Agri-Environmental Schemes (AESs) Adoption, Technical Efficiency and Environmental Indicator : Evidence from France

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Abstract

The agricultural detrimental effects on the environment are a source of concerns. Intensive use of pollution generating inputs has increased the level of pollution and damage to the surface and groundwater, and have deteriorated biodiversity. Public measures, such as Agri-environmental schemes (AES), have been taken accordingly. AES are voluntary payment–based measures that intend to incentivize farmers to adopt more sound environmental practices on the farm. Many studies have analysed the role of farms and farmers' characteristics on AES's participation, but none of them have examined the effects of past performance and environmental indicators on multiple AES adoption. This study intends to fill this gap by analysing the role of the farm's past average technical efficiency and environmental indicators on the probability of adopting an AES. Using a novel approach based on Firth's logistic regression with added covariate (FLAC), the results show heterogeneous effect of TE on AES adoption, possible presence of windfall effects but also neighbourhood effects.

Keywords : Technical Efficiency, Agri-Environmental Schemes, Firth's penalization, Windfall Effects, France.

JEL Codes : **Q12, Q15, Q18.**

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1 Introduction

The adverse effects of agriculture on the environment have been a concern for many actors of the sector (Gołaś et al., 2020). Indeed, agriculture practices become a source of pollution in many countries (Bostian et al., 2019). Through intensive use of pesticides and fertilizers, for instance, agriculture practices increase the level of pollution and damage to the surface and groundwater (Skinner et al., 1997) and deteriorate biodiversity (Tang et al., 2021). There have been concerns about the environment and a rise in social demand for more protection of the environmental ecosystem. These negative externalities can be seen as one of the market organization failures and legitimate the intervention of public policies. Policy-makers have then started to search for more effective strategies that can prevent negative effects of agriculture, while maintaining agricultural productivity.

In that vein, the European Union (EU) through the Common Agricultural Policy (CAP) have started reforms since 1985 to reduce the agriculture pressure on the environment and include environmental protection as a cornerstone of future agricultural policies. Agri-Environmental Schemes (AESs) have been introduced as a means of protecting the environment by either reducing the negative externalities or promoting environmental benefits through practices, while letting the Member State the liberty of deciding the actions and measures.

AESs are area-based payments contracts for five (05) years to incite change of practices on farm. It is designed to help farmers to finance the transition from conventional to more environmentally friendly farming system. The premium is computed to cover additional costs related to change practices or income loss, but also to maintain sustainable practices that have a positive impact on the environment. AES are voluntary, farmers decide themselves to enter a particular (or multiple) AES or to stay in their current state of practices. Therefore, they can decide to allocate only a certain part of their farm to AES or combined multiple AES on the farm (Chabé-Ferret and Subervie, 2013). The agri-environmental payments are co-financed by the European Community and the EU Member States (Commission, 2005). In France, the National Rural Development Programme (PNDR) mainly organizes AESs, and it is the main application of the European Rural Development Regulation (RDR). The total support devoted to AES amounts to 1.150 Million Euro, which represents 23% of the PDRN budget (Barbut and Baschet, 2005).

The environmental impact of these AES depends on two factors: the effective application of required changes in management practices and the adoption of AES by farmers. The former is considered mostly as granted (Vanslembrouck et al., 2002) and is beyond the scope of this study. We are interested in the latter, i.e. the enrolment of farmers into AES. In particular, this research aims at responding to the following question: did a farmer's past economic and environmental performances (measured by technical efficiency and environmental indicators) affect its adoption of AES in France between 2001 and 2007?

Efficiency achieved under conventional farming can indeed influence farmers to adopt more environmental friendly practices. Indeed, Latruffe and Nauges (2014) showed that past performances, proxied by past four-year average technical efficiency, influence positively conversion to organic farming in France from 2002 to 2006. The effect found to be related to farm size, as technical efficient farmers with higher farm size tend to convert more to organic farming. As far as environmental aspect is concerned, it has been shown that environmental awareness of farmers play a positive and significant role in AES adoption (Ruto and Garrod, 2009; Barreiro-Hurlé et al., 2010) and Defrancesco et al. (2018) explained that it is also correlated to the decision of remaining in AES. Indeed, high awareness and positive attitudes toward environment can increase the trust toward AES, can increase the understanding of required practices and then facilitate the compliance of AES demands.

Our paper differs from existing literature and contribute to it in two different ways. Firstly, this study is the first, to the best of our knowledge, to examine the effect of TE and environmental indicator on multiple AES in France. Latruffe and Nauges (2014) study the effect of TE on organic farming. We go beyond their studies by analysing not only the effect of TE but also environmental indicator one multiple AES. The inclusion of environmental indicators allows us to bring some clarity in the debate about windfall effect of AES, i.e. the situation where the most efficient farmers in terms of environment will be the one adopting the AES, which, in turn, will reduce its real environmental effect. Second, we adopt a novel methodology proposed by Puhr et al. (2017) based on Firth's penalization, which is more convenient for small samples and rare events and complete separation problems. To the best of our knowledge, our study is the first application of this methodology in the agricultural sector.

The remainder of this paper is organized as follows. A literature review is presented in section 2. The empirical methodology follows in section 3, first by explaining the computation of TE scores, and then by modelling the AES participation and justifying the novel methodology adopted. In section 4, characteristics that might affect the AES participation will be presented and section 5 describe the different data used. In section 6, the results for each AES under study will be presented. the robustness of our main results will be tested in section 7 and section 8 conclude with policy recommendations, limitations of our results and research avenue for future works.

2 Literature Review

In this section, we present the different determinant of AES participation found in the literature. The farm-level determinants of Agri-Environmental Schemes (AESs) have been studied quite extensively. As the AES are at the core of the agricultural policies of the EU, scholars have devoted much time to understand what can drive farmers to their adoption. Indeed, knowing better what incentivize farmers to choose AES can help better design the future AES and therefore reach more farmers for a greater impact on the environment. In that vein, Gailhard and Bojnec (2015) underlined the role of farms' size, highlighting the fact that determinants vary from one size to another. Likewise, Pavlis et al. (2016) showed that AES participation increase with the farm size. Other characteristics were found to influence AES adoption. Indeed, Mettepenningen et al. (2013) stressed the importance of flexibility in the design of contracts. This can help farmers choose the contract terms and the related payments, as it was the case in Belgium and in the USA. Defrancesco et al. (2008) showed that high dependency on farm-income and labour-intensive farming reduce the probability of AES's adoption in Italy. The participation in the AES is considered as risky, at least at the beginning. Indeed, farmers might need to alter their technologies and adopt new practices. Therefore, those who have low off-farm income may be reluctant to partake in the AES. Adoption of AES can also be influenced by environmental preference. Dupraz et al. (2003) showed that environmental awareness of farmers is a positive and significant driver of AES's adoption. This result is confirmed by Defrancesco et al. (2008, 2018). Indeed, as AES aims at promoting environment through agriculture, farmers who are more aware of environmental challenges are more likely to choose an AES. Other farms and farmers' characteristics have been found to significantly influenced the AES's adoption (see Lastra-Bravo et al. (2015) for a comprehensive literature review).

However, there is no study that analysed the effect of technical efficiency on AES adoption. Most of the studies examine the relationship between TE and organic farming. Kumbhakar et al. (2009) studied the link between technical efficiency and adoption of organic farming. They found a positive role of technical efficiency on the probability of adopting organic farming. The more efficient farmers are, the higher the probability to convert to organic farming. The authors explained this result by the existence of subsidies which are high enough to attract farmers. Subsidies offered are therefore key drivers to the conversion. Latruffe and Nauges (2014) examine the role of technical efficiency of French farmers on the conversion to organic farming. The authors used different methodologies to compute the technical efficiency (SFA, DEA, FDH). Thereafter, they used a logit model to assess the impact of TE on the adoption probability of organic farmers. Their results suggest that TE is a key driver to conversion, but the direction of the effect depends on the size and the type of production. For farmers growing field crops and operating larger farms, a higher TE increase the probability of conversion. For other types of farming, we have the opposite. This is consistent with the idea that farms level determinants of participating in AES differ across farm sizes (Gailhard and Bojnec, 2015). Also, farmers receiving more agri-environmental subsidies are more likely to convert to organic farming (Kumbhakar et al., 2009).

Skolrud (2019) studies the impact of TE, returns to scale, output diversification, and elasticities of substitution between inputs, on conversion to organic milk production in the USA. He uses a multi-output input distance function to estimate simultaneously farm-level TE, returns to scale, and direct elasticities of substitution in the first step. In the second step, he assessed the impact of the estimated technical characteristics on the probability that a conventional farm converts to organic production with a linear random utility model. His results showed that TE is negatively associated with the adoption where returns to scale, suitability between inputs (capital and land for instance) are significant positive drivers of organic adoption. He explained the negative relationship between TE and the odds of organic adoption by the absence of incentive to convert to organic farming. As they were no subsidies, the more efficient farmers were not attracted to convert to organic farming and endure the cost related to new regulations.

In this paper, we want to go a step further. The aim is to analyse the role of both technical and environmental efficiency on AES's adoption. We want to know if farmers' technical and environmental indexes are key drivers of participation in these schemes. The link between environmental efficiency and AES adoption is very important for public policies. Indeed, as shown by Defrancesco et al. (2008, 2018) and Dupraz et al. (2003) environmental awareness can play a significant role in the adoption of AES. This can be amplified in the case where the farmer is aware of the environmental problem targeted by the AES, as shown by

Giovanopoulou et al. (2011) in the nitrate pollution reducing schemes in Greece. However, if farmers have already a high environmental efficiency, they might not need to alter their structure of production. Therefore, their participation to AES will imply very few costs for them. We will then have windfall effects (Chabé-Ferret and Subervie, 2013), i.e. those who do not need incentives to reduce their effects on the environment will benefit more from the AES. Indeed, they will be receiving subsidies to adopt agricultural practices that they would have adopted even without the AES.

The closest study to our work is the paper of Latruffe and Nauges (2014). As a first difference, we will go beyond TE and include environmental indicators based on fertilizers consumption and share of permanent grassland. As a second difference, this paper will not be focused on organic farming, but rather on multiple AESs for the period 2000-2007. This will help us identify the heterogeneity of factors influencing AESs adoption. Finally, as the third difference, we will adopt a novel methodology developed by Puhr et al. (2017) that is more suitable for small samples and rare event's data. This methodology takes into account not only the small proportion of adopters, but also problems related to complete separation. We will develop further in the next section.

3 Methodology

In order to estimate the effect of TE on adoption probability, we will first compute the TE and use it in a second step as our variable of interest to assess its impact on the probability of adopting an AES.

