



The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search
<http://ageconsearch.umn.edu>
aesearch@umn.edu

Papers downloaded from AgEcon Search may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.

No endorsement of AgEcon Search or its fundraising activities by the author(s) of the following work or their employer(s) is intended or implied.



Citation: Le Gloux, F. & Dupraz, P. (2024). Upscaling environmental incentives in the Common Agricultural Policy: an assessment of the potential of transfers from the first to second pillar. *Bio-based and Applied Economics* 13(1): 27-48. doi: 10.36253/bae-14414

Received: February 23, 2023

Accepted: December 11, 2023

Published: May 20, 2024

Data Availability Statement: All relevant data are within the paper and its Supporting Information files.

Competing Interests: The Author(s) declare(s) no conflict of interest.

Guest Editors: Stefano Targetti, Andreas Niedermayr, Kati Häfner, Lena Schaller

ORCID

FL: 0000-0003-3645-4381

PD: 0000-0001-9910-1482

Upscaling environmental incentives in the Common Agricultural Policy: an assessment of the potential of transfers from the first to second pillar

FANNY LE GLOUX^{1,2,*}, PIERRE DUPRAZ¹

¹ SMART, INRAE, Rennes, France

² Fanny Le Gloux's affiliation moved during the peer review process to: Unit Research and Innovation, Directorate-General For Agriculture and Rural Development, European Commission, Brussels, Belgium. The information and views set out in this article are those of the authors and do not necessarily reflect the official opinion of the European Commission

*Corresponding author. E-mail address: legloux.fanny@gmail.com

Abstract. Agri-environment-climate measures and organic farming support have been the main contractual instruments promoting environment-friendly agricultural practices in the European Union since the 90s. They are insufficient in reaching significant environmental improvements, partly because underfunded. Using French panel data from the farm accountancy data network, we evaluate the impact of a budget transfer from income support to environmental incentives on contract uptake. We apply a generalised Tobit model to estimate the adoption probability and the acceptable farm-level payment triggering this adoption and simulate a transfer from direct payments to organic farming support and agri-environment-climate measures budget. Results suggest this mechanism increases adoption. Decreasing direct payments affects participation probabilities and acceptable farm-level payments, differently depending on the type of environmental contract, the type of direct payment and the farm technical orientation. We evaluate several transfer scenarios and provide ex-ante elements on how it could help reaching the Green Deal organic target.

Keywords: common agricultural policy, Tobit model, agri-environment-climate measures, organic farming support.

JEL codes: Q15, Q18, Q58.

1. INTRODUCTION

The agricultural sector accounted for 10% of the European Union's (EU) greenhouse gas (GHG) emissions for the period 1990 to 2018 and is the second largest contributor after the energy sector (EEA, 2020). The continuous intensification of agricultural activities also contributed to natural habitat degradation and dramatic biodiversity decline (Dasgupta, 2021). Behind the concept of agroecological transition lies the idea of moving away from agri-

cultural practices harming ecosystem services, in particular the systematic use of chemical inputs, towards farming systems maintaining or supporting them (Millennium Ecosystem Assessment, 2005). The EU adopted ambitious environmental targets by 2030 and 2050, in particular on the development of organic farming (OF) to reach 25% of organic agricultural land by 2030. Many levers at various scales can foster this transition. An important one is better targeting agricultural support to make agroecological farming more profitable than conventional farming (FAO et al., 2021). The Common Agricultural Policy (CAP) represented 36% of the 2019 EU's budget (58.4 billion euros) (EC, 2019) and is the main EU policy supporting environment-friendly farming practices (Coderoni, 2023). The CAP budget allocated to environmental commitments is low in comparison to income support payments (direct payments of the "first" CAP pillar), the latter including little restrictions on agricultural practices (Dupraz and Guyomard, 2019; European Court of Auditors, 2017; Grethe et al., 2018; Matthews, 2013). Following the definition of the Biodiversity Strategy for 2030 and the Farm to Fork Strategy for the agricultural and food sectors, rethinking the design of the CAP and its instruments is central to triggering the large-scale agroecological transition of farming systems (EC, 2020a, 2020c).

In this study, we develop a farm-based modeling framework to assess a reorientation of the direct payments budget specifically towards environmental contracts in France. In the 2014-2020 CAP programming period, environmental incentives were offered in two voluntary 5-year contractual schemes of the rural development pillar ("second" pillar) of the CAP: (i) support to OF, and (ii) agri-environment-climate measures (AECM). OF support are area-based payments to eligible farms undertaking a conversion towards OF, or to eligible certified organic farms for maintaining their organic practices. AECM are area-based payments to eligible farms complying with a set of management requirements targeting an environmental objective such as the maintenance of biodiversity or the improvement of water quality. OF support has proven to be effective in maintaining the relative competitiveness of OF and is a major driver of the sector development (Casolani et al., 2021; Sanders et al., 2011), while AECM are the CAP instruments the most targeted towards public good provision (Batáry et al., 2015; Dupraz and Guyomard, 2019; European Court of Auditors, 2020; Matthews, 2013). In 2019, direct payments accounted for 69% of the CAP budget (40.5 billion euros), while 8.6% (3.5 billion euros) was allocated to OF support, AECM and Natura 2000 sites altogether (EC, 2019). The literature shows that after 30

years of existence, the voluntary environmental schemes of the CAP were unsatisfactory to improve the state of the environment. The lack and unbalanced funding, as well as poorly designed instruments, led to insufficient participation and effort to reach environmental thresholds (Dupraz et al., 2009; Dupraz and Pech, 2007; Espinosa-Goded et al., 2013; Targetti et al., 2022; Zavalloni et al., 2019). In 2020, only 13% of the EU's UAA was under an AECM contract, and 6% under an OF support contract (EC, 2020b, 2020d). Rather than increasing the policy budget to raise environmental incentives, many argued in favour of rebalancing the budget allocation among the various CAP instruments (Dupraz and Guyomard, 2019; Matthews, 2013). Since the 2014-2020 CAP programming period, Member States have the flexibility to transfer up to 15% of their direct payments budget to increase support to rural development measures, including OF support and AECM (EU, 2013). In France, 7.5% of direct payments have been redirected since 2017 (MAA, 2021). For the 2023-2027 CAP programming period, it has been decided to dedicate 25% of the direct payments budget to finance a new instrument (eco-schemes) open to all farmers and supporting the voluntary implementation of environment-friendly measures (generally less ambitious than OF support or AECM contract requirements) (EC, 2021; Runge et al., 2022). Although the negotiations ruled out this option, dedicating a higher share of the CAP budget to finance more OF support and AECM was another potential (complementary) lever to upscale environmental incentives and was preliminarily evaluated by (Chatellier et al., 2021).

In this paper, we estimate an environmental contract adoption model with observed panel data from the French farm accountancy data network (FADN). We propose a generalised Tobit model estimating the adoption decision and the minimum farm-level payment triggering adoption ("acceptable" farm-level payment). We develop a simulation approach to predict the impact of a budget transfer from direct payments towards the implemented environmental contracts during the 2014-2020 CAP programming period: support to OF and AECM. Simulating a budget neutral transfer under *ceteris paribus* conditions, we decrease the direct payments received by farmers and increase the environmental payments to be distributed to OF support and AECM adopters. Our farm-based model estimates are used to predict a new contract uptake outcome in 2019. Our framework does not integrate the market effects of the simulated budget transfers. It means that we assume that induced farm input and output price changes are negligible.

We find that the transfer of an additional 7.5% (reaching the maximum transfer rate of 15% between

the two CAP pillars) of direct payments towards AECM and OF support results in an increase of participation in AECM from 11% to 23%, and in OF support from 7% to 15%. The predicted participation rate and UAA under environmental contracts increase linearly with the budget transfer rate simulated. Our model suggests that an additional transfer rate of 15.5% to reach 23% of transfer between the two pillars would allow to reach the Green Deal target of 25% of organic UAA. We observe an indirect effect on farmers' behaviour of decreasing direct payments. In particular, the probability of participating in AECM significantly increases with the amount of coupled payments for suckler cows received at the farm level (+0.1% per 1,000€). We also estimate a strong positive effect of decoupled direct payments on OF support acceptable farm-level payments (+1,039€ per 100€/ha), such that our model predicts that farms participate in OF support for lower farm-level payments after the budget transfer. We identify a differentiated impact of the budget transfer according to the type of farm, with an increased incentive for farms specialised in grazing livestock to contract AECM, and for farms specialised in cereal and field crops, permanent crops, dairy, pigs and poultry or mixed farming with field crops and grazing livestock to contract OF support.

Our first contribution is an ex-ante evaluation method of the transfer mechanism from direct payments to environmental contracts. In particular, we model the impact on adoption. To our knowledge, the effect of such a budget transfer has not yet been assessed at the farm level and for an allocation targeting environmental contracts specifically. Previous ex-ante evaluations of the reorientation of direct payments used the CAPRI (Common Agricultural Policy Regionalised Impact) partial equilibrium model (Himics et al., 2020; Schroeder, 2021; Schroeder et al., 2015), or linear programming (Gianakakis et al., 2014), to study the impact on environmental indicators aggregated for farm types and EU regions. Hence, it remains unsure how effective it can be to significantly increase the voluntary adoption of environment-friendly practices at the farm level, and what are the underlying microeconomic mechanisms. Adoption results from the confrontation of the supply of environmental commitments by farmers (farm and farmer characteristics, opportunity costs), and the demand from public authorities (budget, eligibility criteria, technical requirements, payment). Our model partly overcomes the absence of information on the diversity of contract characteristics and eligibility rules by controlling for many factors of farm heterogeneity.

