in line with the one of Pavlis et al. (2016) and Giovanopoulou et al. (2011) who found that a primary diploma increases the probability of adopting AES. Having GAEC or EARL as a legal sta-tus also improves the probability of joining AES08. Based on these results, subsection 4.3 presents the predicted probabilities for each of the AES.

The results found for the three AES under study can differ greatly according to the TF of farms. Indeed, they have different production structures and decisions can be influenced by different factors. Accordingly, we evaluate the heterogeneity of these results in the next section.

4.2. Results by types of farming (TF)

In this section, we investigate whether the main results vary from one TF to another. Therefore, we run the estimations for each TF and each

[9] The 8th decile equals 0.76 and the 9th decile equals 2.94.

AES. Results are presented in the section AppendixC.1 from Table C12 to Table C22. We observe a great heterogeneity for each AES depending on the TF.

Regarding the AES02–Crop Rotation, TF-13 and TF-60 exhibit the same results compared to our main estimations. However, TF-37 shows different patterns, with TE affecting nega-tively and significantly AES02 independently of Crop Diversity Index values.

Regarding the AES08–Pesticide Reduction, TE has a positive and significant effect only when the Crop Protection Index is higher than 11.11 for TF-13 and 7.54 for TF-37. Therefore, our results reveal an antagonism for these two TFs. Nevertheless, the results for other TF are not significant.

As far as AES09–Fertilization is concerned, TF-13 has the same results compared with our main estimations. TE impacts always negatively and significantly the probability of adopting AES09 and the Fertilizer Index impact positively the probability of joining AES09 when TE is higher than 0.54 (meaning if TE $>$ 0.54, farms exerting a greater negative environmental impact will be more likely to join).

All these results show how diverse are farms' decisions depending on their production structure, constraints they are facing, and the type of policies that are offered to them (see Fig. 1).

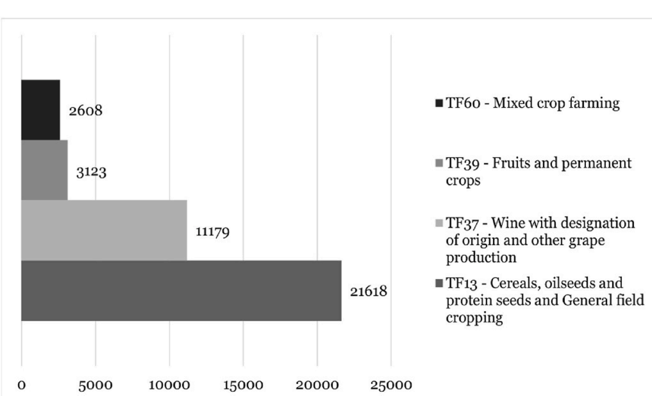

Fig. 1. Observation per type of farming (TF) in our sample.

4.3. Predicted probabilities

This section presents predicted probabilities from our model. We compute the predicted probability according to the interaction between TE and environmental indicators. Fig. 2 displays the predicted proba-bility of joining AES02–Crop Rotation based on competing val-ues be-tween TE and Crop Diversity Index (CDI).

We observe that the predicted probability increases steadily with the TE if CDI $=$ 2. The same effect is also observed when CDI $=$ 1. For values of CDI $<$ 1, an increase of TE reduced the predicted probability of joining the AES02. This graph shows that a good environmental situation (crop diversity) is a prerequisite for farmers to adopt the AES02–Crop Rotation.

Fig. 3 depicts the predicted probability of joining AES08–Pesticide Reduction based on the interaction between TE and Crop Protection Index (CPI). We see that an increase in TE will reduce the predicted probability for any values of CPI, as in our main results. It also shows that there is synergy between the economic and environmental perfor-mances affect-ing negatively the probability of joining an AES.