3.1 Technical Efficiency (TE)

The literature on production frontier has documented mainly two ways of estimating the TE : deterministic and stochastic frontiers. The former is based on a production function that link the output produce thanks to the inputs at hand (Battese, 1992). It does not include a disturbance term in the specification and will not be used in this study. The latter, following Battese (1992) for panel data, is also based on a 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, X_{it} is a vector of inputs, and β is a vector of technology parameters (Kumbhakar and Lovell, 2003). The first error component, V_{it}, measures the effects of statistical noise (the effect of 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. Farmers who are the most efficient have $U_{it} = 0$, meaning that they operate on the frontier. It can be expressed as:

$$\mathrm{U_{it}} = \eta_{\mathrm{it}}\mathrm{U_i} = \{\exp[-\eta(\mathrm{t}-\mathrm{T})]\}\mathrm{U_i} \tag{2}$$

where η is an unknown parameter and $\mathrm{U_i}$ remain constant, increase or decrease with the increase in t, if $\eta = 0$, $\eta < 0$ or $\eta > 0$. U_i is assumed to be i.i.d non-negative truncations of $N(\mu,\sigma_v)$ (Battese and Coelli, 1992)

The Technical Efficiency (TE) can be defined as the ratio between the observed output at the given time period Y_{it} and the maximum possible output conditional on inputs used by the farm Y_{it}^* (Battese, 1992). It can be expressed as follows:

$$\begin{aligned} TE_{it} &= Y_{it}/Y_{it}^* \\ &= Y_{it}/Y_{it}^* \\ &= \frac{f(X_{it};\beta)\cdot\exp\{V_{it}-U_{it}\}}{f(X_{it};\beta)\cdot\exp\{V_{it}\}} \\ &= \exp\{-U_{it}\} \end{aligned}$$

In our analysis, we will use the transcendental logarithmic (Translog) function for efficiency estimates (Christensen et al., 1971, 1973), which is more flexible than the Cobb-Douglass and CES function (Corbo and Meller, 1979). It allows to have variable returns to scale and variable elasticities of substitution (Bravo-Ureta, 1985). The general form of the Translog function (Christensen et al., 1971) is as follows:

$$\begin{aligned} lnY_{it} &= \beta_0 \\ &+ \sum_{i=1}^{4}\beta_k lnX_{kit} \\ &+ \frac{1}{2}\sum_{k=1}^{4}\sum_{l=1}^{4}\beta_{kl} lnX_{kit} * lnX_{lit} \\ &+ V_{it} - U_{it} \end{aligned}$$

where $k,l = 1,..,4$ the number of inputs, lnX_{kit} is the logarithm of the input k for farm i in t, β_k and β_{kl} measure respectively the output elasticities and the complementarity of inputs. The inputs variables are: the fixed assets (K), the Utilized Agricultural Area (L), the Annual Working Hours in the farms (W) and the Intermediary Consumption (C). The output variable is the gross agricultural production. The intermediary consumption and the total assets of farms are deflated by the price indices of the means of agricultural production (base 100 in 2010). The output variable is deflated by the price indices of agricultural products (base 100 in 2010)[1].

Since U_{it} is non-negative ($U_{it} \geq 0$), inefficiency will always reduce the output Y_{it}, whereas V_{it} can have either a positive or a negative effect on the production. We also allow the efficiency to vary over time, as in Equation 2 following Battese and Coelli (1992). In details for our estimations, we will have:

$$
\begin{aligned}
lnY_{it} = {} & \beta_0 + \beta_1 lnK_{it} + \beta_2 lnL_{it} + \beta_3 lnW_{it} + \beta_4 lnC_{it} \\
& + \frac{1}{2}\beta_5 lnK_{it}^2 + \beta_6 lnK_{it} * lnL_{it} + \beta_7 lnK_{it} * lnW_{it} + \beta_8 lnK_{it} * lnC_{it} \\
& + \frac{1}{2}\beta_9 lnL_{it}^2 + \beta_{10} lnL_{it} * lnW_{it} + \beta_{11} lnL_{it} * lnC_{it} \\
& + \frac{1}{2}\beta_{12} lnW_{it}^2 + \beta_{13} lnW_{it} * lnC_{it} \\
& + \frac{1}{2}\beta_{14} lnC_{it}^2 \\
& + V_{it} - U_{it}
\end{aligned}
$$

However, SF methods have some drawbacks. Indeed, it supposes that a known relationship between variables at hand. When we do not have any idea about the relationship, we might have misspecification errors. Therefore, we combine SFA methods with DEA.

Data Envelopment Analysis (DEA) can be defined as a data-oriented approach used to assess the performance of Decision-Making Units (DMUs), which produce multiple outputs based on multiple inputs (Cooper et al., 2011). Here, there is no parametric specification imposed. Rather, the idea is to construct a frontier thanks to linear programming and efficiency is measured based on the distance to that frontier. Observations which are on this frontier are considered as efficient and have a score of one. The one below are considered as non-efficient and their scores are lower than one. DEA is well suited when we do not know the functional form of the link between variables. The mathematical program for the output orientation can be written as follows:

[1]The price indices are obtained from The National Institute of Statistics and Economic Studies (INSEE). Each of the input has its own index and that index is used to deflate the corresponding variable.

$$
\begin{aligned}
&\beta^* = \max \beta \\
&\text{subject to} \\
&\sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{io} \quad i = 1,2,\ldots,m \\
&\sum_{j=1}^{n} \lambda_j y_{rj} \geq \beta y_{ro} \quad r = 1,2,\ldots,s \\
&\sum_{j=1}^{n} \lambda_j = 1 \\
&\lambda_j \geq 0 \quad j = 1,2,\ldots,n
\end{aligned}
\tag{3}
$$

where x_{ij} is the amount of input i consumed by the farmer j, y_{rj} is the output y_r produce by the farmer j, β is the proportionate increase the farmer should achieve in order to be efficient and λ_j is the weight for each farmer j. If $\beta = 1$, it means that there is no room for improvement. Therefore, the farmer is efficient. If $\beta > 1$, the same input could be used to produce a greater amount of output, the farmer is considered as inefficient.

One drawback of the non-parametric methods is they are very sensitive to outliers (atypical observations). In order to deal with this problem, we first start by a manual processing of data at hand. Then, we used the procedure of outliers detection and removal proposed by Wilson (1993). This procedure is based on Andrews and Pregibon (1978) statistic to identify the relative importance of deviant and/or influential observations in the sample. The idea is to measure the relative change of the sample due to the deletion of the outliers. The statistic computed will be a ratio of the geometric volume of the sample after deleting deviant observations and the geometric volume of the original sample. A small ratio indicates that the i observations deleted can be considered as outliers and can influence greatly on the estimates.

Another drawback of DEA is their sensitivity to sampling variation. Indeed, DEA is a benchmarking technique and the true production function, from which efficiency are computed, is estimated but not observed (Simar and Wilson, 1998). Therefore, a variation of the sample at hand can modify the estimate of the true production frontier and therefore the efficiency scores. To obtain bias-corrected estimation of efficiency measures, we adopt the bootstrap procedure of Simar and Wilson (1998). Indeed, bootstrap can help us analyse the sensitivity of the TE estimates. The idea behind the bootstrap procedure is to simulate data, through re-sampling for instance, and apply the estimator to the re-sampled data. We can describe the procedure as follows[2]: first, we compute the TE scores following Equation 3; second, a random sample is generated from the TE scores estimated; third, pseudo-samples are generated conditionally on output and on the bootstrapped inputs of observations corresponding to TE scores in the random sample generated; fourth, we can then compute the bootstrap estimates of TE scores (Simar and Wilson, 1998). This procedure is finally repeated 2000 times. With the bootstrap values computed, the bootstrap bias is derived, which is merely the difference between the expected value of the estimator and its true value (Simar and Wilson, 2000). The difference between the bootstrap values of TE scores and the bias will give the bias-corrected estimator used in our study.

In order to assess the robustness of our results, we also perform an order-m efficiency estimation (Cazals et al., 2002). The Order-m efficiency is known to be more robust to extreme values, noise and outliers than DEA and FDH, as it does not envelop all the data points (Daraio and Simar, 2007). It is among the family of partial efficiency. The idea is to draw m peers from the observations with replacement, and the benchmarking is based on the expected best performance into the sample (Tauchmann, 2012). In other words, if we consider an input-oriented efficiency, "it is the expected minimum value of input achievable among a fixed number of m firms drawn from the population of firms producing at least a level of output y; it represents another reasonable benchmark value for a firm producing a level of output y"(Daraio and Simar, 2007, p.69).

We start by computing TE for the period 1997-2007. As they might be heterogeneity between farmers, they were gathered according to their TFs. As DEA is a benchmarking technique, this helps us reduce the heterogeneity by comparing farms that are more similar.

The objective of this paper is to see the effect of past performances on the AES adoption probability. Therefore, we compute the average of the four-year TE preceding the adoption. For each farm that adopt 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 as in Latruffe and Nauges (2014).

Table 1 presents the average past four year SFA TE, the bootstrap TE and the Order-m between 1997 and 2007 for adopters and non-adopters.

The TE of SFA are higher than the TE from DEA and Order-m. It means that, when idiosyncratic shocks play a significant role in the French agricultural and, farmers performed better, when these shocks are taken into account. On average and for SFA TE, we can see

[2] A more detailed procedure of bootstrap is presented in the AppendixA.

Table 1: TE for adopters and non-adopters of AES

Type of Farming	SFA TE		Order-M TE		Bootstrap	
	Non Adopters	Adopters	Non Adopters	Adopters	Non Adopters	Adopters
TF13 - Cereals, oilseeds and protein seeds	0.705	0.754	0.380	0.337	0.253	0.176
TF14 - General field cropping	0.690	0.643	0.372	0.281	0.253	0.150
TF37 - Wine and other grape production	0.683	0.688	0.240	0.144	0.169	0.090
TF39 - Fruits and permanent crops	0.632	0.751	0.291	0.282	0262	0.152

that adopters from all the TFs, except from TF14, have a higher technical efficiency in average than non-adopters. We will use the SFA estimate for the main results and DEA and Order-m for the robustness.

3.2 Environmental Indicators

We compute two (02) environmental indexes for this study: the fertilizer ratio and the share of permanent grassland. France FADN data do not offer large possibilities in terms of environmental indicator. In fact, the environmental dimension is not well represented, as FADN is more concerned about the economic dimension (Kelly et al., 2018). This makes the use of environmental indicator complexed when using FADN data. Therefore, the indicators computed are as follows:

- *Fertilizer Ratio (FR)* : we derive the consumption of fertilizer by deducing inventory change to the fertilizers expenses. The resulting consumption was divided by the Agricultural production to obtain the consumption per unit produced. Thereafter, we compute the average consumption per unit produced for each TF and calculate the ratio of consumption per unit produced of the farm over the average consumption per unit produced of its TF:

  $$FR_i = \frac{X_i}{\bar{X}}$$

  with X_i being the fertilizer consumption per unit produced of the farm i and $\bar{X}$ the average fertilizer consumption per unit produced of the related TF.