Our second contribution is to capture the effect of direct payments on both the environmental contract

adoption decision and the associated acceptable farm-level payment in France under the 2014-2020 CAP framework. Beyond a direct positive effect on the participation of an increased budget available to finance environmental contracts, one can expect an indirect effect of the transfer on farmers' response to environmental incentives, resulting from the decrease of direct payments (lower income support). Monetary aspects from different sources, including direct payments, are important drivers of the decision to adopt AECM and OF (Darnhofer et al., 2019; Jaime et al., 2016; Sanders et al., 2011; Van Herzele et al., 2013). Allaire et al. (2011) and Pufahl and Weiss (2009) found different effects of direct payments coupled to production on participation in AECM, with an overall positive effect in Germany, and a marginal or negative effect in France for extensive grassland measures. Moreover, a positive effect of the decoupling of direct payments on the adoption of OF was found in Sweden (Jaime et al., 2016). This literature proved that both direct payments and environmental payments affect the decision to adopt environment-friendly practices, showing the importance of considering direct and indirect effects when evaluating the potential of a budget transfer in boosting more adoption. In our study, we complement previous studies by looking at the effect of direct payments on not only the adoption decision, but also the amount of payment to allocate to farms to trigger this adoption.

The paper is organised as follows. Section 2 presents the data, theoretical framework and econometric model of environmental contract adoption, and the procedure to simulate a reorientation of the CAP budget. Section 3 describes the estimated econometric models and presents the predicted results. Section 4 discusses the methodological approach and the findings. Finally, section 5 draws some conclusions.

2. MATERIALS AND METHODS

Our methodological approach to simulate a change of CAP budget allocation comprises three steps:

1. Estimation of the model of voluntary contract adoption under the current budget allocation.
2. Prediction of new probabilities and acceptable farm-level payments with a reduction of direct payments.
3. Starting from the farm with the highest probability to participate, allocation of the initial instrument budget plus an additional amount from the direct payments budget to participants, up to their estimated acceptable farm-level payment, until the budget is exhausted.

In this section, we present how we applied this methodological approach using observed French data from the 2014-2020 CAP programming period with two types of environmental contracts: OF support and AECM.

2.1 Data

The French Metropole FADN data for the years 2015 to 2019 were used in the study. The data represent an unbalanced panel of 36,251 farm observations and include information on the total farm-level payment (€) received for AECM contracts on the one hand, and OF support contracts on the other hand. The dataset does not include information on the surfaces enrolled in each contract type, nor on the specific measures adopted, but knowing the organic certification and organic conversion status of the farms allows us to identify whether a recipient of OF support has a conversion OF support contract or maintenance OF support contract. The national FADN is designed to be representative of

medium and large farms contributing to more than 90% of the gross production and utilised agricultural area (UAA) and covers the scope of 65% of all farms (Agreste, 2022). This data source is therefore particularly relevant for ex-ante CAP evaluations.

From 2015 to 2019, a total of around 1.6 billion was allocated to the farms of our FADN sample for engaging in AECM and OF support (Table 1). The highest budget was for 2019, with 228 million € to 11% of sample farms for AECM, 66 million € to 1.5% of sample farms for conversion OF support and 138 million € to 5% of sample farms for maintenance OF support. For that same year (2019), the French Government reported allocating a total of 244 million € for AECM, 191 million € for conversion OF support and 58 million € for maintenance OF support (DDT Ariège, 2020). In terms of participation rate, it corresponds to around 11% of metropolitan farms having contracted an AECM, 5% conversion OF support and 3% maintenance OF support (DDT Ariège, 2020; INSEE, 2022). Hence, the FADN sample describes the allocation of 93% of the

Table 1. Common Agricultural Policy budget and beneficiaries in 2015-2019¹.

Year	Direct payments	Decoupled direct payments	Coupled direct payments for suckler cows	AECM	OF support	Conversion OF support	Maintenance OF support
Budget (million €)²							
2015	7,288.4	6,095.6	667.5	165.3	122.5	23.6	99.0
2016	6,955.9	5,781.6	631.5	136.5	123.5	18.7	104.8
2017	7,124.9	5,880.6	651.6	159.4	140.0	19.4	120.6
2018	6,727.5	5,576.2	623.7	189.7	147.2	30.6	116.6
2019	6,676.0	5,561.1	655.0	227.9	203.3	65.7	137.6
Beneficiary farms (%)							
2015	85.7	84.1	24.9	6.2	5.6	0.9	4.7
2016	85.5	84.2	25.2	6.6	5.8	0.7	5.1
2017	85.1	83.6	25.9	7.8	5.6	0.6	5.0
2018	85.6	84.4	25.8	8.9	5.3	0.8	4.5
2019	85.3	84.1	26.5	10.8	6.9	1.5	5.4
Beneficiaries' UAA (%)							
2015	97.9	97.3	34.0	8.8	4.2	0.8	3.5
2016	98.4	98.1	34.1	9.1	4.4	0.7	3.8
2017	98.4	98.0	35.3	10.3	4.9	0.5	4.3
2018	98.4	98.1	35.0	11.9	4.9	0.9	4.0
2019	98.6	98.1	35.8	14.5	6.3	1.6	4.7

AECM: agri-environment-climate measures. OF: organic farming.

¹ All figures are weighted by the extrapolation coefficient of each observation.

² To compute the total policy instrument budget for year t, we corrected for delayed payments distributed at year t+1 or t+2. Less than 0.2% of the direct payments were distributed at t+1 for 2015, 2016, 2017, 2018 and 2019, and at t+2 for 2015 and 2017. Less than 8.0% of the AECM and OF support payments were distributed at t+1 for 2018 and 2019. We could not correct for 2019 instrument budgets distributed in 2021 (data not available at the time of the study).

Source: 2015-2020 French FADN data.

AECM budget and 82% of the OF support budget to a representative ratio of participants/non-participants in 2019. However, it does not represent well the repartition between conversion OF support and maintenance OF support and overestimates the allocation of OF support to certified farms relative to farms in conversion. Yet, we observed the ratio within the OF support eligible population (i.e. farms converting to OF or already certified in 2019) is well represented in the FADN, at least when it comes to the utilised agricultural area (UAA) (see Appendix A1) (Agence bio, 2020).

2.2 Theoretical model of voluntary adoption of an environmental contract

For a given type of environmental contract (AECM on the one hand, and OF support on the other hand), we represent the demand for environmental commitments from authorities during a CAP programming period by a function $\theta(M, B, \Gamma)$ describing a set of measures M (the diversity of technical requirements belonging to the contract type), a total budget B , and policy parameters Γ defining exclusion rules. For OF support contracts, M includes a diversity of measures designed for specific land use, and either for *maintaining* organic practices (maintenance OF support) or for *converting* to organic practices (conversion OF support). For AECM contracts, M includes a diversity of measures designed for a specific land use and generally an environmental target (water quality, biodiversity...). In France, not all farmers are eligible to AECM contracts and maintenance OF support contracts. The exclusion rules are based on the location of the farm and described by Γ . The confrontation of demand and supply of environmental commitments results in an uptake equilibrium such that $B = \sum_i P_i(M, \Gamma_i, a_i, k_i, e_i)$. With P_i the farm-level payment allocated to farms, Γ_i whether the farm is eligible to the environmental contract type (location in the eligible area), a_i the farm characteristics affecting eligibility to a subset of environmental measures of M (location, land use, organic certification status...), k_i other farm and farmer characteristics (economic size, surface, age, education, technical orientation...), and e_i the farm economic context (market prices, CAP support, etc).

We assume the supply of environmental commitments by farmers is driven by the profitability of adoption and eligibility. In practice, the payment for an environmental contract is delivered as a payment per hectare enrolled, and for most measures, the farmer can decide to enrol all or part of his/her farmland. However, the binary adoption decision (participation vs. no participation) is made at the farm level. Therefore, we assume

the farmer decides based on whether the total farm-level payment received for enrolling his/her profit-maximising amount of farmland in an environmental contract is sufficient to make participation profitable. The decision D_i^* of farmer i to participate and the binary participation D_i are defined as follows:

$$D_i = \begin{cases} 1 & \text{if } D_i^* \geq 0 \\ 0 & \text{otherwise} \end{cases}; D_i^*(M, \Gamma_i, a_i, k_i, e_i) = \Phi_i(m_i^*(M, \Gamma_i, a_i, k_i, e_i) - P_i^*(m_i^*, a_i, k_i, e_i)) \quad (1)$$

With $m_i^* \in M$ the characteristics of the measure(s) adopted by the farm (technical requirements, payment per hectare), $\Phi_i \geq 0$ the maximum farm-level payment the farm is eligible to for adopting m_i^* on all eligible surfaces, and $P_i^* > 0$ the minimum farm-level payment triggering the adoption of m_i^* (acceptable farm-level payment) by the farmer. $m_i^* = m_i^*(M, \Gamma_i, a_i, k_i, e_i)$ is the optimal contract uptake and the solution to the profit maximisation programme of farm i . If $\forall m_i \in M, \Phi_i(m_i, \Gamma_i, a_i, k_i, e_i) = 0$ or $0 < \Phi_i(m_i, \Gamma_i, a_i, k_i, e_i) < P_i^*(m_i, a_i, k_i, e_i)$ (the farmer is not eligible or participation is not profitable for any contract), then $D_i^* < 0$ and the farm is not participating. If $\exists m_i \in M, \Phi_i(m_i, \Gamma_i, a_i, k_i, e_i) \geq P_i^*(m_i, a_i, k_i, e_i)$, the farmer is eligible to at least one contract profitable for him or her, and the farmer decides to participate with the optimal contract uptake m_i^* such that $D_i^* \geq 0$. Φ_i represents the constraint of demand for environmental commitments faced by the farmer (the maximum payment public authorities are willing to allocate for adopting an environmental contract), while P_i^* represents the constraint of supply (opportunity costs of conventional farming and farm size). In this setting, the farm-level payment allocated to farms P_i is:

$$P_i(M, \Gamma_i, a_i, k_i, e_i) = \begin{cases} P_i^*(m_i^*(M, \Gamma_i, a_i, k_i, e_i), k_i, e_i) & \text{if } D_i^*(M, \Gamma_i, a_i, k_i, e_i) \geq 0 \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

2.3 Empirical model of voluntary adoption of an environmental contract

Following the theoretical framework, we aim to estimate a model of adoption of environmental contracts during a CAP programming period proposing the menu of measures M . Due to the censored nature of the farm-level payment, an estimation of the acceptable farm-level payment with least squares methods is not applicable. We apply a generalised Tobit model (Amemiya, 1984; Wooldridge, 2010) to simultaneously estimate two dependent variables: the decision to participate (selec-

tion equation) and the acceptable farm-level payment (outcome equation), as functions of observed determinants from a sample of participants and non-participants. We estimate one model for each type of environmental contract: OF support and AECM. While both contract types require the implementation of low-input environment-friendly practices, the implications on the farm business are different. On the one hand, adopting an OF support contract is associated with the prospect of obtaining or maintaining the organic certification of the farm and accessing the organic market in the long term. It also often implies implementing organic practices on all the farmland. On the other hand, adopting an AECM is associated with a medium-term commitment to low-input farming, and for most measures, on a flexible share of the farmland. For at least those two reasons, it appears relevant to consider that the decision-making process as well as the acceptable farm-level payment triggering the profitability of adoption differ between AECM and OF support.