For AES09–Fertilization, Fig. 4 shows that an increase in TE im-proves the predicted probability when FI $=$ 2. When FI is low (1 or below), an increase in TE will reduce the pre-dicted probabilities. The antagonism revealed by our main results are displayed in the pre-dicted probabilities.

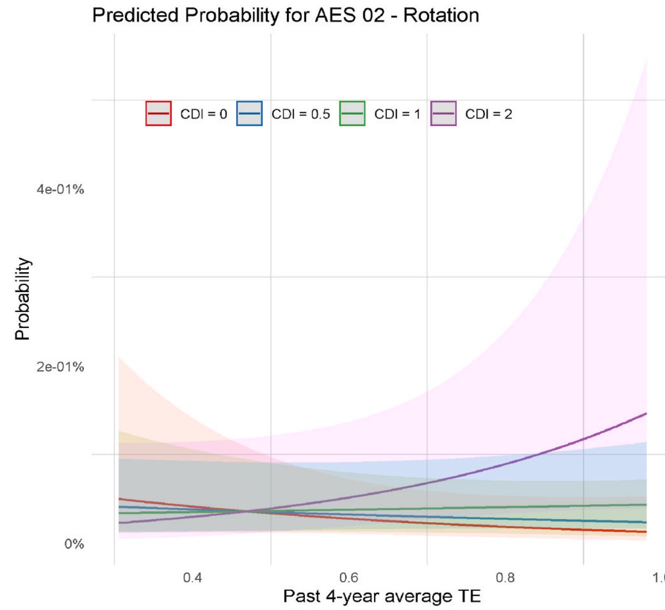

Fig. 2. Predicted probabilities for AES02–Crop Rotation based on the interaction between TE and Crop Diversity Index (CDI).

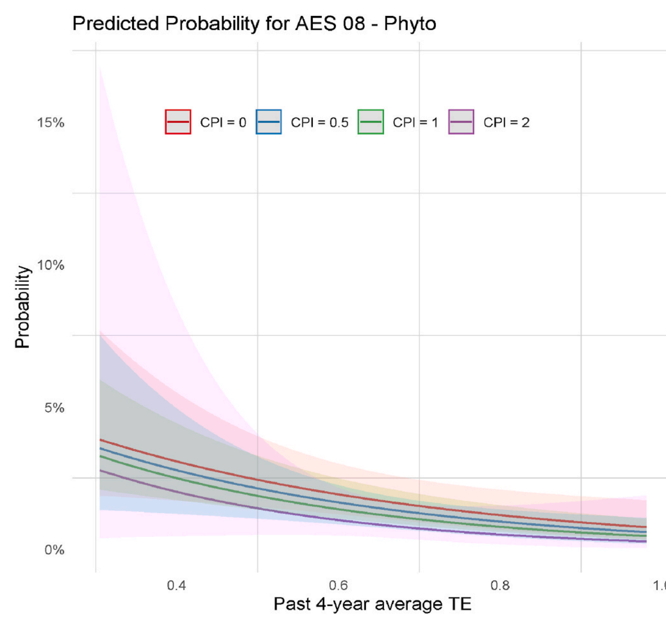

Fig. 3. Predicted probabilities for AES02–Crop Rotation based on the interaction between TE and Crop Protection Index (CPI).

4.4. Robustness checks

To check the robustness of our result, we propose alternative meth-odologies to FLAC regression. First, we use the rare event logistic regression (Relogit) model from King and Zeng.

(2001). Relogit models are also known to account for the small sample bias and were used by Latruffe and Nauges (2014). Second, we use a simple logit model to estimate the effect of TE and environmental indicators on the probability of adopting different AES. Even if the logit model might not be adapted to our sample, as we have low participation rates, it might be convenient, especially for distinguishing the amount of bias with our main estimation. The results are presented in Table C6, Table C7 and Table C8 for the Relogit model and in Table C9, Table C10 and Table C11 for the logit model in the appendix. The signs and