  If FR_i is > 1, the farm is using more fertilizers than the average of its TF. Even though the average of the TF might not be completely explicit in terms of environmental impact, being above one means that the farm exert a greater negative impact on the environment compared to its peers. Therefore, this ratio highlights, somehow, the intensity of usage in terms of fertilizers. This is a negative indicator, meaning that a higher value highlights a negative impact on the environment.

- *Share of Permanent Grassland (SPG)* : the RICA database contains information on the unproductive permanent grassland area (Surface Totale en Herbe (STH)) for each farm. The unproductive permanent grassland are natural grassland or sown for at least 5 years. They are used mainly for grazing of livestock or fodder production. In France, they are assimilated to permanent grassland, which are valued for their capacity to form sustainable carbon sinks (Kirsch, 2017). This variable is divided by the UAA of the farm to obtain the share of permanent grassland as in Bareille and Dupraz (2020) and Kirsch (2017):

$$SPG_i = \frac{STH_i}{UAA_i}$$

  It is a positive indicator, the higher the share of unproductive grassland, the greater the positive impact on the environment.

These measures have drawbacks that we are aware of. For instance, a farm can use fewer fertilizers but more of other substances that can be more harmful to the environment. The ratio of fertilizer use does not take into account this aspect. We would rather prefer to see this ratio as a proxy of the intensity of fertilizer use. In addition, as the intensity also determines the effect on the environmental, we believe that this ratio allows capturing, somewhat, the environmental aspect of the farming system.

3.3 Modelling Participation to AES

Agri-environmental schemes (AES) are voluntary measures proposed to farmers. They have decided whether to partake in an AES and then received a subsidy or to do not participate in. Farmers will choose the option that gives them a better utility.

Let's $U_{i0} = \mathbf{X}'_{i0}\beta + \varepsilon_{i0}$ be the utility of not participating, and $U_{i1} = \mathbf{X}'_{i1}\beta + \varepsilon_{i1}$ the utility associated to the participation in an AES, with $\mathbf{X}'_i$ the vector of characteristics of farmers and ε_i the stochastic part of the utility. A farmer will choose to partake in if : $U_{i1} \geq U_{i0}$ i.e. the expected net utility of participating in AES is higher than the expected utility of not participating. Unfortunately, we are not able to observe both utilities. If farmers choose AES, we will only see U_1 and if they don't, we will observe U_0. Therefore, the only aspect that can be observed is the decision taken by farmers. They will choose whether to enter in AES or not. This is a classic dichotomous choice problem in economics.

Let us:

$$V_{it} = \mathbf{X}'_{it}\beta + \xi_{it} \tag{4}$$

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

$$d_{it} = Prob(V_{it} > 0) = \mathbf{F}(\mathbf{X}'_{it}\beta) + \upsilon_{it} \tag{5}$$

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

In our sample, we have a few adopters, which gives rise to the small sample problems. The problems of small sample bias are common in binary outcome models and provoke infinite estimates and probability fitted to 0 or 1. It can be due to either rare events or small data sets. Moreover, whenever these problems are combined with complete separation, the coefficient estimates and probabilities will suffer more from the analytic bias. Separation problem occurs if a variable or a linear combination of variables can perfectly separate the responses and the non-responses (Heinze and Schemper, 2002). It leads to an infinite Maximum Likelihood (ML) estimate of the effect of the variable responsible for the separation.

One solution is the modification of the score function of logistic regression. The idea is to apply the Firth correction bias for the ML in the case of logistic regression. Practically, this method consists of using a penalty terms in ML function that produces parameters estimates and standards errors. The penalty term introduced is known as the invariant prior of Jeffreys (1946), i.e. the square root of the Fisher's information matrix determinant. As the penalty terms is asymptomatically negligible (Puhr et al., 2017), i.e. converge to 0, Firth's penalized likelihood is well suited for small sample bias (Firth, 1993).

Puhr et al. (2017) have shown recently that "... in the situation of rare events, Firth's penalization is prone to overestimate predictions" (Puhr et al., 2017, p.2304). They have proposed the Firth's logistic regression with intercept-correction (FLIC) and Firth's logistic regression with added covariate (FLAC). The former excludes the intercept in the penalization and generates better probability predictions. The latter discriminates original and pseudo-observations by creating an alternative formulation of Firth's estimation. An augmented data set is created based on the original observation and two pseudo-observations with a weight for each of them while the other covariate are held constant and the binary response values are set to $y = 0$ and $y = 1$. Puhr et al. (2017) showed that the FLIC and FLAC correction of Firth's penalization outperformed the King and Zeng (2001) procedure adopted by Latruffe and Nauges (2014) especially in terms of probability estimates. We will then use the FLAC procedures in our main estimation as recommended by Puhr et al. (2017).

4 Characteristics Affecting Participation in AES

The literature have identified many characteristics that influence the AES adoption. Lastra-Bravo et al. (2015) and Pavlis et al. (2016) offer an extensive literature review of main drivers of AES participation and Table B4 summarize the effects found for all the characteristics under study as well as the expected sign in our results. Hereafter, we will present the characteristics used in this study.

4.1 Technical Efficiency

We assume that technical efficiency could play a significant role in the farmer's decision to partake in AES. We define technical efficiency as the ability to produce the highest possible agricultural products given the levels of inputs used (output orientation). Indeed, farmers who are technically efficient might be more at ease with a novel technology of production. As the AES should only compensate the loss due to the change of the production structure, farmers technically efficient can oversee a way to adopt eco-friendly practices while keeping their technical efficiency. Therefore, they will face little reduction, if they do, when partaking in AES. Latruffe and Nauges (2014) showed that technical efficiency is a significant driver to organic farming, which is among the AES proposed in France.

However, farmers can have doubts about the change that will happen with participation in AES. Indeed, they might be afraid to lose their efficiency as they lower the use of some inputs (pesticides and crop protection product for instances). It will be the case, especially if their efficiency depends largely on these inputs. Indeed, farmers may be only be concerned with the production of the output and not the impact it will have on the environment. If they tend to produce the final product in detriment to a large amount of these inputs, they might be considered technically efficient as well. Therefore, they will be less likely to partake in an AES insofar as it might reduce their polluting generating input and their efficiency.

4.2 Environmental Indicator

Environmental performance can be either positive or negative drivers to AES. On the one hand, farmers who are already efficient environmentally can decide to do not enrol themselves in an AES because they have already reached desirable sustainable practices. Therefore, participation in AES will be another constraint that they do not need. On the other hand, farmers who are better off at using pollution-generating inputs can also choose an AES for different reasons. First, they might want to be more efficient and the environmental aspect of the AESs might be appealing to them. Indeed, partaking in AES can help them benefit from technical advice or certified practices that have an impact on the environment. They will see the AES as a programme that can help achieve their goals or pursuit it. Defrancesco et al. (2008) documented that AESs participation increase with personal environmental attitude, measured by the experience of sustainable practices without payments. In the same vein, Defrancesco et al. (2018) that showed attitudes and personal motivations toward environment were positively correlated to the decision of remaining in AES. Second, they might perform well in reducing their environmental impact yet being technically inefficient. This will put them in a complex situation where they are facing economic difficulties due to their favourable practices to the environment. As AES intend to cover the cost of required practices, they might see it as an economic opportunity.

4.3 Other characteristics

Some other characteristics have been shown to influence the AES adoption in the literature. Among others, we have the household head age. We expect age can have a significant impact on the decision to partake in an AES. However, the sign of the effect is ambiguous and depends greatly on the age group. On the one hand, AES require a change in a production structure to cope with the requirements imposed. Therefore, farmers need to be flexible and to adapt themselves to changes. Young farmers can fit more in this role. Indeed, they might be more concerned about the future and the environmental impact of their practices. As the negative impact of climate change will be seen mainly in the future, younger might be more inclined to change the conventional practices and shift to a more environmental-friendly production system. Pavlis et al. (2016) showed that younger landowners (below 30 years old) were more inclined to partake in AES compared to older one (more than 70 years old). They explained it because of higher flexibility, capacity for learning new knowledge and adaptation to different and new farming techniques. The same conclusion was reached by Wynn et al. (2001) who found that entrants were likely to be less aged than non-entrants in an environmentally sensitive area schemes in Scotland.

On the other hand, the age of the farm's head can be viewed as the amount of experience accumulated. As AES' participation require a shift in the production process, farmers with more experience can be more at ease when it comes to modify the production structure. Therefore, they might face less constrains than it required to choose an AES. We will then have older farmers joining more AES than youngster. Moreover, Defrancesco et al. (2008) found that resistant non-adopters and passive adopters were younger than active adopters and conditional one. This result is explained by the fact that agri-environmental measures (AEMs) proposed were more similar to conventional farming practices and therefore were more appealing to older farmers. Wilson (1997) showed that there is a difference in the motive for participation between older and younger. Younger farmers tend to participate for conservation reason, whereas older participate for economic reason. We can see that there is an ambiguity in the effect of age on participating through AESs.

Education can also play a significant role in the AESs participation. Farmers that are more educated might be more willing to partake in AES. Indeed, they might have a better learning capacity and will adapt more easily to change and requirements of AES. Giovanopoulou et al. (2011) found that farmers that are more educated had 48% more probability to adopt an AES. Similarly, Pavlis et al. (2016) found that post-primary education has a positive and significant effect on AES participation. However, Defrancesco et al. (2008) found that higher level of education did not influence the adoption. In fact, resistant non-adopters were more educated than adopters were. They explained it by the prevalence of young farmers in the non-adopter group. Therefore, the effect of education can depend on the level of education, on the age of farmers but also on the type of education. In this study, we will use general education as a proxy of the education level.

Another important characteristic is the farm size. Farm size can have a significant impact on the decision to adopt an AES. Farmers with large areas have better capacities to practise extensive farming. As extensive farming can help protect the environment and maintain biodiversity, farmers with larger size might be more willing to partake in AES. Pavlis et al. (2016)

showed AES were more appealing to farmers with large size of property. Farmers with more than 10 ha of utilized agricultural areas (UUA) tend to participate more to AES.