With panel data, the decision to participate of farmer i in year t is represented by the latent variable D_{it}^* explained by observed covariates $Z_{it}=(a_i, k_{it}, e_{it})$ defined in the following paragraphs, environmental contract exclusion criteria Γ_i and an error term ε_{it} . To control for individual fixed effects, we rely on the Chamberlain-Mundlak device and control for the individual mean of the subset of time-varying covariates \bar{Z}_i (Mundlak, 1978; Wooldridge, 2010). α , γ , ξ and ι are the intercept and vectors of parameters to be estimated. The observed participation can be described by a binary random variable $D_{it}=\{0,1\}$ (Equation (3)).

$$D_{it}^* = \alpha + \gamma Z_{it} + \xi \Gamma_i + \iota \bar{Z}_i + \varepsilon_{it}, \quad \varepsilon_{it} \sim N(0,1), \quad (3)$$

$$D_{it} = \begin{cases} 1 & \text{if } D_{it}^* \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

Our outcome of interest is the acceptable farm-level payment P_{it}^* triggering participation, which is explained by the observed covariates $Z_{it}=(a_i, k_{it}, e_{it})$, environmental contract exclusion criteria Γ_i , the individual mean of the subset of time-varying covariates \bar{Z}_i and an error term u_{it} (Equation (4)). β , δ , η and κ are the intercept and vectors of parameters to be estimated. For identification, the outcome equation must include one less explanatory variable than the selection equation. The total farm-level payment P_{it} received by farm i at year t is observed in the data and is only different from zero for participating farms (censored variable at zero).

$$P_{it}^* = \beta + \delta Z_{it} + \eta \Gamma_i + \kappa \bar{Z}_i + u_{it}, \quad u_{it} \sim N(0, \sigma^2),$$

$$P_{it} = \begin{cases} P_{it}^* & \text{if } D_{it}^* \geq 0 \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

Based on the literature on the factors affecting AECM and OF adoption and our theoretical approach (Allaire et al., 2011; Defrancesco et al., 2008; Elliott and Image, 2018; Espinosa-Goded et al., 2013; Pavlis et al., 2016), we selected a set of variables to model contract uptake.

Explanatory variables were included to control for factors of eligibility to the diversity of environmental measures (a_{it}) of the set M defined by public authorities in the CAP 2014-2020 programming period. We include one dummy variable equal to 1 if the farm is certified organic (*organic certification*). Controlling for organic certification captures the effect of eligibility to maintenance OF support or conversion OF support, as only certified organic farms can apply to the former. Moreover, most AECM contracts are designed specifically for some land use and areas with high natural value. We control for the share of permanent grasslands in the UAA (*permanent grasslands*), and the load of grazing livestock per hectare (*grazing livestock density*). We add a dummy equal to 1 if half of the farm's UAA is located in a Natura2000 area (*Natura2000*).

Accounting for farm and farmer characteristics (k_{it}) captures heterogeneous difficulties in meeting contract requirements and preferences. We control for economic size (*standard gross production*), UAA (*utilised agricultural area*), total labour per hectare of UAA (*labour*), the share of rented land (*rented UAA*), assets depreciation per hectare of UAA (*depreciation*) and for the reception of LFA payment (*LFA*). We account for farm specialisation (1 dummy per technical orientation or group of technical orientations). Farmer's characteristics are age (*age*) and education (*general education* and *agricultural education*). In addition, we control for past participation. To do that we estimate the adoption models with 2016-2019 data (28,967 observations) and use 2015 data to construct a variable equal to 1 if the farm already adopted the environmental contract in 2015, and 0 otherwise (*observed participation in AECM in 2015* and *observed participation in OF support in 2015*). In addition, we capture part of the interaction between OF support and AECM uptake by controlling for observed participation in AECM (OF support respectively) at time $t-1$ when estimating the decision to participate in OF support at time t (AECM respectively) (*observed participation in AECM at t-1* and *observed participation in OF support at t-1*). For model identification, we exclude this variable from the simultaneous outcome equation. As we have unbalanced panel data, it has to be noted that information on past participation is missing for observations that were not sampled the year before.

Regarding the farm economic context (e_{it}), we control for the effect of CAP direct payments by including the amount of decoupled direct payments received per hectare of UAA (*decoupled payment*). We control the amount of direct payments for suckler cows at the farm level (*coupled payment for suckler cows*) as it is the production receiving the highest coupled support in France. We further control for the cost of land lease per hectare of UAA (*land lease*), and the observed fuel and lubricant price of the farm (*fuel price*), the only variable input price that can be computed with FADN data. Fuel price is likely correlated to other farm input prices on the market (mineral fertilisers), and is an indicator of opportunity costs from adopting less input-intensive agricultural practices. When fuel price is not observed for a given observation (8.4% of the sample), we replace it with the mean of the observed fuel prices from the other years for the same farm (3.3% of the sample), or the annual mean of the sample (5.1% of the sample).

Explanatory variables were included as part of Γ_i to characterise eligibility to the environmental contract types defined by public authorities in the CAP 2014-2020 programming period. Maintenance OF support eligibility depends on the region, with some not proposing those contracts in all or part of their territory after 2017. We therefore account for farm location (1 dummy variable per region) in the model. In practice, location criteria Γ_i also prevent some farms from participating in AECM based on their location. In particular, only farms located in an agri-environment-climate project (with a geographical scale smaller than the region) are eligible. We do not have enough information in the FADN to identify and exclude non-eligible farms in the case of AECM. Without information to characterise the exclusion criteria Γ_{it} , the actual model estimated for AECM is the following one:

$$D_{it}^* = \alpha + \gamma Z_{it} + i\bar{Z}_i + v_{it}, \quad v_{it} \sim N(0, 1), \\ D_{it} = \begin{cases} 1 & \text{if } D_{it}^* \geq 0 \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

$$P_{it}^* = \beta + \delta Z_{it} + \kappa Z_i + w_{it}, \quad w_{it} \sim N(0, \sigma^2), \\ P_{it} = \begin{cases} P_{it}^* & \text{if } D_{it}^* \geq 0 \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

With v_{it} and w_{it} the error terms. We have an omitted-variable bias on γ equals to $\xi \frac{\text{Cov}(Z_{it}, \Gamma_i)}{\text{Var}(Z_{it})}$ in Equation (5) and on δ equals to $\eta \frac{\text{Cov}(Z_{it}, \Gamma_i)}{\text{Var}(Z_{it})}$ in Equation (6).

Descriptive statistics of the covariates are presented in Table 2 and Appendix A2.

The latent continuous variable D_{it}^* is estimated with a Probit regression model with the binary variable D_{it} as

Table 2. Descriptive statistics of the 2016-2019 FADN sample used for the estimations (N=28,967)¹.

	Mean	Standard deviation ²
<i>Dependent variables</i>		
Participation in AECM	0.09	-
Participation in OF support	0.06	-
AECM payment (€) (D=1)	7,129.68	6,691.92
OF support payment (€) (D=1)	8,834.07	9,752.82
<i>Independent variables</i>		
Decoupled payment (€/ha)	193.42	379.42
Coupled payment for suckler cows (€)	2,179.01	4,552.01
Land lease (€/ha)	650.72	3,278.06
Fuel price (€/l)	0.63	0.12
Standard gross production (€)	173,838.99	194,712.41
Utilised agricultural area (ha)	89.14	76.73
Labour (AWU/ha)	0.24	3.23
Share of rented area	0.73	0.36
Depreciation (€/ha)	2,006.75	34,780.83
LFA	0.28	-
Age (years)	51.08	9.58
Share of permanent grasslands	0.22	0.31
Grazing livestock density (LU/ha)	0.55	1.17
Natura2000 area	0.04	-
Certified organic	0.08	-
Observed participation in AECM in 2015	0.05	-
Observed participation in OF support in 2015	0.04	-
Observed participation in AECM at t-1	0.07	-
Observed participation in OF support at t-1	0.05	-

AECM: Agri-Environment-Climate Measure. OF: Organic Farming. AWU: Annual Work Unit. LFA: Less Favoured Area. LU: Livestock Unit.

¹ All figures are weighted by the extrapolation coefficient of each observation.

² Standard deviations are reported for the non-dichotomous variables. Source: 2015-2019 French FADN.

dependent variable over the sample of participants and non-participants. The acceptable farm-level payment is estimated for each farm of the sample based on the estimation of the outcome equation using the participating farms. We control for year-fixed effects with dummy variables. The individual mean of the time-varying variables \bar{Z}_i controlling for individual-fixed effects are all the covariates included in Z_i but location in a less favoured or Natura2000 area, age, education, farm specialisation, the region, and observed participation in AECM or OF support in 2015. We also include the individual mean of the time dummies because we have an unbalanced panel (Wooldridge, 2019). We do not impose an upper limit to the estimated acceptable farm-level payments to capture the behaviour of farmers requiring a strong financial

incentive to participate. We impose acceptable farm-level payments that cannot be lower than 300€, which is the minimum required by French public authorities to start a contract (MAA, 2020).

The Tobit regression model provides estimated coefficients of the effect of the explanatory variables on both the decision to participate in an environmental contract and the acceptable farm-level payment triggering participation, as well as the correlation ρ of the error terms of the two equations. The marginal effects of each variable are computed at sample means so that coefficients can be more easily interpreted.