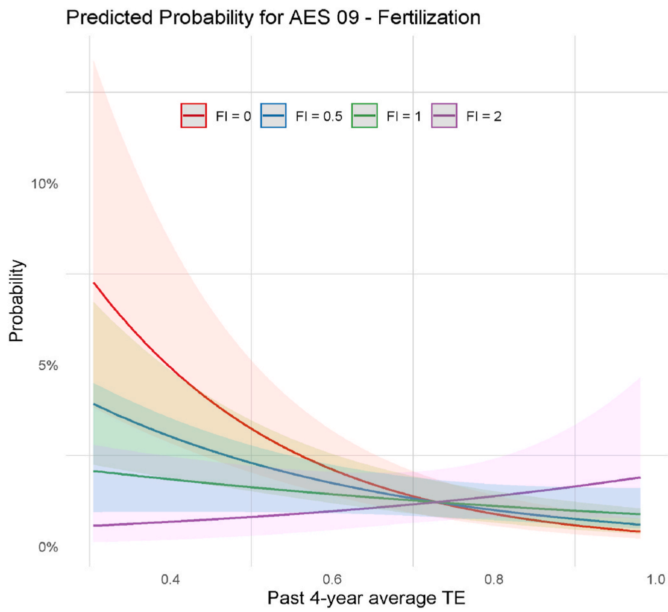

Fig. 4. Predicted probabilities for AES09–Fertilization based on the interaction between TE and Fer-tilizer Index (FI).

significance remain the same for the two models when compared with our main FLAC estimations. Even though these two models do not offer the best specification for the particular case of our sample, their results can give us confidence in our main estimations.

We also estimate non-linear specification with the household head age and TE. The re-sults, presented in Table C29, Table C30, Table C31 for the household head age, and in Ta- ble C32, Table C33, Table C34 for TE, did not provide evidence for non-linear effect.

Apart from our main results, we also run our main estimations with the adoption rate at the cantonal level. The adoption rate allows us to capture neighboring effects already documented in the literature. Results are presented in Table C26, Table C27 and Table C28, respectively for AES02–Crop Rotation, AES08–Pesticide Reduction and AES09–Fertilizer. The cantonal adoption rate plays a positive and significant role in participating in AES. For all AES under study, the results show that the presence of neighborhood effect at the cantonal level can influence positively the adoption of environmental practices. This confirms previ-ous results in the literature (Defrancesco et al., 2018; Schmidtner et al., 2011). Even though the results are qualitatively similar to our main results, they should be taken with caution as we are unable to fully address potential endogeneity due to unobserved heterogeneity for instance. Indeed, the effect might be related to unobserved variables such as the existence of the agricultural chamber in the canton or the quality of land that can influence the perfor-mances and the adoption. This will affect directly the error term, leading to biased results.

5. Discussion

5.1. Linkages between TE, environmental indicators and AES adoption

Appendix Table C35 summarizes the main findings. We discuss here the main results regarding TE and environmental indicators in relation to AES adoption.

TE exhibits varied effects on AES adoption, contingent upon the specific AES and the level of environmental index. First, TE does not influence the adoption of AES02–Crop Ro-tation, while TE is found to negatively influence the adoption of AES08–Pesticide Reduction. Second, TE positively impacts the likelihood of AES09–Fertilization adoption, but solely for farms exhibiting higher fertilizer usage (Fertilization Index >1.380). Thus, initial economic performance enhances the probability of AES09 participation only among farms exerting greater environmental pressure relative to their peers.

For environmental indicators, their effects on AES adoption suggest that windfall effects might occur, *i.e.*, situation where farmers are paid to adopt practices that they would have adopted without financial support (Chabé-Ferret and Subervie, 2013; Kuhfuss and Subervie, 2018). In detail, we find that more crop-diversified farms tend to adopt AES02, while more crop-protected farms and farms that use more fertilizers do not tend to adopt AES08 and AES09, respectively. This result is particularly interesting insofar as the AESs aim at reducing the environmental impact of agricultural practices. If AES adopters have already a good en-vironmental situation, the scheme might not provide much additional environmental ben-efits. This means that the cost to cover transition to AES might be overestimated for some farms as they have already an edge in environmental practices, but also AES environmental practices will likely bring small additionality, if any, in terms of environmental benefits.