The expected subsidies are also an important driver in AESs participation. Farmers tend to compare the cost and benefit from participating in AES. Benefit will be the preservation of the environment, but also the subsidies received. Costs are related to the change of the production structure (reduction of the use of pollution generating inputs). Benefit related to the environment will be seen mostly long after. Therefore, farmers are more worried about the financial cost in the short run. If subsidies do not cover the cost of complying with the requirement of AESs, farmers will have little incentive to partake in. Therefore, we expect the subsidies to be a positive and significant driver of participation. The higher the subsidies received, the higher the possibility to cover costs related to AES requirements.

In the RDR1 database, we have the amount of subsidies that farmers, partaking in AES, are expecting to receive during the program. As the subsidies depend on the TF, we compute the average subsidy per ha within each TF. This average is then imputed to all corresponding observations of the TF. If the TFs of the farm is not available in our database, we choose the mean of subsidies across all TFs as a proxy.

Apart from the above-mentioned characteristics, we believe, as in Bostian et al. (2019), that a farm's financial health may be a significant driver of AES adoption. Indeed, when farms are better off in terms of finance, they are more resilient to shocks but also have more capacities to change agricultural practices and by the way encounter the cost related to it. Therefore, financial health can play be a significant role in the process of adopting an AES. We hypothesized that financial health is a positive driver of adoption. In our study, we follow Piet and Desjeux (2021) by using the ratio between operating surplus and the number of unpaid workers, i.e., the associates of the farmer. This ratio highlights the profitability of the farming activity, as it is not subject to fiscal optimization strategies (Piet and Desjeux, 2021).

Finally, there may be spatial neighbouring effect in participation. Indeed, farmers can be more willing to participate in an AES if there are more farms in the same commune that have chosen to partake in an AES as well. Defrancesco et al. (2018) showed that there exists neighbourhood effect, as an increase of 1% of the adoption rate in the municipality raise the odds-ratio of remaining in the AES by 3.3%. A similar result was found by Schmidtner et al. (2011) who stated that farmer decision to convert to organic farming is positively related to a high share of organically managed land in the same region. Therefore, the adoption rate in the commune is included to capture this potential influence on other farms. We used the Agricultural Census data in 2000 in order to obtain the total number of farms in a commune. We match it with the information on the commune of adopters in the RDR1 database and derive the adoption rate as in (Defrancesco et al., 2018).

5 Data

5.1 Data Description

The French Farm Accountancy Data Network (FADN) offers detailed microeconomics data on farms. Data related to their characteristics and income are available for a sample of farmers each year. Based on the agricultural census, strata are designed according to the type of farms (TFs) and the region. Within each stratum, a fixed number of farmers are chosen. Therefore, the procedure of selection resembles the quota sampling. As selected ones are not the same through years, the FADN is an unbalanced panel. Farmers are classified according to their type of farms (TF) but also to their economic dimension (*Classe de Dimension économique des EXploitations (CDEX)*). Small farmers that are under a specific threshold (25000 €) of Standard Gross Production are not taken into account in the survey. Therefore, the FADN database, and then the analysis hereafter, is entirely focused on commercial farms.

The data on farm characteristics are combined with those of AES from the European Rural Development Regulation (RDR). This is part of the National Rural Development Programme (PNDR) in France, which aims at improving the competitiveness of rural areas, reinforcing the agricultural and forestry sector and preserving the environment. AESs are an essential component of the Common Agricultural Policy (CAP). They are designed to impact agricultural practices. The AES-RDR1 data, which is the first planning for the period 2000–2006, gather all the different AES implemented in France. Information on the time of adoption and on the subsidies received by farmers are also provided. We merge the RDR database with those FADN data. The final database contains farmers with their respective characteristics, the year they enrolled themselves in a specific AES, if they do, and the subsidies received for the period 2000–2006. As we are interested in the effect of previous TE on adoption, the overall period of the database is 1997–2007.

In our sample, we focus only on four (04) specific types of farming (TF) which are: Specialist cereals, oilseeds and protein seeds (TF 13), General field cropping(TF 14), Wine with designation of origin and Other grape production (TF 37)[3], Specialist fruits and permanent crops (TF 39). We decide to focus on two (02) specific AES[4]: extension of the crop rotation and diversity (AES02 - Rotation) and modification of the phytosanitary treatments to reduce pollution or develop organic crop protection (AES08 - Phyto).

AES02 consists of, among others, introducing a new crop into soil, interrupting intensive monocultures with a fallow and crop diversification in the crop rotation. AES08 wants to implement biological control, establish or extend grass cover under perennial woody crops, replace a chemical treatment with a mechanical treatment, etc. These AESs aim at preserving the water quality and soil fertility, but also promote biodiversity and landscapes. They are also important in the fight against soil erosion and natural hazards. Furthermore, these AESs are more related to the TFs selected in our sample.

5.2 Descriptive Statistics

The Table 2 presents the mean, standard deviation (between parentheses) and the proportion of each variable. The name and the units of variable are described in Table B1.

The mean of agricultural output range from 246 218 € to 340 544 € with a great dispersion within each TF. The TF39 - Specialist fruits and permanent crop is more labour-intensive with a mean annual working hour of 4393 per year. The TF13 - Specialist cereals, oilseeds and protein seeds seems to be less intensive in terms of input usage per unit of UUA. We observe differences in inputs usage and outputs between TFs. This gives credit to our choice to compute efficiency score by TFs.

The Table 3 highlights differences between adopters and non-adopters of AES for inputs and outputs variables and SFA estimates.

[3]We combined the TF - 37 and TF - 38 as they are all related to vineyards.

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

Table 2: Descriptive statistics by type of farms (TF) from 1997 to 2007

Variables	TF - 13, N = 3350	TF - 14, N = 1037	TF - 37, N = 1877	TF - 39, N = 397
Agricultural Output	293551 (357269) [19731, 1745202]	340544 (398850) [8151, 1736992]	231299 (304799) [267, 1734593]	246218 (325401) [19357, 1676020]
Intermediate Consumption	137774 (167585) [5422, 1059950]	160437 (196008) [5562, 1403693]	79557 (108649) [3104, 1013044]	101690 (154279) [7118, 1052912]
UAA	108 (48) [15,334]	75 (37) [3, 199]	24 (19) [2, 167]	22 (13) [6, 71]
Annual Working Hours	2136 (842) [1200, 6836]	2713 (1810) [1236, 20096]	3244 (1498) [1200, 9716]	4393 (2564) [1462, 19424]
Fixed assets	62848 (140590) [0, 2266398]	68385 (176112) [0, 3822307]	40373 (109896) [0. 3149888]	35450 (89523) [0, 835937]
Age of the Household Head	47 (8) [21, 82]	47 (8) [26, 65]	47 (9) [21, 83]	46 (9) [16, 65]
General Education				
Prim. Educ	1610 (48%)	518 (50%)	884 (47%)	213 (54%)
Sec. Educ	1679 (50%)	506 (49%)	957 (51%)	173 (44%)
Higher Educ	61 (1.8%)	12 (1.2%)	36 (1.9%)	11 (2.8%)
Agricultural Education				
No Agr. Educ.	291 (8.7%)	50 (4.8%)	171 (9.1%)	49 (12%)
Prim. Agr. Educ	1281 (38%)	440 (42%)	668 (36%)	201 (51%)
Sec. Agr. Educ	1594 (48%)	502 (48%)	985 (52%)	145 (37%)
Higher Agr. Educ	184 (5.5%)	44 (4.2%)	53 (2.8%)	2 (0.5%)

Statistics presented: mean (SD) [Min, Max]; n (%). Statistical tests performed: t-test for continuous variables; chi-square test of independence for categorical variables. The UAA is in ha.

Table 3: Descriptives statistics for adopters and non-adopters before and after the AES implementation

Variables	Before AES (1997-1999)			After AES (2002-2007)		
	Non-Adopters	Future adopters	p-value	Non-Adopters	Adopters	p-value
Agricultural Output	652138 (502080) [18236, 1745202]	685181 (474340) [56817, 1674931]	0.4	142630 (78093) [267, 808285]	166632 (88019) [26910, 585207]	<0.001
Intermediate Consumption	285083 (238856) [5520, 1403693]	297303 (212095) [9298, 789445]	0.5	62297 (36224) [3104, 284859]	69188 (32776) [7741, 190324]	0.009
UAA	70 (51) [2, 241]	92 (54) [7, 331]	<0.001	75 (55) [2, 334]	96 (64) [9, 312]	<0.001
Annual Working Hours	2680 (1409) [1200, 15127]	2365 (1041) [1309, 6255]	<0.001	2698 (1622) [1472, 20096]	2732 (1530) [1600, 7680]	0.8
Fixed assets	133358 (223851) [0, 3822307]	176425 (235124) [0, 1063984]	0.018	25107 (65122) [0, 3149888]	35310 (47879) [0, 341639]	0.009
Fertilizers Consumption per unit produced	0.0018 (0.0017) [0.0000, 0.0226]	0.0016 (0.0010) [0.0000, 0.0053]	0.004	0.0014 (0.0017) [0.0000, 0.0474]	0.0011 (0.0007) [0.0000, 0.0038]	<0.001
Phytosanitary Consumption per unit	0.0022 (0.0025) [0.0000,	0.0015 (0.0014) [0.0003,	<0.001	0.0024 (0.0124)	0.0014 (0.0018)	<0.001

The first panel shows the difference between adopters and non-adopters before the AES implementation. Adopters and non-adopters differ significantly (p-value lower than 0.05) in all variables except the agricultural output and Intermediate consumption. Basically, adopters have more UAA but are less labour-intensive and used fewer fertilizers and phytosanitary per unit produced. They are also less inefficient technically. The AES implementation changes some aspect as adopters became more labour-intensive and have a higher agricultural production and intermediate consumption.

The Table 4 presents the number and the proportion of AESs' Adopters and Non-Adopters within each TFs[5].

Table 4: AES Adoption percentage for each type of farm from 2002 to 2007

Types of farming	Non Adopters	Adopters	Total
TF13 - Specialist cereals, oilseeds and protein seeds and General field cropping	2054 (94%)	1400 (6%)	2194 (100%)
TF37 - Wine with designation of origin and other grape production	1306 (95%)	54 (5%)	1360 (100%)
TF39 - Specilist fruits and permanent crops	224 (95%)	7 (5%)	231 (100%)
Total	3584 (94%)	201 (6%)	3785 (100%)

Farmers specialized in cereals, oilseeds and protein seeds and General Field cropping (TF13) are more represented in our database, followed by Wine with designation of origin and other grape production (TF37). Farms belonging to TF13 have a higher percentage of adoption (6%) and the overall rate of adoption is 6%. It is very small and confirms the trend about of AES measures. Only few farmers tend to adopt at least one AES.