2.4 Simulation of CAP budget transfer

We predict the impact on contract uptake of increasing the budget allocated to AECM and OF support while decreasing direct payments in 2019. On the side of the demand for environmental commitments, it corresponds to a change in demand θ , such that the new budget in 2019 is $B_{19} + \tilde{B}_{19}$. Direct payments distributed to the sample in 2019 (DP_{19}) accounted for 6.7 billion €. The 2019 CAP budget already includes a 7.5% transfer to rural development measures (MAA, 2021). We first assume an additional transfer of 7.5% to reach 15%, which is the maximum rate allowed under current CAP regulations. The additional budget $\tilde{B}_{19} = \frac{DP_{19}}{1-0.075} * 0.075$ to be allocated is 541 million €. We keep the current budget ratio among the instruments: 53% to AECM ($\tilde{B}_{19}^{AECM} = 286$ million €) and 47% to OF support ($\tilde{B}_{19}^{OFS} = 255$ million €). The budget to be allocated to sample farms is now $B_{19}^{AECM} + \tilde{B}_{19}^{AECM} = 514$ million € and $B_{19}^{OFS} + \tilde{B}_{19}^{OFS} = 458$ million €.

In practice, criteria Γ_i prevent some farms from participating in environmental contracts based on their location. Because we do not have enough information in the FADN to identify and control for non-eligibility in the case of AECM, our simulation approach is such that all farms of the sample become eligible to AECM under a new budget allocation scenario. Another (strong) necessary assumption is that the menu of measures M (technical requirements, area payment) is not affected by a budget transfer so that the estimated effects of the farm and farmer characteristics (a_{it}, k_{it}) and the economic context (e_{it}) on the adoption decision and acceptable farm-level payments can be considered the same with a different budget allocation.

In the first stage, model estimates are used to predict farm probabilities and acceptable farm-level payments for enrolling in AECM (OF support respectively) in 2019 with a decrease of 7.5% of decoupled payments

and coupled payments for suckler cows received. In the second stage, farms are ranked according to decreasing predicted probabilities of adopting AECM (OF support respectively). In the third stage, $B_{19}^{AECM} + \tilde{B}_{19}^{AECM}$ ($B_{19}^{OFS} + \tilde{B}_{19}^{OFS}$ respectively) is allocated to farms up to their predicted acceptable farm-level payment, starting with the farm with the highest probability to the lowest, until the budget is exhausted.

While keeping the budget ratio among instruments (53% to AECM and 47% to OF support), we also conduct additional simulations to identify the rate of budget transfer that would result in enough conversion OF support uptake to reach the target of 25% of organic area in France.

3. RESULTS

3.1 Estimated models of AECM and OF support uptake

To evaluate the model quality, we compare the observed participation and farm-level payments in 2016-2019 to the predicted probabilities of participation and acceptable farm-level payments (Table 3). The AECM adoption model tends to underestimate the probability of participating in AECM. On average, the estimated acceptable farm-level payments of AECM participants are in the range of their observed farm-level payments, although the standard deviation is lower, suggesting the model does not capture well extreme values. The OF support adoption model better captures the probability to participate, on average for the sample and in particular for maintenance OF support. The acceptable farm-level payment of participants is lower than observed farm-level payments on average, particularly for conversion OF support. Similarly to AECM, the model does not capture well the more extreme values. The difference between estimated and observed data for AECM can be partly explained by an omitted variable bias. In particular, missing data on whether the farm is located in an agri-environment-climate project area (exclusion criteria) may largely explain why the probability of AECM participation is underestimated. Similarly, it seems there are important factors explaining participation in conversion OF support that the model does not capture.

The marginal effects of our covariates of interest on the latent decision to participate and acceptable farm-level payment are summarized in Table 4. The marginal effects and the coefficients of all the model covariates are reported in Appendix A3. The estimated effects describe the equilibrium of supply and demand of environmental commitments during the 2016-2019 period. The effect of each factor is a net effect and captures both the

Table 3. Comparison between observed and estimated adoption behaviour¹.

	All sample	Participants
Agri-Environment-Climate Measures		
Observations	28,967	2,442
Observed participation (discrete)	0.09	1.00
Estimated participation probability (discrete)	0.05	0.49
Observed farm-level payment (€)	-	7,130 (6,692)
Estimated acceptable farm-level payment (€)	6,194 (5,728)	7,294 (3,757)
OF support		
Observations	28,967	1,657
Observed participation (discrete)	0.06	1.00
Estimated participation probability (discrete)	0.05	0.71
Observed farm-level payment (€)	-	8,834 (9,753)
Estimated acceptable farm-level payment (€)	10,360 (8,608)	8,236 (6,718)
Maintenance OF support		
Observations	28,967	1,364
Observed participation (discrete)	0.05	1.00
Estimated participation probability (discrete)	0.05	0.83
Observed farm-level payment (€)	-	8,143 (8,881)
Estimated acceptable farm-level payment (€)	6,850 (7,563)	7,792 (6,544)
Conversion OF support		
Observations	28,967	293
Observed participation (discrete)	0.01	1.00
Estimated participation probability (discrete)	0.00	0.03
Observed farm-level payment (€)	-	12,680 (12,963)
Estimated acceptable farm-level payment (€)	10,659 (8,625)	10,708 (7,124)

¹ All figures are weighted by the extrapolation coefficient of each observation. Standard deviation in parentheses.

Source: own elaboration.

effect of the demand $\theta(M, B, \Gamma)$ each farm faces (menu of measures and payments each farm is eligible to) and the effect of the characteristics Z_{it} of the supplying farms (opportunity costs, fixed costs, number of eligible hectares...). The effect of demand on the one hand, and supply, on the other hand, cannot be isolated. In particular, the effects of the covariates on AECM and OF support acceptable farm-level payments are difficult to interpret due to the high heterogeneity of contract requirements, payments per hectare and farm size. A positive effect on the acceptable farm-level payment reveals that ceteris

paribus, the participation of a farmer is triggered either for a measure with a higher payment per hectare or for enrolling more hectares. The estimated marginal effects of the explanatory variables on the adoption decision can be more easily confronted to the literature.

The correlation estimates ρ of the selection and outcome equations are significant in both models. In particular, the acceptable farm-level payment for adopting AECM decreases with a higher probability of participation (significantly negative ρ), while the acceptable farm-level payment for adopting OF support increases with a higher probability of participation (significantly positive ρ). In other words, farms with a high likelihood of participating in AECM tend to participate for lower farm-level payments than other farms (participation is profitable for lower levels of farm-level payments), and farms with a high likelihood of participating in OF support tend to participate for higher farm-level payments than other farms (participation is profitable for higher levels of farm-level payments). This result supports our assumption that farmers behave differently regarding their adoption of AECM or OF support contracts, and confirms the relevance of estimating two different models. This difference may be explained by the fact that adopting an OF support contract often implies adopting organic practices on all the farmland and tends to be more costly to implement than AECM.

We observe that the probability of participating in OF support is not significantly affected by the amount of direct payments. Regarding AECM, while the effect of decoupled payments is also not significant, the probability of participation significantly increases with the amount of coupled payments for suckler cows received at the farm level (+0.1% per 1,000€). Decoupled direct payments have the opposite effect on OF support and AECM acceptable farm-level payments. Higher decoupled payments tend to increase OF support acceptable farm-level payments (+1,039€ per 100€/ha) and decrease AECM acceptable farm-level payments (-93€ per 100€/ha). Moreover, the model suggests the effect of coupled direct payments for suckler cows is significantly positive on AECM acceptable farm-level payments (+41€ per 1,000€) and not significant on OF support acceptable farm-level payments. We interpret the positive effect of coupled payments on AECM adoption probability as resulting from the large set of AECM contracts designed in France for grazing livestock farming systems, more likely to have suckler cows on the farm (MAA, 2020). In the literature, the effect of coupled support on AECM adoption depends on the study (Allaire et al., 2011; Pufahl and Weiss, 2009). Our results confirm those of Pufahl and Weiss (2009) in Germany, but we can expect the effect to vary according to the Member

Table 4. Generalised Tobit models estimation: marginal effects at the sample mean.

	AECM		OF support	
	Participation decision (D_i^*)	Acceptable farm-level payment (P_i^*) in 1,000€	Participation decision (D_i^*)	Acceptable farm-level payment (P_i^*) in 1,000€
Decoupled payments (100€/ha)	0.000 (0.000)	-0.093* (0.020)	-0.000 (0.000)	1.039*** (0.220)
Coupled payment for suckler cows (1,000€)	0.001*** (0.001)	0.041+ (0.009)	0.000 (0.000)	0.053 (0.011)
ρ	-0.034*** (0.005)	-	0.133*** (0.011)	-
σ	-	5.581*** (0.013)	-	6.978*** (0.020)
Number of observations	28,967	2,442	28,967	1,657
Log-likelihood		-504,317		-318,531
AIC		1,008,948		637,376
Schwarz criterion		1,010,826		639,254
Pseudo-R2 (McFadden)		0.241		0.378

Significance levels: *** p-value <0.001, ** p-value <0.01, * p-value<0.05, + p-value<0.1. Standard errors in parentheses. AWU: annual work unit. LU: livestock unit.

Source: own elaboration.

States and the set of AEPM contracts that were designed according to local priorities.

The effects of the other covariates controlling for the economic context (fuel price, land lease), and the farm and farmer characteristics are also significant, in particular on participation probabilities. Most findings confirm the literature. For instance, the negative effects of age, the cost of land lease and depreciation on AEPM adoption probability are coherent with (Andreoli et al., 2022; Damianos and Giannakopoulos, 2002; Defrancesco et al., 2018; Mack et al., 2020; Pavlis et al., 2016; Pufahl and Weiss, 2009; Uthes and Matzdorf, 2013; Vanslembrouck et al., 2002; Zimmermann and Britz, 2016). The positive effects of the economic size, UAA, shares of grasslands and rented area, location in a Natura2000 area, education and past participation on AEPM adoption probability also confirm previous findings (Allaire et al., 2011; Andreoli et al., 2022; Chatzimichael et al., 2014; Damianos and Giannakopoulos, 2002; Defrancesco et al., 2018; Giovanopoulou et al., 2011; Mack et al., 2020; Pavlis et al., 2016; Pufahl and Weiss, 2009; Uthes and Matzdorf, 2013; Zimmermann and Britz, 2016). Regarding OF support adoption, the negative effect of age and the positive effects of general education and being located in a less favoured area are coherent with other studies (Kallas et al., 2010; Koesling et al., 2008; Läpple and Rensburg, 2011). Similarly, to the literature (Andreoli et al., 2022; Koesling et al., 2008; Mack et al., 2020; McGurk et al., 2020), we observe that the farm specialisation and region are significant factors of adoption for both OF support and AEPM. As expected, we find that a higher fuel price increases the probability of adopting an environmental contract. *Ceteris paribus*, we also see that participation in AEPM (OF

support respectively), significantly decreases if the farm participated in OF support (AEPM respectively) the year before. We also find some surprising results. We find a negative effect of location in a less favoured area on the probability of participating in AEPM, which differs from previous results (Allaire et al., 2011; Andreoli et al., 2022; Mack et al., 2020; Zimmermann and Britz, 2016). Other unexpected results are the negative effect of agricultural education and the positive effect of the grazing livestock load on the probability of participating in OF support (Koesling et al., 2008; Läpple and Rensburg, 2011).