The presence of windfall effects can be attributed to the intrinsic characteristics of AES, as they are voluntary programs and farmers have the autonomy to decide whether to partic-ipate. Consequently, farmers may choose to join an AES even if they already meet, or do not require additional incentives to meet, the criteria. Some farms may only opt to join when minimal changes are needed in their practices, as demonstrated by Calvet et al. (2019) in France, illustrating a classic information asymmetry issue (Ferraro, 2008; Calvet et al., 2019). As farmers have already high environmental performance, they may not need to alter their production structure. Therefore, their participation in AES may incur minimal costs, if any, leading to windfall effects, *i.e.*, those who do not require incentives to reduce their envi-ronmental impact benefit more from AES (Chabé-Ferret and Subervie, 2013; Kuhfuss and Subervie, 2018). Furthermore, Hynes and Garvey (2009) and Cullen et al. (2021) have shown the potential impact of path dependency in AES adoption. Participants who previously en-gaged in an AES were more likely to engaged in a five-year AES contract. Even though our study is based on a first time implementation, the past environmental performance might be a indicator of environmental sensitivity. Therefore, we might have a path dependency issue that entails more reflection on the public policy design itself rather than incentives.

The results also show potential antagonism and synergy between economic and environ-mental performances in AES adoption decisions in our study, implying a potential trade-off for farmers. The trade-off between TE and fertilization usage for AES09–Fertilization might demonstrate a fear of production contraction. If farms see the AES09 requirements as too strict, they might prefer to stay conventional and wait until reaching a desirable level of pro-ductivity before entering the AES. Indeed, the AES09 is attractive for farms with high fertiliza-tion usage only when they achieve a certain level of TE (0.707). Economic performances also play a role, as evidenced by the findings regarding AES09–Fertilization, suggesting that wind-fall effects may occur more often among farms with lower TE. As AES are designed to com-pensate only for losses resulting from changes in production structures, technically efficient farms can potentially adopt eco-friendly practices while maintaining their TE. Therefore, the low level of subsidies highlighted by Skolrud (2019) will no longer be an obstacle as they are already technically efficient. Participating in AES is considered risky, especially initially, as farmers may need to alter their technologies when adopting new practices. Therefore, farm-ers with low TE may be hesitant to join the scheme. Consequently, one potential approach to mitigate windfall effects could be to enhance the economic performance (*i.e.*, TE) of farms.

5.2. Limitations and further research directions

Some limitations might be worth mentioning. For instance, production technology het-erogeneity can be an important factor in the link between AES adoption and TE, as shown by Dakpo et al. (2022). As we face a convergence problem in TE estimation, we provided het-erogeneity estimations based on each type of farming (TF). While this approach might not capture the complex heterogeneity aspect of the production system, these results might help in understanding the nuances between different types of production in our sample.

Moreover, while we address simultaneity bias, endogeneity may still exist due to omitted variables or unobserved heterogeneity. A possible way to deal with endogeneity that could threaten our results is the use of instrumental variables. A potential candidate for an instru-mental variable is wind erosion. On one hand, Prăvălie et al. (2024) have recently shown that wind erosion is a threat to land productivity in Europe. This might, in turn, affect the ability of farms to obtain the best possible outcome from their inputs, *i.e.*, TE. Additionally, it can also impact the level of fertilizer use, as farms might be more inclined to increase the fertil-izer dose following land degradation. On the other hand, directly linking wind erosion to AES adoption is challenging, as their relationship likely transits through TE and fertilizer usage. Unfortunately, the FADN is mainly centered on farms' characteristics and income and does not provide such variables (Kelly et al., 2018; Uthes et al., 2019). Integrating agronomic and geospatial data into the FADN could address this gap, enabling the computation of crucial variables like wind erosion, soil nutrient balances, and GHG emissions.