6 Results

Table 5 and Table 6 present, respectively, the results of marginal effects for AES02-Rotation and AES08-Phyto. we compute also the pseudo R^2 McFadden and the AIC of each model in order to assess the goodness of fit of models. All variables are one-year lagged year except

[5]The proportion of adopters for each AES under study are presented in Table B2, Table B3 and **??**.

from the TE, which is a past four-year average, and the expected subsidies. The Translog specification will be presented and the DEA and Order-M specification will be used for robustness.

6.1 Results for AES02-Rotation

The results of the impact of TE and environmental indicator on the probability to adopt AES02 Rotation are presented in Table 5. There are three models estimated. They differ by the number of independent variables introduced in the model.

Table 5: Marginal Effects for adopting AES02-Rotation with Translog TE

	Model 1		Model 2		Model 3	
	Estimate	S.Error	Estimate	S.Error	Estimate	S.Error
Intercept	0.25146	18.0364	0.29391	17.91806	0.2512	18.01901
Translog TE	0.04055	2.21983			0.01418	2.37775
SPG			0.05286 **	1.18589	-0.55128 **	16.02294
SPG * Translog TE					0.85642 **	22.40545
UAA	-8,00E-05	0.00319	-0.00008 *	0.00317	-0.00012 **	0.00334
Subsidies	-9,00E-05	0.00437	-9,00E-05	0.00439	-9,00E-05	0.00436
Age	-0.00052	0.02126	-0.00057	0.02101	-0.00043	0.02181
Adoption Rate	0.09781 ***	1.35926	0.10468 ***	1.35858	0.09779 ***	1.39724
Prim. Educ	–	–	–	–	–	–
Sec. Educ	-0.01058 *	0.33172	-0.01152 **	0.33253	-0.00772	0.34098
Higher Educ	-0.03072	1.675	-0.0285	1.65479	-0.02091	1.59052
Income	0	0	0	0	0	0
EI	–	–	–	–	–	–
GAEC	0.02723 ***	0.49732	0.02732 ***	0.51108	0.02646 ***	0.51917
EARL	0.00616	0.36443	0.00682	0.3645	0.00409	0.3766
SCEA	0.01645	0.77096	0.01657	0.77509	0.01789	0.76928
Other	0.00037	1.87208	0.00048	1.86256	0.00046	1.94217
Dummy 2002	–	–	–	–	–	–
Dummy 2003	0.05142 ***	1.34831	0.05055 ***	1.34668	0.05667 ***	1.50115
Dummy 2004	-0.00642	1.89341	-0.00644	1.89391	0.00366	1.99238
Dummy 2005	0.06511 ***	1.33871	0.06429 ***	1.33622	0.07144 ***	1.49902
Dummy 2006	0.02787	1.45676	0.02751	1.45259	0.03643 *	1.60314
Dummy 2007	0.00469	1.87033	0.00366	1.8655	0.01233	1.98269
AIC	-85.244		-89.994		-93.169	
R^2 McFadden	-0.349		-0.368		-0.394	
Observations	2323		2323		2323	

Note: * p>0.10, ** p>0.05, *** p>0.01. The TE variable is four years lagged. The other variables are all 1-year lagged except from the Expected Subsidies.

For all the models, the R^2 McFadden range from -0.394 to -0.349. This tell us that our models represent an excellent fit (McFadden et al., 1977). The preferred specification is the model 3 with lower AIC and better pseudo R^2 McFadden.

The results show that the effect of the environmental indicator on the probability of adopting AES Rotation, namely the share of permanent grassland (SPG), depends on the level of TE. Hence, the environmental index play a positive and significant role for farmers who have at least 0.65 of average past-four year TE. If the farm has an average past-four TE under 0.65, the effect of the SPG will be negatively significant. In other words, the environmental performance play a positive role in partaking in the AES only if farms reach a certain level of efficiency.

Possible explanations can be as follows. Less inefficient farmers might think that adopting the AES Rotation will not decrease their efficiency. They consider themselves able to comply with the AES requirements without reducing their efficiency. Therefore, the AES will be more appealing as it for those farmers as they have high environmental performances.

In the opposite, if farmers have already a strong positive environmental impact and in the meantime are more inefficient, they will not see any advantage in joining the scheme, as they are more interested in improving their TE.

This result is particularly interesting insofar as the AESs, basically, aim at reducing the environmental impact of agricultural practices. One of the threat of this scheme is the existence of windfall effect, meaning the situation where farmers are paid to adopt practices that they would have adopted without financial support (Chabé-Ferret and Subervie, 2013). Based on our results, windfall effects may exist only for the more efficient farmers.

The farm size (UAA) seems to influence negatively the likelihood of adopting AES Rotation. The effect is significant for all the specification. It means that the AES Rotation attract more the small size farm. This effect goes against previous studies' results (Pavlis et al., 2016; Wynn et al., 2001).

The legal status of the farm play a significant role in partaking in AES Rotation. Farmers who are in a "groupement agricole d'exploitation en commun" (GAEC) are more likely to adopt AES Rotation than the reference type of holding ("Entreprise Individuelle" (EI)). Farmers from GAEC juridical status seems to be less intensive in fertilizers and phytosanitary usage according to Table B5. Therefore, they seem to be less dependent on the pollution generating input and may be more favourable to join the AES.

Another interesting result is the positive and significant impact of the adoption rate in the commune on joining AES - Rotation. This documents the existence of neighbourhood effect in AES adoption. Having more farmers who joined AES give more information about the subsidies received, but also about the requirements and potential environmental benefits, their impact on productivity and basically the risk of adoption (Dessart et al., 2019). This result confirms the one found earlier in the literature (e.g. (Defrancesco et al., 2018; Schmidtner et al., 2011)).

The household head age seems to decrease the probability of adopting the AES Rotation, but it is not significant. Likewise, the two types of education (general and agricultural) and the level of income do not have a significant effect on partaking in this AES.

6.2 Results for AES08 - Phyto

The results of AES - Phyto are presented in the Table 6. The model 3 is the preferred specification because it has lower AIC and better R-square McFadden.

The TE has a negative and significant effect on partaking in the AES. The more farmers are efficient technically, the less is the likelihood to see them joining the AES - Phyto. This result may be explained by the fact that farmers can see in the AES - Phyto a threat to their efficiency. It is mainly the case if the requirements of the scheme are perceived to be difficult. 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.

As far as the environmental indexes are concerned, they appear to affect negatively the probability of adopting AES Phyto. The effect is even significant for the fertilizer index. It means that more intense farmers in fertilizer usage, i.e. the ones who have greater negative impact on the environment, tend to do not partake in this AES.

This result also highlights the possible presence of windfall effect for AES - Phyto as in AES - Rotation. Farmers might consider that the AES - Phyto do not cover enough for the loss they will endure by joining the scheme. Indeed, the subsidies should cover the cost related to the application of requirements. However, here, we can see that the expected subsidy is not a significant driver of partaking in AES. Therefore, farmers using more polluting inputs might be reluctant due to financial costs.

The juridical status have also a significant effect in joining the AES - Phyto. Farms with GAEC status are less likely to adopt AES than the Individual Enterprise status, whereas farms

Table 6: Marginal Effects for AES08 - Phyto with Translog TE

	Model 1		Model 2		Model 3	
	Estimate	S.Error	Estimate	S.Error	Estimate	S.Error
Intercept	0.00602	1.73548	-0.04337 ***	1.23491	0.02052	1.79125
Translog TE	-0.0912 ***	2.06311			-0.10134 ***	2.13615
Fertilizer Ratio			-0.00521 *	0.23166	-0.00661 **	0.23517
UAA	5,00E-05	0.00282	0	0.0027	4,00E-05	0.00278
Subsidies	0	0.00027	0	0.00026	0	0.00026
Age	-8,00E-05	0.01849	-5,00E-05	0.01885	-6,00E-05	0.01829
Adoption Rate	0.03224	2.04973	0.03511	1.97274	0.02947	2.05661
Prim. Educ	–	–	–	–	–	–
Sec. Educ	-0.00175	0.29857	-0.00227	0.29697	-0.00251	0.29822
Higher Educ	-0.02004	1.54437	-0.02251	1.55733	-0.02086	1.53005
Income	0	0	0	0	0	0
EI	–	–	–	–	–	–
GAEC	-0.02587 **	1.41685	-0.026 **	1.4071	-0.02638 **	1.41501
EARL	0.00871 **	0.31442	0.00797 **	0.31172	0.0093 **	0.31586
SCEA	-0.01703	1.5248	-0.01879	1.50425	-0.02049	1.57358
Other	0.00259	1.07798	0.00781	1.035	0.0013	1.0811
Dummy 2002	–	–	–	–	–	–
Dummy 2003	0.00153	0.44573	0.00183	0.44419	0.00126	0.44525
Dummy 2004	-0.0378 ***	1.38087	-0.03701 ***	1.38129	-0.03806 ***	1.37641
Dummy 2005	0.00765	0.40528	0.0087 *	0.40314	0.00663	0.40633
Dummy 2006	-0.00723	0.51807	-0.00553	0.5131	-0.00821	0.51723
Dummy 2007	-0.04006 ***	1.38853	-0.03718 ***	***	-0.04094 ***	1.38004
AIC	-32.923		-23.622		-36.973	
R^2 McFadden	-0.149		-0.126		-0.164	
Observations	3566		3566		3566	

Note: * p>0.10, ** p>0.05, *** p>0.01. The TE variable is four years lagged. The other variables are all 1-year lagged except from the Expected Subsidies.

with EARL status are more likely to join AES 08 compared to EI status.

7 Robustness

In order to check the robustness of our result, we will use two other estimators of efficiency, namely DEA and Order-m. The parametric and non-parametric version of efficiency estimates are not exactly the same insofar as the parametric version take into account the statistical noise. This latter is essential in agriculture as it encompasses whether related shocks and other important factors that greatly influence the efficiency. The results of the Order-m estimations are presented in Table 7 for the AES Rotation and Table 8 for AES Phyto (Table C6 and Table C7 in AppendixC present the Bootstrap TE results).