A finding of this study is that the adoption behaviour of AEPM and OF support differs. In addition to differences regarding the effects of direct payments, we find opposite effects of some covariates on the probabilities of participation in AEPM and OF support (agricultural education, location in a Natura2000 or less favoured area, economic size, depreciation, cost of land lease and share of grasslands) on the probabilities of participation in AEPM and OF support. On the supply side (farmers), it can be explained by the fact that the implications of both types of contracts are different. One is the prospect of a long-term commitment to OF, while the other is a mid-term commitment (5 years). On the demand side (public authorities), the defined eligibility rules result in some contract types and measures not being open to all types of farms, driving or constraining farmers' behaviour.

3.2 Results of the simulations

The predicted impact on farmers' uptake of environmental contracts of a transfer of an additional 7.5%

(reaching the maximum transfer rate of 15% between the two CAP pillars under current regulations) of direct payments to AECM and OF support in 2019 in France is presented in Table 5. Participation in AECM increases from 11% to 23%, and in OF support from 7% to 15%. While the AECM budget more than doubles (+126%), participation and the UAA of participants increase proportionally less (+115% and +111% respectively). It suggests decreasing returns of a budget increase and that AECM participants with the new budget allocation tend to have smaller farms. Regarding OF support, participation (+123%) increases proportionally to the budget increase (+125%), but the UAA of participants increases proportionally more (+142% respectively). Contrary to AECM, predicted OF support beneficiaries under the new budget allocation tend to have larger farms. In addition, after the budget transfer, the share of the sample participating in both OF support and AECM increased from 0.8% to 7.5%. The share of AECM participants with an OF support contract increases from 7.7% to 32.1%, while the share of OF support participants with an AECM increases from 12.1% to 29.9%.

Two combined incentives explain this result. First, there is a direct effect of more budget dedicated to financing environmental commitments. More acceptable farm-level payments can be covered and participation becomes profitable for a larger share of farms. This additional budget is taken from 85% of observations receiving direct payments (99.0% of the UAA) and is redistributed to 27.5% of observations (33.0% of the UAA). 19.9% are new adopters of environmental contracts and 7.5% are observed participants in 2019 to which the simulation allocates an additional payment (adoption of additional measures or enrolment of additional hectares). Second, there is an indirect effect of the decrease of direct payments on acceptable farm-level payments.

The average change of acceptable farm-level payment per farm is -197€ for OF support and +8€ for AECM. The “savings” observed for OF support contracts contribute to financing the participation of even more farms.

We identify a differentiated impact of the budget transfer according to the type of farm (Table 6). The farms losing the most income from lower direct payments are specialised in mixed cattle (-3,115 €/farm on average in otex 47) and in mixed farming with field crops and grazing livestock (-3,015€/farm on average in otex 83). The less affected farms are specialised in horticulture (-56€/farm on average in otex 29) and quality wine (-205€/farm on average in otex 37). On the one hand, the reorientation of the budget particularly incentivises farms specialised in grazing livestock to contract AECM (otex 45, 46, 47, 48, 73 and 83). This result seems driven by the effect of lower coupled payments for suckler cows which tends to decrease the AECM acceptable farm-level payment. Farms specialised in grazing livestock typically receive more coupled payments for suckler cows than other farm types and decide to participate in AECM for lower farm-level payments after the budget transfer. In addition, for farms with grazing livestock, the effect of the amount of coupled payments for suckler cows on the AECM acceptable farm-level payment compensates for the opposite effect of decoupled payments. Therefore, contrary to other farm specialisation, AECM acceptable farm-level payments tend to decrease or remain stable for farms specialised in beef (-23€/farm on average in otex 46), mixed cattle (-8€/farm on average in otex 47) or mixed farming with field crops and grazing livestock (+0.2€/farm on average in otex 83). On the other hand, the reorientation of the budget particularly incentivises farms specialised in cereal and field crops, permanent crops, dairy, pigs and poultry or mixed farming with field crops and grazing livestock to contract OF

Table 5. Predicted impact of an additional decrease of 7.5% in direct payments in 2019 (N=7,194)¹.

	Baseline			With a budget transfer		
	AECM	OF support	AECM or OF support	AECM	OF support	AECM or OF support
Budget (1,000€)	227,862	203,267	431,130	514,752	457,679	972,431
Share of farms (%)	10.8	6.9	16.8	23.2	15.3	33.0
Total UAA of participants (ha)	3,808,678	1,657,456	5,148,400	8,043,437	4,015,962	10,423,722
Share of total UAA (%)	14.5	6.3	19.6	30.7	15.3	39.7
Payment of participants (€) (D=1)	7,279 (6,768)	10,238 (12,032)	8,843 (9,758)	7,661 (3,777)	10,348 (8,514)	10,186 (7,900)
Acceptable farm-level payment (€)	6,473 (5,692)	10,624 (7,918)	-	6,481 (8,689)	10,427 (7,884)	-

¹ All figures are weighted by the extrapolation coefficient of each observation.

Standard deviation in parentheses.

Source: own elaboration.

Table 6. Allocation of environmental incentives (%) among the types of farms with and without a transfer of an additional 7.5% of the direct payments budget in 2019 (N=7,194)¹.

Technical orientation	AECM - baseline	AECM – budget transfer	OF support - baseline	OF support - budget transfer
Cereals, oleaginous, protein crops	16.69	9.31	16.46	18.00
Other field crops	3.96	2.22	6.35	4.06
Vegetable gardening	0.74	0.32	4.93	4.36
Horticulture	0.00	0.11	1.76	1.93
Wine with quality label	3.75	2.99	14.79	11.77
Other wine	0.75	0.38	0.11	0.49
Other permanent crops	1.16	0.84	6.35	9.05
Dairy farming	17.67	21.14	18.08	19.23
Beef farming	24.87	25.86	7.34	7.67
Mixed cattle farming	4.79	6.81	1.39	0.95
Sheep and goat farming	6.25	8.90	5.57	3.37
Pigs and poultry farming	2.60	2.14	2.48	4.65
Mixed crops farming	0.78	0.18	2.79	2.76
Mixed livestock dominated by grazing livestock	0.18	0.73	1.92	2.03
Mixed livestock dominated by granivores	1.09	0.68	1.31	1.22
Mixed farming: field crops and grazing livestock	10.37	13.58	3.66	4.81
Mixed farming: other combination of crops and livestock	4.31	3.79	4.71	3.66

¹ All figures are weighted by the extrapolation coefficient of each observation.

Source: own elaboration.

support (otex 15, 38, 39, 45, 50 and 83). Those results are driven by the decrease in acceptable farm-level payments associated with lower decoupled payments (on average -227€/farm in otex 15, -235€/farm in otex 45 and -242€/farm in otex 83). On average, those farm types decide to participate in OF support for lower farm-level payments after the budget transfer.

The outputs of simulations in terms of predicted shares of farms and share of UAA participating in environmental contracts under different budget transfer scenarios from the first pillar to AECM and OF support (in addition to the 7.5% already transferred from direct payments to the measures of the second pillar since 2017) are presented in Figure 1 and Figure 2¹. The share of UAA is calculated from the sum of the UAAs of the farms for which we predict participation, divided by the total UAA. We conducted several simulations up to a maximum of 30% of transfer between the two pillars, as the higher the additional transfer compared to the observed situation, the less realistic our prediction becomes. We observe that the participation rate and UAA under environmental contracts increase linearly with the budget transfer rate. In 2019, almost 9% of the UAA was organic (including the total UAA of all farms

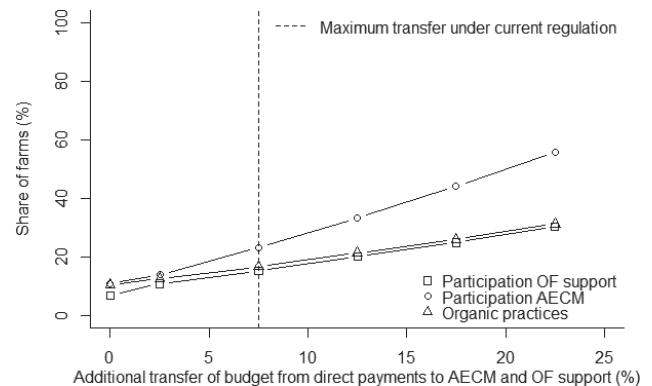


Figure 1. Participation in environmental contracts and implementation of organic practices under several scenarios of an additional budget transfer from direct payments to AECM and OF support in 2019 (N=7,194). All figures are weighted by the extrapolation coefficient of each observation. AECM: agri-environment-climate measures. OF: organic farming. Budget allocation assumption: 53% AECM/47% OF support. Source: own elaboration.

certified organic and in conversion, whether they receive OF support or not). In the scenario of a 15% transfer between the two pillars (7.5%+7.5%), the uptake of conversion OF support is such that the organic UAA doubles. To reach 25% of organic UAA (Green Deal objective by 2030), our model suggests an additional transfer

¹ Note that we maintain the budget allocation ratio of 53%/47% between AECM and OF support in all our scenarios.