Finally, the three environmental indexes may not fully capture the complexity of agri-cultural practices' environmental effects. Nonetheless, they provide insights into pollution-generating inputs and their potential environmental impact. A promising extension of our work would be to determine an ecological footprint for the farms, as a composite indicator of their environmental performances (Ma et al., 2022).

6. Conclusion

This study fills a crucial gap by examining the influence of technical efficiency (TE) and environmental performances on the likelihood of joining agri-environmental schemes (AES) within the Common Agricultural Policy (CAP) of the EU. Using FLAC on French FADN data from 1997 to 2007, our findings reveal diverse effects of TE across different AES. While TE negatively impacts AES08–Pesticide Reduction, its effect varies depending on environmen-tal aspects for AES09–Fertilization, while being insignificant for AES02–Crop Rotation. We also identify potential windfall effects, particularly in AES08 and AES02, and for farmers with certain TE levels in AES09. Additionally, we observe significant heterogeneity between farm-ing types in AES adoption decisions.

Our findings yield valuable policy insights. The lack of sufficient incentives for farmers with higher detrimental environmental impacts to participate constitutes a significant bar-rier to increasing the additionnality of AES. To enhance AES additionnality, policymakers should refine targeting strategies and improve farmer incentives. One possible policy re-sponse would be to uniformly increase AES payments. However, this could lead to higher budgetary costs, making the AES less cost-effective.

Thus, two options to improve additionality without affecting the cost-effectiveness of AES exist. The first is to offer result-based payments (Massfeller et al., 2022), as recently dis-cussed in the CAP reform (EU-Commission, 2018). While Saint-Cyr et al. (2023) have high-lighted its limited effect on the additionality of a large bunch of Payments for Environmen-tal Services, this option seems to be a source of additionnality improvement in the specific case of AES (Wuepper and Huber, 2022). Another possible response is to propose person-alized payments by adopting a policy learning approach (Athey and Wager, 2021) based on the characteristics of the farms. This is similar to recent developments in Machine Learning (Athey, 2018), which are used to define payment allocation rules that optimize the prediction of the program's effectiveness (Andini et al., 2022; Esposti, 2024).

Additionally, improving economic performance could alleviate constraints for low-pro- ductive farms. Indeed, policymakers could also focus on enhancing TE through training and information dissemination on soil conservation practices, aligning with broader envi-ronmental and economic goals (Solís et al., 2007). These measures could rely on network-ing farmers through cooperatives and/or unions, but we expect it is important to connect farmers with research institutes in order to enhance social learning towards agroecological practices based on scientific evidence (Fouillet et al., 2022; Deperrois et al., 2023).

Finally, our results showed that farms with higher environmental performances were more likely to participate in the AES. This might also be related to path dependency (Hynes and Garvey, 2009; Cullen et al., 2021). Accordingly, a radical change in public policies de-sign could be envisaged rather than modifying the AES incentive. This might take the form of different requirement for different levels of environmental performances or low levels of conditionnality for the first implementation period with gradually increasing requirements. Integrating agronomic and geospatial data into the FADN could also enhance modeling ac-curacy, better informing policy decisions.

CRediT authorship contribution statement

ThiernoBocar Diop: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization, Data curation, Visualization. **Stéphane Blancard:** Supervision, Methodology, Project administration, Funding acquisition. **Sophie Legras:** Writing – review & editing, Project administration, Methodology, Funding acquisition. **Sébastien Marchand:** Writing – review & editing, Methodology, Supervision. **Lionel Védrine:** Writing – original draft, Supervision, Project administration, Methodology, Conceptualization, Funding acquisition, Validation, Writing – review & editing.

Declaration of competing interest

None.

Data availability

The data that has been used is confidential.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2024.121519.

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