Table 7: Marginal Effect for AES02 - Rotation with Order-m TE

	Model 1		Model 2		Model 3	
	Estimate	S.Error	Estimate	S.Error	Estimate	S.Error
Intercept	0.28709	17.82334	0.29391	17.91806	0.36601	18.41274
Order-m TE	0.01924	0.98795			0.00079	1.16195
SPG			0.05286 **	1.18589	-0.06975	3.26065
SPG * Order-m TE					0.40709 ***	9.46061
UAA	-8,00E-05	0.00319	-8,00E-05	0.00317	-0.00012 **	0.00334
Subsidies	-9,00E-05	0.00436	-9,00E-05	0.00439	-0.00011 *	0.00451
Age	-0.00055	0.02113	-0.00057	0.02101	-0.00039	0.02166
Adoption Rate	0.10332 ***	1.33613	0.10468 ***	1.35858	0.10408 ***	1.36922
Prim. Educ	–	–	–	–	–	–
Sec. Educ	-0.01038 *	0.33311	-0.01152 **	0.33253	-0.00766	0.33907
Higher Educ	-0.03219	1.67234	-0.0285	1.65479	-0.02074	1.58806
Income	0	0	0	0	0	0
EI	–	–	–	–	–	–
GAEC	0.02737 ***	0.49628	0.02732 ***	0.51108	0.02771 ***	0.51658
EARL	0.00632	0.3627	0.00682	0.3645	0.00518	0.37071
SCEA	0.01466	0.78637	0.01657	0.77509	0.01742	0.78107
Other	0.00117	1.87168	0.00048	1.86256	0.00209	1.89625
Dummy 2002	–	–	–	–	–	–
Dummy 2003	0.05044 ***	1.34214	0.05055 ***	1.34668	0.04844 ***	1.32342
Dummy 2004	-0.00749	1.88973	-0.00644	1.89391	-0.00552	1.86285
Dummy 2005	0.06419 ***	1.33099	0.06429 ***	1.33622	0.06185 ***	1.31004
Dummy 2006	0.02668	1.44929	0.02751	1.45259	0.02675	1.4272
Dummy 2007	0.00195	1.86373	0.00366	1.8655	-0.00781	1.99332
AIC	-85.367		-89.994		-95.495	
R2 McFadden	-0.349		-0.368		-0.404	
Observations	2323		2323		2323	

Note: * p>0.10, ** p>0.05, *** p>0.01. The TE variable is four-years lagged. The other variables are all 1-year lagged except from the Expected Subsidies.

Table 8: Marginal Effect for AES08 - Phyto with Order-m TE

	Model 1		Model 2		Model 3	
	Estimate	S.Error	Estimate	S.Error	Estimate	S.Error
Intercept	-0.04512 ***	1.21011	-0.04337 ***	1.23491	-0.03805 **	1.23937
Order-m TE	-0.03255 **	1.41315			-0.03216 *	1.41838
Fertilizer Ratio			-0.00521 *	0.23166	-0.00498 *	0.22569
UAA	4,00E-05	0.00304	0	0.0027	3,00E-05	0.00303
Subsidies	0	0.00026	0	0.00026	0	0.00026
Age	-1,00E-05	0.01884	-5,00E-05	0.01885	-2,00E-05	0.01873
Adoption Rate	0.03775	2.00803	0.03511	1.97274	0.03535	2.01944
Prim. Educ	–	–	–	–	–	–
Sec. Educ	-0.00202	0.29786	-0.00227	0.29697	-0.00253	0.29725
Higher Educ	-0.02124	1.55797	-0.02251	1.55733	-0.02273	1.55932
Income	0	0	0	0	0	0
EI	–	–	–	–	–	–
GAEC	-0.02592 **	1.40892	-0.026 **	1.4071	-0.02613 **	1.40428
EARL	0.00856 **	0.31488	0.00797 **	0.31172	0.00874 **	0.31476
SCEA	-0.01658	1.50555	-0.01879	1.50425	-0.01746	1.49881
Other	0.00733	1.04193	0.00781	1.035	0.00695	1.04061
Dummy 2002	–	–	–	–	–	–
Dummy 2003	0.00201	0.44401	0.00183	0.44419	0.00179	0.44311
Dummy 2004	-0.03744 ***	1.3812	-0.03701 ***	1.38129	-0.03745 ***	1.3759
Dummy 2005	0.0082 *	0.40438	0.0087 *	0.40314	0.00765	0.40409
Dummy 2006	-0.0064	0.51717	-0.00553	0.5131	-0.007	0.51603
Dummy 2007	-0.03765 ***	1.38351	-0.03718 ***	1.38437	-0.0382 ***	1.3786
AIC	-23.719		-23.622		-25.225	
R2 McFadden	-0.126		-0.126		-0.134	
Observations	3566		3566		3566	

Note: * p>0.10, ** p>0.05, *** p>0.01. The TE variable is four years lagged. The other variables are all 1-year lagged except from the Expected Subsidies.

Basically, the results from SFA and Order-m do not differ greatly for each AES under study. The interaction between SPG and TE is still significant for AES Rotation. The adoption rate and the GAEC status play also a significant role in the decision to adopt the AES. For the AES Phyto, the result are basically the same, but the significance of the TE and fertilizer ratio become 10%.

As far as the Bootstrap TE are concerned, the results differ from the SFA estimates meaning. Overall, our results from SFA are not robust for a change of efficiency estimator. This can be explained by the fact that SFA, DEA and Order-m can be quite different when it comes to measuring TE in Agriculture.

8 Conclusion

Agri-environmental schemes (AESs) are essential in the Common Agricultural Policy (CAP) of the European Union (EU). They intend to offer payment to farmers that adopt more environmentally friendly practices on farms. In this article, we study the factors affecting AESs participation. Specifically, we want to know how technical efficiency (TE) and environmental indices based on crop protection and fertilizer consumption can influence the probability of joining an AES. In order to do so, we use FADN combined with data on AES in France, and we use a new methodology named Firth's Logistic Added Covariate (FLAC), which is more suited for rare events. This study is the first to use this methodology in agricultural economics, but also it is the first paper studying the effect of TE on AESs.

The results show, first, that TE has diverse effect depending on the AES. It has negative and significant effect on AES - Phyto, but its effect depend on the environmental aspects for the AES - Rotation. Second, we documented the presence of windfall effect, i.e. a situation where farmers receive payments for practices that could have been adopted without the AESs, for farmers reaching a certain level of TE in AES - Rotation and for farmers partaking in AES - Phyto. Farmers exerting more pressure on the environment are less likely to partake in AES. Moreover, we document the presence of neighbourhood effect for AES - Rotation, showing how the adoption rate of AESs in the same commune can influence positively the participation of other farmers. Finally, the juridical status plays a significant role, with farmers have status involving many stakeholders more likely to partake in AES than farmers with individual enterprise status.

Our paper suffers from some drawbacks. Firstly, we do not fully address possible endogeneity. We address the simultaneity bias with our independent variables being lagged. However, there might still exist endogeneity due to omitted variables. Unfortunately, we do have an instrumental variable in the FADN database that will allow us to fully address it. Secondly, our environmental indices might not capture the full complexity of the environmental effect of agricultural practices. However, we believe that they, somehow, show the intensity of pollution generating inputs and therefore the potential effect on the environment. Thirdly, the low numbers of adopters make it difficult to conduct estimations by TFs.

We can derive some policy implications from our results. Indeed, farmers putting more pressure on the environment are less likely to participate in AESs according to our estimations. These results highlight a problem of targeting. If public policies want the AESs to have a greater impact on the environment, much effort should be made to better target farmers and incentivize them to join the schemes. It can be accompanied by an increase of subsidies but also more information about the schemes through trade unions or cooperatives, for instance. The results question also the additionality of the AES on the environment. To what extent the AES reduce agricultural pressure on the environment? Is it detrimental to farmers' productivity, or is it a complement? These questions seem to be an interesting research avenue that we plan to study in the near future.

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9 Appendices

AppendixA DEA-Bootstrap Details à la Simar and Wilson (1998)

We adapt the procedure presented in Simar and Wilson (1998) for the output orientation. The following steps describe it:

Step 1 : For each combination of input and output (x_k, y_k) $k = 1, \dots, n$ compute $\hat{\beta}_k$, the output efficiencies, by the linear program (cf. Equation 3).

Step 2 : Using the smooth bootstrap presented by Simar and Wilson (1998), a random sample of size n is generated from $\hat{\beta}_i, i = 1, \dots, n$ providing $\beta^*_{1b}, \dots, \beta^*_{nb}$.

Step 3 : Compute $Y^*_b = \{(x_i, y^*_{ib})\, i = 1, \dots, n\}$, where $y^*_{ib} = \beta^*_{ib} * \hat{y}_i, i = 1, \dots, n$. This is obtained from the definition of output efficiency from Farrell (1957). Y^*_b is the output correspondence set of the production frontier containing bootstrapped outputs, y^*_{ib} is the output corresponding to the bootstrapped score β^*_{ib} and $\hat{y}_i$ is the maxim feasible output conditioning on the inputs and the technology of production.

Step 4 : Compute the bootstrap estimate $\hat{\beta}^*_{k,b}$ of $\hat{\beta}_k$ for $k = 1, \dots, n$ by solving

$$
\begin{aligned}
&\hat{\beta}^*_{k,b} = \max \beta \\
&\text{subject to} \\
&\sum_{i=1}^{n} \gamma_i x_{k,b} \leq x_k \\
&\sum_{i=1}^{n} \gamma_i y^*_i \geq \beta y_k \\
&\sum_{i=1}^{n} \gamma_i = 1 \\
&\gamma_i \geq 0 \quad i = 1, \dots, n
\end{aligned}
\tag{6}
$$

Step 5 : Repeat steps 2−4, B(=2000 times here) to have $k = 1, \dots, n$ a set of robust estimates

$$\left\{\hat{\beta}^*_{k,b}, b = 1, \dots, B\right\}.$$

AppendixB Others Descriptive statistics

Table B1: Variables description and sources

Variable	Name	Description	Units	Source
Age	AGECH	Age of the farm's head	Years	FADN
Intermediary consumption	CINTR	Charges related to water, electricity, irrigation, rent, etc	Euro	FADN
Gross Production	PROBR	Production for the year plus on-farm consumption	Euro	FADN
Utilized Agricultural Area (UAA)	SAUTI	Arable lands, permanent crops, kitchen garden and permanent grassland	Ha	FADN
Annual Working Hour	UTATO	Annual Working Hour for the farm (1 Annual Agricultural Unit = 1600 h)	Hour	FADN
Farmers' education	FOGEN	The level of education of the farm's head	Categorical	FADN
AES Subsidies	MT	Subsidies received for participation in AES	Euro	MAE RDR-2000-2006
Adopt Rate	TX	Adoption Rate in each department for each AES	Rate	Authors Calculations
Agricultural Price Indices	INDEX	Price indices of agricultural products and Price indices of the means of agricultural production	Index	INSEE

Table B2: AES - Rotation adoption from 2002 to 2007

Types of farming	Non Adopters	Adopters	Total
TF13 - Specialist cereals, oilseeds and protein seeds	1452 (97.4%)	39 (2.6%)	1491 (100%)
TF14 - General field cropping	429 (98.8%)	5 (1.2%)	434 (100%)
Total	1881 (97.7%)	44 (2.3%)	1925 (100%)