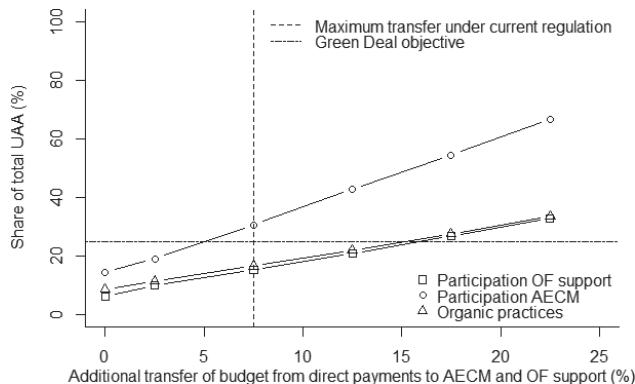


Figure 2. UAA of the farms participating in environmental contracts and implementing organic practices under several scenarios of an additional budget transfer from direct payments to AECM and OF support in 2019 (N=7,194). All figures are weighted by the extrapolation coefficient of each observation. AECM: agri-environment-climate measures. OF: organic farming. UAA: utilised agricultural area. Budget allocation assumption: 53% AECM/47% OF support. Source: own elaboration.

rate of 15.5% (to reach 23% of transfer between the two pillars). If we restrict eligibility to OF support to non-certified farms (if we allocate the additional OF support budget to conventional farms or farms converting to OF, as in some French regions since 2017 and now at the national level in the current CAP 2023-2027), the additional transfer rate to meet the Green Deal objective is 10.5% (to reach 18% of transfer between the two pillars). However, this finding needs to be carefully interpreted, as it results from estimations using empirical data for which such eligibility restriction did not exist in a majority of French regions. Removing maintenance OF support is a strong policy change for which our empirical model would likely no longer fit to represent the uptake behaviour of farms.

4. DISCUSSION ON THE LIMITS OF THE MODELLING APPROACH

This study proposes a methodological approach to model farmers' behaviour at a national scale regarding the uptake of environmental commitments within the framework of the CAP 2014-2020 in France, applied using FADN data available in all EU countries. We used it to evaluate ex-ante the impact of CAP budget allocation changes on the adoption of environmental contracts while capturing the effect of income support instruments on this adoption behaviour. The results can be analysed at the farm level, highlighting a differentiated impact according to farm specialisation.

Nevertheless, the predicted results need to be interpreted with care, as they depend on the quality of the adoption model estimated. In particular, our model tends to underestimate the probabilities of adoption compared to observed data, in particular for AECM and conversion OF support.

We identify four main limits to the modelling approach we propose. First, there is insufficient information in the FADN to precisely capture AECM eligibility and the characteristics of the measures adopted by farmers. In particular, not controlling for the diversity of the payments per hectare and surfaces enrolled for the different AECM and OF support contracts remains an important limitation of this work, as they represent sources of heterogeneity across farms that we do not capture. To improve this aspect, one possibility is to merge the FADN sample with the dataset on participants to rural development measures collected each year for the annual implementation report (RAMO) and collect some of the missing information (surfaces under contract, measure adopted by each farm, municipalities eligible to AECM). Second, beyond measure characteristics and contract eligibility, there are additional unobserved factors explaining farmers' adoption that our model does not capture. AECM and OF support payments are typically defined as compensation payments based on income foregone and often do not represent significant economic incentives. As a result, the (unknown) intrinsic motivation due to personal concerns towards the environment is likely to play a major role in explaining the adoption behaviour of a farmer. Moreover, in the case of OF support adoption, other existing policies to support the organic market such as the tax abatement in France, as well as the demand for organic products expressed by consumers, also drive farmers' decisions. Neighbourhood effects may also determine farmers choice to adopt environment-friendly practices. To correct the matrix of covariances for spatial dependence of observations and allow for spatial correlation of the error terms, applying non-parametric methods based on the definition of an economic distance metric among agents could be envisaged with the relevant data (Schlenker and Roberts, 2009; Conley, 1999). A third important limit to the study is that the reliability of the predictions decreases for higher rates of reduction of direct payments. A transfer of budget from the first pillar to AECM and OF support is a significant policy change that would likely have repercussions on agricultural input and output markets, and in particular, affect the price of organic and conventional products. Therefore, our simulation approach using *marginal* effects to model a change in farmers' behaviour becomes less real-

istic the larger the budget transfer we simulate. Finally, our model could also be subject to a simultaneity bias for some of the covariates, as participation in AECM or OF support may affect some farm characteristics such as the standard gross production.

5. CONCLUDING REMARKS

AECM and OF support are currently the most ambitious environmental contracts in the CAP. We evaluated the potential to upscale their adoption without increasing the CAP budget, by transferring part of the budget for direct payments with little environmental conditionality to fund additional environmental contracts in France in 2019. Our findings suggest this mechanism successfully increases participation by combining two incentives. First, we identify a direct effect of more public money dedicated to financing environmental commitments. Second, we identify an indirect effect on farmers' behaviour of receiving lower direct payments, which tends to decrease the acceptable farm-level payment triggering their decision to participate in OF support, making even more money available to finance more environmental commitments.

Our empirical findings support the relevance of decreasing payments with little environmental conditionality and increasing payments targeted towards the delivery of environmental public goods in the CAP. Previous evaluation of the reorientation of 15% of direct payments towards rural development measures in the EU28 and in Germany with the CAPRI partial equilibrium model identified marginal impacts on environmental indicators (Schroeder, 2021; Schroeder et al., 2015). Another study in Greece suggests that 50% transfer would lead to an extensification of farming practices and improve water quality and biodiversity (Giannakis et al., 2014). While a transfer from direct payments to environmental incentives with the current regulation (maximum 15%) is unlikely to be sufficient to achieve the Farm to Fork target of 25% of organic land, our results suggest it can significantly contribute to it. The French government decided to limit eligibility to OF support to non-certified farms in the 2023-2027 CAP programming period. Our predictions show this targeting would theoretically encourage the conversion of new land to organic and facilitate reaching the Green Deal objective. However, removing maintenance OF support can hinder the Green Deal objective in the long term if keeping organic practices is not profitable through the market. Finally, other levers can be applied such as improving environmental contract design to increase their attrac-

tiveness and environmental effectiveness, as well as supporting the development of the organic market. The new eco-schemes financed with 25% of the direct payments envelope in the CAP for the 2023-2027 programming period for which all EU farmers are eligible, could also contribute to triggering more voluntary adoption. However, a study analysing the French eco-schemes showed that almost all farms would fulfil the technical requirements without changing their current practices, casting doubt on the possibilities to reach significant environmental additionality with this new policy instrument (Lassalas et al., 2023).

The limitations of the study highlight the need for complementary research to improve the modelling of environmental contract adoption. In particular, the intrinsic motivation and values of farmers, but also locational factors play an important role in the adoption of AECM and OF support. They are not sufficiently documented in the FADN. While the upcoming transformation of the FADN into the Farm Sustainability Data Network (FSDN) may contribute to facilitate access to a larger set of social, economic, and environmental factors, currently, combining different secondary farm datasets, collecting more data through farmers surveys, and/or using spatial data on pedoclimatic and meteorological conditions would be necessary to better understand farmers adoption behaviour.

ACKNOWLEDGEMENT

This research is funded by the Horizon 2020 programme of the European Union (EU) under Grant Agreement No. 817949 (CONSOLE project, <https://console-project.eu/>). The French FADN data are provided by the "Service de la Statistique et de la prospective" in the French Ministry of Agriculture. Access to these confidential data has been made possible within a secure environment offered by CASD - Centre d'accès sécurisé aux données (Ref. 10.34724/CASD). We thank two unknown referees for their valuable comments.

REFERENCES

Agence bio. (2020). *Les chiffres 2019 du secteur bio. 2019 organic sector figures (in French)*. Retrieved from <https://www.agencebio.org/vos-outils/les-chiffres-cles/>

Agreste. (2022). Réseau d'information comptable agricole (RICA) - Exercice 2019. Farm accountancy data network - 2019 (in French). Retrieved November 9, 2022, from Sources, définitions, méthodes web-

site: [https://agreste.agriculture.gouv.fr/agreste-web/methodon/S-RICA 2019/methodon/](https://agreste.agriculture.gouv.fr/agreste-web/methodon/S-RICA%2019/methodon/)

Allaire, G., Cahuzac, E., & Simioni, M. (2011). Spatial diffusion and adoption determinants of European agri-environmental supports related to extensive grazing in France. *5èmes Journées de Recherches En Sciences Sociales*, 25. Dijon.

Amemiya, T. (1984). Tobit models: A survey. *Journal of Econometrics*, 24(1–2), 3–61. [https://doi.org/10.1016/0304-4076\(84\)90074-5](https://doi.org/10.1016/0304-4076(84)90074-5)

Andreoli, M., Bartolini, F., Dupraz, P., Issanchou, A., Le Gloux, F., Olivieri, M., ... Vergamini, D. (2022). *Deliverable D4.1: Modelling land tenure and land dynamics in AECPGs provision. Reports on the role of land tenure and land dynamics in AECPGs provision.* Retrieved from <https://console-project.eu/>

Batáry, P., Dicks, L. V., Kleijn, D., & Sutherland, W. J. (2015). The role of agri-environment schemes in conservation and environmental management. *Conservation Biology*, 29(4), 1006–1016. <https://doi.org/10.1111/cobi.12536>

Casolani, N., Nissi, E., Giampaolo, A., & Liberatore, L. (2021). Evaluating the effects of European support measures for Italian organic farms. *Land Use Policy*, 102(July 2020), 105225. <https://doi.org/10.1016/j.landusepol.2020.105225>

Chatellier, V., Detang-Dessendre, C., Dupraz, P., & Guyomard, H. (2021). *The sensitivity of the income of French farms to a reorientation of aid under the future post-2023 CAP (in French)* (No. 21–03).

Chatzimichael, K., Genius, M., & Tzouvelekas, V. (2014). Informational cascades and technology adoption: Evidence from Greek and German organic growers. *Food Policy*, 49, 186–195. <https://doi.org/10.1016/j.foodpol.2014.08.001>

Coderoni, S. (2023). Key policy objectives for European agricultural policies: Some reflections on policy coherence and governance issues. *Bio-Based and Applied Economics*, 12(2), 85–101. <https://doi.org/10.36253/bae-13971>

Conley, T.G. (1999). GMM estimation with cross sectional dependence. *Journal of Econometrics*, 92(1), 1–45. [https://doi.org/10.1016/S0304-4076\(98\)00084-0](https://doi.org/10.1016/S0304-4076(98)00084-0)

Damianos, D., & Giannakopoulos, N. (2002). Farmers' participation in agri-environmental schemes in Greece. *British Food Journal*, 104(3), 261–273. <https://doi.org/10.1108/00070700210425705>

Darnhofer, I., D'Amico, S., & Fouilleux, E. (2019). A relational perspective on the dynamics of the organic sector in Austria, Italy, and France. *Journal of Rural Studies*, 68(April 2018), 200–212. <https://doi.org/10.1016/j.jrurstud.2018.12.002>

Dasgupta, P. (2021). *The Economics of Biodiversity: the Dasgupta Review*. <https://doi.org/10.2458/jpe.2289>

DDT Ariège. (2020). *Calendrier prévisionnel de paiement des aides de la PAC pour la campagne 2019 et bilan des paiements 2019. Provisional timetable for the payment of CAP support for the 2019 campaign and balance of payments for 2019*. Retrieved from <https://www.ariege.gouv.fr/Politiques-publiques/Agriculture/Aides-de-la-Politique-Agricole-Commune-PAC/Paiements-et-beneficiaires-de-la-PAC/Paiements-lies-a-la-campagne-PAC-2019>

Defrancesco, E., Gatto, P., & Mozzato, D. (2018). To leave or not to leave? Understanding determinants of farmers' choices to remain in or abandon agri-environmental schemes. *Land Use Policy*, 76, 460–470. <https://doi.org/10.1016/j.landusepol.2018.02.026>

Defrancesco, E., Gatto, P., Runge, F., & Trestini, S. (2008). Factors affecting farmers' participation in agri-environmental measures: A northern Italian perspective. *Journal of Agricultural Economics*, 59(1), 114–131. <https://doi.org/10.1111/j.1477-9552.2007.00134.x>

Dupraz, P., & Guyomard, H. (2019). Environment and climate in the common agricultural policy. *EuroChoices*, 18(1), 18–25. <https://doi.org/10.1111/1746-692X.12219>

Dupraz, P., Latouche, K., & Turpin, N. (2009). Threshold effect and co-ordination of agri-environmental efforts. *Journal of Environmental Planning and Management*, 52(5), 613–630. <https://doi.org/10.1080/09640560902958164>

Dupraz, P., & Pech, M. (2007). Effects of agri-environmental measures [in French]. *INRA Sciences Sociales*, 2, 1–4.

EC. (2019). Definitive adoption 2019/333 of the European Union's general budget for the financial year 2019. *Official Journal of the European Union*, L(67), 1–2350. Retrieved from <https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX:32019B0333>

EC. (2020a). *A Farm to Fork Strategy for a fair, healthy and environmentally-friendly food system COM/2020/381 final*. Retrieved from <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52020DC0381>

EC. (2020b). Environment and Climate Action (Summary). Retrieved October 27, 2022, from Agridata - CAP Indicators website: <https://agridata.ec.europa.eu/extensions/DashboardIndicators/Environment.html>

EC. (2020c). *EU Biodiversity Strategy for 2030 COM/2020/380 final*. Retrieved from <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52020DC0380&qid=1631519394558>

EC. (2020d). Organic Production. Retrieved from Agri-data - CAP Indicators website: <https://agridata.ec.europa.eu/extensions/DashboardIndicators/OrganicProduction.html>

EC. (2021). *Political agreement on new Common Agricultural Policy: fairer, greener, more flexible [Press release]*. 2021, June 25. Retrieved from https://ec.europa.eu/commission/presscorner/detail/en/IP_21_2711

EEA. (2020). *Annual European Union greenhouse gas inventory 1990-2018 and inventory report 2020. Submission to the UNFCCC Secretariat*. Retrieved from EEA website: <https://www.eea.europa.eu/publications/european-union-greenhouse-gas-inventory-2020>

Elliott, J., & Image, M. (2018). Design of Agri-Environmental Schemes – evidence from the monitoring and evaluation GLAS in Ireland. *166th EAAE Seminar Sustainability in the Agri-Food Sector*, 12. Galway.

Espinosa-Goded, M., Barreiro-Hurlé, J., & Dupraz, P. (2013). Identifying additional barriers in the adoption of agri-environmental schemes: The role of fixed costs. *Land Use Policy*, 31, 526–535. <https://doi.org/10.1016/j.landusepol.2012.08.016>

EU. (2013). Regulation (EU) No 1307/2013 establishing rules for direct payments to farmers under support schemes within the framework of the common agricultural policy. *Official Journal of the European Union*, 347, 608–670. Retrieved from <http://data.europa.eu/eli/reg/2013/1307/oj>

European Court of Auditors. (2017). *Greening: a more complex income support scheme, not yet environmentally effective. Special report No 21* (Vol. 21). Retrieved from https://www.eca.europa.eu/Lists/ECADocuments/SR17_21/SR_GREENING_EN.pdf

European Court of Auditors. (2020). *Biodiversity on farmland. Special report No 13*.

FAO, UNDP, & UNEP. (2021). *A Multi-Billion-Dollar Opportunity: repurposing agricultural support to transform food systems*. <https://doi.org/https://doi.org/10.4060/cb6562en>

Giannakis, E., Efstratoglou, S., & Psaltopoulos, D. (2014). Modelling the impacts of alternative CAP scenarios through a system dynamics approach. *Agricultural Economics Review*, 15(2), 48–67. <https://doi.org/10.22004/ag.econ.253682>

Giovanopoulou, E., Nastis, S. A., & Papanagiotou, E. (2011). Modeling farmer participation in agri-environmental nitrate pollution reducing schemes. *Ecological Economics*, 70(11), 2175–2180. <https://doi.org/10.1016/j.ecolecon.2011.06.022>

Grethe, H., Arens-Azevedo, U., Balmann, A., Biesalski, H., Birner, R., Bokelmann, W., ... Weingarten, P. (2018). For an EU Common Agricultural Policy serving the public good after 2020: Fundamental questions and recommendations. *Berichte Über Landwirtschaft*, (225), 1–85. <https://doi.org/https://doi.org/10.12767/buel.v0i225.220>

Himics, M., Fellmann, T., & Barreiro-Hurle, J. (2020). Setting Climate Action as the Priority for the Common Agricultural Policy: A Simulation Experiment. *Journal of Agricultural Economics*, 71(1), 50–69. <https://doi.org/10.1111/1477-9552.12339>

INSEE. (2022). Exploitations agricoles selon la dimension économique. Agricultural holdings by economic size (in French). Retrieved February 15, 2022, from Chiffres-clés website: <https://www.insee.fr/fr/statistiques/5358766#graphique-figure1>

Jaime, M. M., Coria, J., & Liu, X. (2016). Interactions between CAP Agricultural and Agri-Environmental Subsidies and Their Effects on the Uptake of Organic Farming. *American Journal of Agricultural Economics*, 98(4), 1114–1145. <https://doi.org/10.1093/ajae/aaw015>

Kallas, Z., Serra, T., & Gil, J. M. (2010). Farmers' objectives as determinants of organic farming adoption: The case of Catalonian vineyard production. *Agricultural Economics*, 41(5), 409–423. <https://doi.org/10.1111/j.1574-0862.2010.00454.x>

Koesling, M., Flaten, O., & Lien, G. (2008). Factors influencing the conversion to organic farming in Norway. *International Journal of Agricultural Resources, Governance and Ecology*, 7, 78–95. <https://doi.org/10.1504/ijarge.2008.016981>

Läpple, D., & Rensburg, T. Van. (2011). Adoption of organic farming: Are there differences between early and late adoption? *Ecological Economics*, 70(7), 1406–1414. <https://doi.org/10.1016/j.ecolecon.2011.03.002>

Lassalas, M., Chatellier, V., Détang-Dessendre, C., Dupraz, P., & Guyomard, H. (2023). Access to the French eco-scheme of the CAP through the environmental certification path (in French). *Economie Rurale*, 384, 59–76. <http://doi.org/10.4000/economierurale.11331>

MAA. (2020). *Instruction technique relative aux Mesures AgroEnvironnementales et Climatiques et aux aides en faveur de l'agriculture biologique de la période 2015–2020 (in French)* (Vol. 2).

MAA. (2021). *Construire une politique agricole commune au service de l'agriculture française. Building a common agricultural policy to serve French agriculture (in French)*. Retrieved from <https://agriculture.gouv.fr/dossier-de-presse-construire-une-politique-agricole-commune-au-service-de-lagriculture-francaise>

Mack, G., Ritzel, C., & Jan, P. (2020). Determinants for the Implementation of Action-, Result- and Multi-Actor-Oriented Agri-Environment Schemes in Switzerland. *Ecological Economics*, 176, 106715. <https://doi.org/10.1016/j.ecolecon.2020.106715>

Matthews, A. (2013). Greening agricultural payments in the EU's common agricultural policy. *Bio-Based*

and Applied Economics, 2(1), 1–27. <https://doi.org/10.13128/BAE-12179>

McGurk, E., Hynes, S., & Thorne, F. (2020). Participation in agri-environmental schemes: A contingent valuation study of farmers in Ireland. *Journal of Environmental Management*, 262, 110243. <https://doi.org/10.1016/j.jenvman.2020.110243>

Millennium Ecosystem Assessment. (2005). Food and Ecosystems. In *Ecosystems and Human Well-Being: Policy Responses* (pp. 173–212). Retrieved from <https://www.millenniumassessment.org/en/Responses.html#download>

Mundlak, Y. (1978). On the Pooling of Time Series and Cross Section Data. *The Econometric Society*, 46(1), 69–85. Retrieved from <https://www.jstor.org/stable/1913646%0AJSTOR>

Pavlis, E. S., Terkenli, T. S., Kristensen, S. B. P., Busck, A. G., & Cosor, G. L. (2016). Patterns of agri-environmental scheme participation in Europe: Indicative trends from selected case studies. *Land Use Policy*, 57, 800–812. <https://doi.org/10.1016/j.landusepol.2015.09.024>

Pufahl, A., & Weiss, C. R. (2009). Evaluating the effects of farm programmes: Results from propensity score matching. *European Review of Agricultural Economics*, 36(1), 79–101. <https://doi.org/10.1093/erae/jbp001>

Runge, T., Latacz-Lohmann, U., Schaller, L., Todorova, K., Daugbjerg, C., Termansen, M., ... Blanco Velazquez, F. J. (2022). Implementation of Ecoschemes in Fifteen European Union Member States. *EuroChoices*, 21(2), 19–27. <https://doi.org/10.1111/1746-692X.12352>

Sanders, J., Stolze, M., & Padel, S. (2011). *Use and efficiency of public support measures addressing organic farming*. Braunschweig.