Table B3: AES - Phyto adoption from 2002 to 2007

TF13 - Specialist cereals, oilseeds and protein seeds	1506 (98.9%)	16 (1.1%)	1522 (100%)
TF14 - General field cropping	421 (98.1%)	8 (1.9%)	429 (100%)
TF37 - Wine with designation of origin	554 (98.1%)	11 (1.9%)	535 (100%)
TF39 - Specilist fruits and permanent crops	162 (98.1%)	2 (1.2%)	164 (100%)
Total	2643 (98.6%)	37 (1.4%)	2680 (100%)

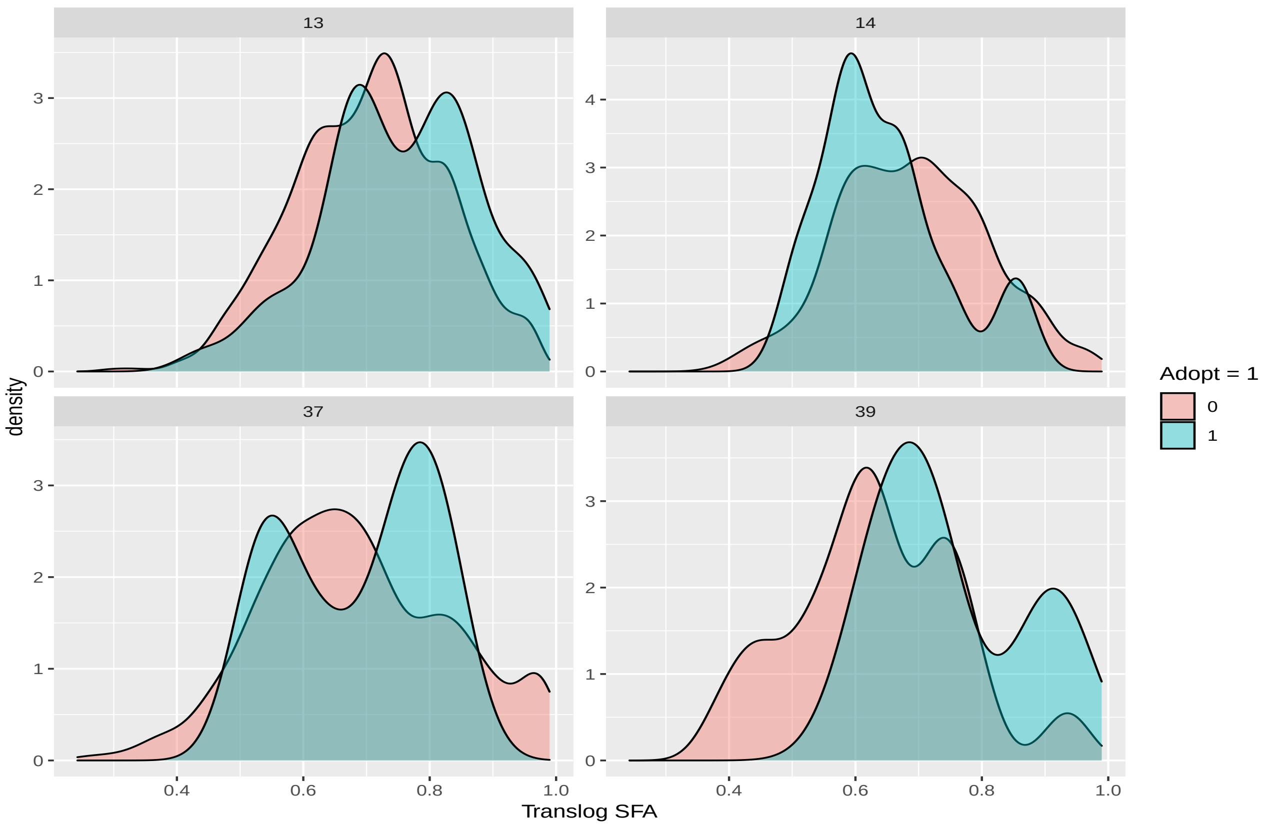

Figure B1: Density of Translog TE for Adopters and Non Adopters by TF.

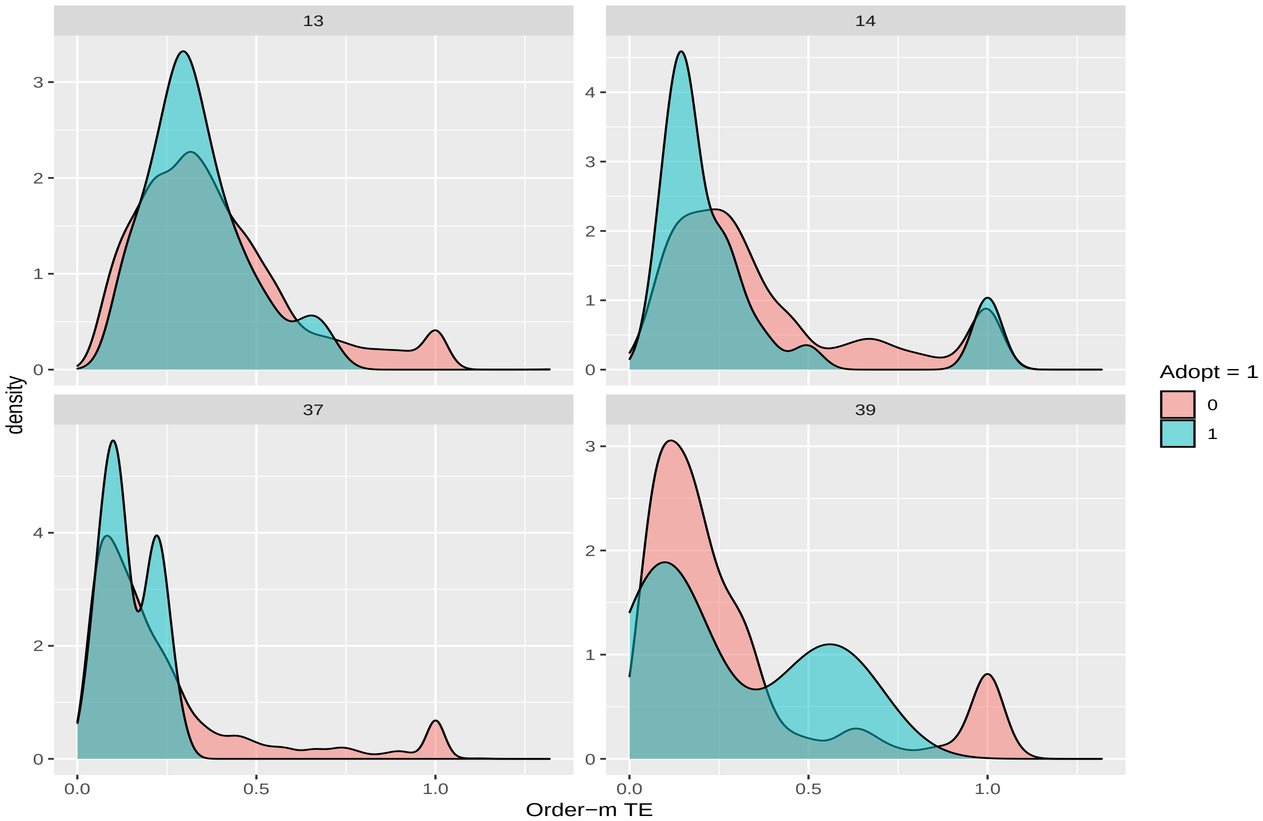

Figure B2: Density of Order-m TE for Adopters and Non Adopters by TF.

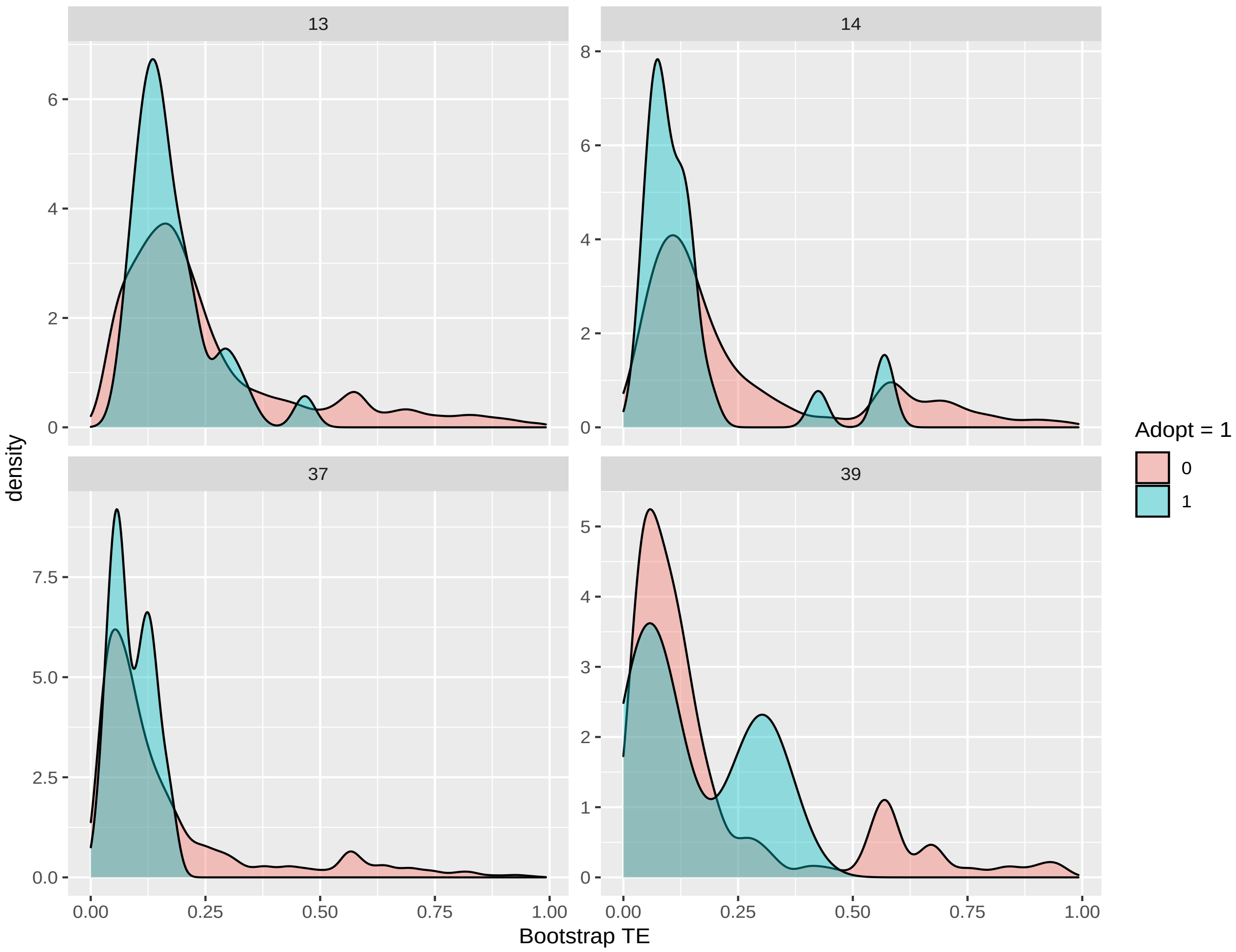

Figure B3: Density of Bootstrap TE for Adopters and Non Adopters by TF.

Table B4: Literature review on AES characteristics

Variables	Example of Studies	Sign found	Effects in the literature	Expected Effects in our study
Age	Pavlis et al. (2016); Wynn et al. (2001); Defrancesco et al. (2008); Wilson (1997)	+/-	The age effect is mixed. Some papers say that he less aged farmers are, the more likely they will partake in an AES. It is related to the thought that older farmers tend to be more conservative and less flexible. However, Defrancesco et al. (2008) found that non-adopters were younger and Wilson (1997) show that there is difference in the motive for participation between older and younger. Younger farmers tend to participate for conservation reason whereas older participate for economic reason	-
Education	Giovanopoulou et al. (2011); Pavlis et al. (2016)	+	Post primary diploma increase the probability to adopt AES	+
TE	Latruffe and Nauges (2014)	+	Latruffe and Nauges (2014) study concerns the organic farming, and they found that TE play a positive and significant role in the probability of conversion	+
Farm size	Pavlis et al. (2016); Wynn et al. (2001)	+	Large farms in terms of size are more likely to partake in AES. They will be more able to dedicate some area to AES requirement.	+
Subsidies	Latruffe and Nauges (2014); Wilson (1997)	+	Positive effect of the total Agri-environmental subsidies received, but the potential conversion subsidy was not significant. Wilson (1997) stated that payment are important factor for participation in ESA	+
Financial Health	Bostian et al. (2019)	+	When farms are better off in terms of finance, they are more resilient to shocks but also have more capacities to change agricultural practices and by the way encounter the cost related to it.	+
Adoption rate (neighbourhood effect)	Schmidtner et al. (2011); Defrancesco et al. (2018)	+	Neighbourhood effect plays a significant role in AES participation as it increase the odds' ratio of remaining by 3,3% and showed that i higher share of organic farmers is positively and significantly related to farmer decision to convert to organic farming	+
Environmental Awareness	Defrancesco et al. (2008, 2018); Dupraz et al. (2003)	+	Environmental awareness is found to affect positively the adoption of AES. Farmers who are more sensitive to environmental concerns tend to participate more than the others do.	+

Table B5: Descriptive statistics according to juridical status

Characteristic	Others, N = 177	EARL, N = 1311	El, N = 4618	GAEC, N = 460	SCEA, N = 95
Agricultural Output	470114 (488045) [21709, 1701636]	330144 (369591) [19357, 1745202]	247625 (319598) [267, 1744525]	418734 (467603) [36236, 1741606]	171150 (71785) [23971, 314128]
Intermediate Consumption	200463 (222031) [14169, 1013044]	143822 (171628) [7542, 1403693]	109564 (147741) [3104, 1059950]	174688 (204558) [9648, 871699]	76403 (44982) [17349, 194268]
UAA	61 (55) [7, 207]	100 (55) [2, 249]	65 (47) [2, 280]	102 (75) [7, 334]	81 (68) [6, 205)
Annual Working Hours	3494 (1474) [1455, 8048]	3052 (1848) [1527, 20096]	2397 (1348) [1200, 19424]	3796 (1140) [1600, 7600]	3850 (1855) [1600, 8096]
Fixed assets	97453 (173365) [0, 901161]	63635 (163758) [0, 3822307]	50893 (127925) [0, 3149888]	73515 (134235) [0, 1086721]	18898 (29090) [0, 191862]
ACHEN	38134 (63261) [0, 317389]	33402 (50573) [0, 378131]	24958 (43678) [0, 584627]	40450 (60254) [0, 331617]	12856 (13310) [0, 64967]
ACHPH	42068 (53052) [1381, 269468]	27808 (37126) [0, 352333]	21072 (31477) [0, 469709]	33495 (41958) [641, 212347]	11563 (7244) [1197, 27584]
Fertilizers Consumption per ha	555 (679) [0, 3613]	348 (482) [0, 3789]	374 (535) [0, 5073]	412 (557) [0, 3430]	146 (107) [0, 620]
Phytosanitary Consumption per ha	905 (1105) [88, 6303]	392 (653) [0, 8907]	449 (759) [0, 15269]	459 (728) [1, 6554]	232 (181) [39, 898]
Fertilizers Consumption per unit produced	0.0014 (0.0014) [0.0000, 0.0093]	0.0011 (0.0008) [0.0000, 0.0189]	0.0018 (0.0018) [0.0000, 0.0474]	0.0010 (0.0008) [0.0000, 0.0051]	0.0011 (0.0010) [0.0000, 0.0069]
Phytosanitary Consumption per unit produced	0.0029 (0.0030) [0.0004, 0.0180]	0.0014 (0.0019) [0.0000, 0.0230]	0.0026 (0.0109) [0.0000, 0.7075]	0.0015 (0.0019) [0.0000, 0.0207]	0.0019 (0.0023) [0.0002, 0.0118]

AppendixC Other Results

Table C6: Marginal Effects for adopting AES02-Rotation with Bootstrap TE

	Model 1		Model 2		Model 3	
	Estimate	S.Error	Estimate	S.Error	Estimate	S.Error
Intercept	0.75185	42.26616	0.74778	42.32572	0.74548	42.21005
Bootstrap TE	0.03459	2.12917			0.0312	2.36158
SPG			0.05599 **	1.31111	0.02523	3.62333
SPG * Bootstrap TE					0.17312	18.8841
UAA	-6,00E-05	0.00315	-7,00E-05	0.00314	-7,00E-05	0.00316
Subsidies	-0.00021	0.01022	-2,00E-04	0.01024	-2,00E-04	0.01021
Age	-0.00057	0.02189	-0.00056	0.02184	-0.00059	0.02164
Adoption Rate	0.09052 ***	1.33639	0.09062 ***	1.35345	0.09091 ***	1.34981
Prim. Educ	-	-	-	-	-	-
Sec. Educ	-0.01015 *	0.33018	-0.01036 *	0.33022	-0.00976	0.32974
Higher Educ	-0.03705	1.64644	-0.03243	1.62572	-0.03109	1.60308
Income	0	0	0	0	0	0
EI	-	-	-	-	-	-
GAEC	0.03306 ***	0.50431	0.03193 ***	0.51949	0.0318 ***	0.51679
EARL	0.00829	0.36506	0.00769	0.36606	0.00672	0.36914
SCEA	0.01438	0.7704	0.01442	0.7664	0.01147	0.78436
Other	-0.00026	1.79663	-0.00271	1.7975	0.00068	1.77066
Dummy 2002	-	-	-	-	-	-
Dummy 2003	0.05745 ***	1.34588	0.05756 ***	1.35079	0.05627 ***	1.32553
Dummy 2004	-0.0054	1.87368	-0.00435	1.87704	-0.00437	1.84676
Dummy 2005	0.07338 ***	1.33652	0.07277 ***	1.34067	0.07255 ***	1.31631
Dummy 2006	0.03128	1.45522	0.03094	1.45675	0.03215	1.43396
Dummy 2007	0.00308	1.85994	0.00376	1.86739	0.00425	1.82076
AIC	-72.546		-76.227		-72.583	
R2 McFadden	-0.318		-0.332		-0.331	
Observations	2038		2038		2038	

Note : * p>0.10, ** p>0.05, *** p>0.01. The TE variable is four-years lagged. The other variables are all 1-year lagged except from the Expected Subsidies.

Table C7: Marginal Effects for adopting AES08 - Phyto with Bootstrap TE

	Model 1		Model 2		Model 3	
	Estimate	S.Error	Estimate	S.Error	Estimate	S.Error
Intercept	-0.04683 **	1.49519	-0.03839 **	1.53276	-0.03478 *	1.55378
Bootstrap TE	-0.03759	2.55166			-0.03384	2.55958
Fertilizer Ratio			-0.00878 ***	0.29297	-0.00849 **	0.28896
UAA	2,00E-05	0.00321	0	0.00299	1,00E-05	0.00321
Subsidies	0	4,00E-04	0	0.00041	0	0.00041
Age	-7,00E-05	0.02095	-0.00011	0.02078	-8,00E-05	0.02081
Adoption Rate	0.0154	2.726	0.00708	2.76173	0.00755	2.76869
Prim. Educ	-	-	-	-	-	-
Sec. Educ	0.00365	0.33096	0.00339	0.33026	0.00333	0.32962
Higher Educ	-0.01678	1.59563	-0.01758	1.58726	-0.01745	1.58539
Income	0	0	0	1,00E-05	0	1,00E-05
EI	-	-	-	-	-	-
GAEC	-0.02205	1.40621	-0.02199	1.40857	-0.02239	1.40463
EARL	0.01184 ***	0.33231	0.01179 ***	0.33258	0.01209 ***	0.33363
SCEA	-0.0142	1.51049	-0.01631	1.51058	-0.01551	1.50514
Other	0.01094	1.08671	0.00935	1.09035	0.00881	1.0925
Dummy 2002	-	-	-	-	-	-
Dummy 2003	0.00476	0.48349	0.0045	0.48447	0.00465	0.48243
Dummy 2004	-0.0344 ***	1.3819	-0.03406 ***	1.38484	-0.03439 ***	1.37828
Dummy 2005	0.00907	0.45687	0.00922 *	0.45322	0.00816	0.45707
Dummy 2006	-0.0049	0.57466	-0.00445	0.56615	-0.00586	0.57368
Dummy 2007	-0.0345 ***	1.3866	-0.03421 ***	1.38605	-0.03505 ***	1.37989
AIC	-13.674		-19.138		-18.058	
R2 McFadden	-0.125		-0.141		-0.143	
Observations	2890		2890		2890	

Note : * p>0.10, ** p>0.05, *** p>0.01. The TE variable is four-years lagged. The other variables are all 1-year lagged except from the Expected Subsidies.