Schlenker, W., & Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to US crop yields under climate change. *Proceedings of the National Academy of Sciences*, 106(37), 15594–15598. <https://doi.org/10.1073/pnas.0906865106>

Schroeder, L. A. (2021). *Quantitative modelling of the Rural Development Programs of the Common Agricultural Policy - EU-wide and region-specific effects* (University of Bonn). Retrieved from <https://bonndoc.ulb.uni-bonn.de/xmlui/handle/20.500.11811/8992>

Schroeder, L. A., Gocht, A., & Britz, W. (2015). The Impact of Pillar II funding: Validation from a Modelling and Evaluation Perspective. *Journal of Agricultural Economics*, 66(2), 415–441. <https://doi.org/10.1111/1477-9552.12091>

Targetti, S., Marconi, V., Raggi, M., Piorr, A., Villanueva, A. J., Häfner, K., Kurttila, M., Letki, N., Costica, M., Nikolov, D., & Viaggi, D. (2023). Provision of public goods and bads by agriculture and forestry. An analysis of stakeholders' perception of factors, issues and mechanisms. *Bio-Based and Applied Economics*, 11(4), 351–371. <https://doi.org/10.36253/bae-12843>

Uthes, S., & Matzdorf, B. (2013). Studies on agri-environmental measures: A survey of the literature. *Environmental Management*, 51(1), 251–266. <https://doi.org/10.1007/s00267-012-9959-6>

Van Herzele, A., Gobin, A., Van Gossum, P., Acosta, L., Waas, T., Dendoncker, N., & Henry de Frahan, B. (2013). Effort for money? Farmers' rationale for participation in agri-environment measures with different implementation complexity. *Journal of Environmental Management*, 131, 110–120. <https://doi.org/10.1016/j.jenvman.2013.09.030>

Vanslembrouck, I., Van Huylenbroeck, G., & Verbeke, W. (2002). Determinants of the willingness of Belgian farmers to participate in agri-environmental measures. *Journal of Agricultural Economics*, 53(3), 489–511. <https://doi.org/10.1111/j.1477-9552.2002.tb00034.x>

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. <https://doi.org/10.2307/j.ctv5rdzwc.1>

Wooldridge, J. M. (2019). Correlated random effects models with unbalanced panels. *Journal of Econometrics*, 211(1), 137–150. <https://doi.org/10.1016/j.jeconom.2018.12.010>

Zavalloni, M., Raggi, M., & Viaggi, D. (2019). Agri-environmental Policies and Public Goods: An Assessment of Coalition Incentives and Minimum Participation Rules. *Environmental and Resource Economics*, 72(4), 1023–1040. <https://doi.org/10.1007/s10640-018-0237-9>

Zimmermann, A., & Britz, W. (2016). European farms' participation in agri-environmental measures. *Land Use Policy*, 50, 214–228. <https://doi.org/10.1016/j.landusepol.2015.09.019>

APPENDICES

*Appendix A1. Farm Accountancy Data Network sample coverage of farms with organic practices***Table A1.1.** Sample coverage of farms with organic practices in 2019.

	In conversion to organic farming	Certified organic	Certified or in conversion to organic farming
France			
Number of farms	n.a	n.a	47,196
Share of farms (%)	n.a	n.a	10.4
UAA (ha)	565,574	1,675,711	2,241,345
Share of UAA (%)	1.9	5.8	8.3
Sample¹			
Number of farms	5,905	24,805	30,710
Share of farms (%)	2.0	8.6	10.6
UAA (ha)	545,601	1,705,243	2,250,844
Share of UAA (%)	2.1	6.5	8.6

¹ All figures are weighted by the extrapolation coefficient of each observation.

Sources: 2019 French FADN data, 2019 Agence Bio data.

*Appendix A2. Descriptive statistics of the Farm Accountancy Data Network sample***Table A2.1.** Education level of the farms of the sample (N=28,967)¹.

Level of education	%
Agricultural	
None or training of less than 120 hours	6.85
Primary agricultural education	12.57
Secondary agricultural education (short)	41.27
Secondary agricultural education (long)	27.57
Agricultural higher education (short)	10.53
Agricultural higher education (long)	1.20
General	
None	7.14
Primary school certificate	11.82
Secondary education (short)	50.52
Secondary education (long)	26.30
Non-agricultural higher education	4.22

¹ All figures are weighted by the extrapolation coefficient of each observation.

Sources: 2016-2019 French FADN data.

Table A2.2. Regions of the farms of the sample (N=28,967)¹.

Region	%
Île de France	1.42
Champagne-Ardenne	6.23
Picardie	3.52
Haute-Normandie	2.20
Centre	5.97
Basse-Normandie	3.90
Bourgogne	4.99
Nord Pas de Calais	3.40
Lorraine	2.54
Alsace	2.25
Franche-Comté	1.98
Pays de la Loire	8.16
Bretagne	8.31
Poitou-Charentes	5.69
Aquitaine	7.62
Midi-Pyrénées	8.40
Limousin	2.55
Rhône-Alpes	6.66
Auvergne	4.59
Languedoc Roussillon	5.25
Provence-Alpes-Côte d'Azur	3.84
Corse	0.54

¹ All figures are weighted by the extrapolation coefficient of each observation.

Sources: 2016-2019 French FADN data.

Table A2.3. Technical orientations of the farms of the sample (N=28,967)¹.

Technical orientation	OTEX number	%
Cereals, oleaginous, protein crops	15	18.25
Other field crops	16	6.70
Vegetable gardening	28	1.73
Horticulture	29	2.07
Wine with quality label	37	13.81
Other wine	38	1.50
Other permanent crops	39	2.46
Dairy farming	45	14.97
Beef farming	46	10.39
Mixed cattle farming	47	3.53
Sheep and goat farming	48	5.47
Pigs and poultry farming	50	5.48
Mixed crops farming	61	1.64
Mixed livestock dominated by grazing livestock	73	1.20
Mixed livestock dominated by granivores	74	1.35
Mixed farming: field crops and grazing livestock	83	7.36
Mixed farming: other combination of crops and livestock	84	2.10

¹ All figures are weighted by the extrapolation coefficient of each observation.

Sources: 2016-2019 French FADN data.

*Appendix A3. Coefficients and marginal effects of the generalised Tobit models***Table A3.1.** Estimates of the generalised Tobit models for the uptake of agri-environment-climate measures and organic farming support.

	AECM		OF support	
	Participation decision (D_i^*)	Acceptable farm-level payment (P_i^*) in 1,000€	Participation decision (D_i^*)	Acceptable farm-level payment (P_i^*) in 1,000€
Intercept	-1.149*** (0.047)	0.635 (0.456)	-3.585*** (0.071)	-10.008*** (0.740)
Decoupled payments (100€/ha)	0.001 (0.001)	-0.119* (0.056)	-0.001 (0.001)	1.242*** (0.132)
Coupled payment for suckler cows (1,000€)	0.014*** (0.004)	0.052+ (0.029)	0.006 (0.007)	0.063 (0.055)
Fuel price (€/l)	0.453*** (0.034)	-0.133 (0.288)	0.168*** (0.048)	0.137 (0.403)
Land lease (100€/ha)	-0.002*** (0.000)	-0.009 (0.011)	0.007*** (0.001)	0.046+ (0.027)
Standard gross production (100,000€)	0.053*** (0.007)	-0.232*** (0.061)	-0.042*** (0.007)	-0.269*** (0.067)
Labour (AWU/ha)	-0.003* (0.001)	0.008 (0.245)	-0.472*** (0.026)	0.844 (0.848)
Utilised agricultural area (100ha)	0.277*** (0.024)	-0.402* (0.200)	0.455*** (0.039)	10.757*** (0.501)
Depreciation (10,000€/ha)	-0.020*** (0.004)	0.029 (0.099)	0.122* (0.054)	-9.692*** (1.167)
Share of rented land	0.063* (0.032)	1.682*** (0.293)	0.143*** (0.038)	-0.697* (0.340)
Less favoured area	-0.031*** (0.007)	-0.781*** (0.057)	0.129*** (0.011)	-0.085 (0.090)
Cereals, oleaginous, protein crops, other field crops	-0.507*** (0.009)	0.458*** (0.082)	0.014 (0.015)	1.084*** (0.137)
Vegetable gardening, horticulture	-1.208*** (0.026)	-0.019 (0.339)	0.136*** (0.023)	-0.054 (0.188)
Wine with quality label, other wine	-0.468*** (0.013)	-0.139 (0.141)	-0.102*** (0.018)	0.713*** (0.159)
Other permanent crops	-0.529*** (0.021)	0.911*** (0.215)	0.741*** (0.020)	2.832*** (0.167)
Dairy farming	-0.100*** (0.009)	1.941*** (0.078)	0.360*** (0.016)	2.879*** (0.135)
Beef farming	0.041*** (0.010)	0.711*** (0.076)	0.242** (0.018)	-1.638*** (0.149)
Mixed cattle farming	0.143*** (0.012)	1.347*** (0.092)	0.195*** (0.025)	0.162+ (0.225)
Sheep and goat farming	0.147*** (0.011)	0.556*** (0.089)	0.034* (0.018)	-0.489* (0.147)
Pigs and poultry farming, mixed livestock dominated by granivores	-0.329*** (0.013)	-0.331** (0.117)	0.193*** (0.019)	0.299** (0.170)
Mixed crops farming	-0.482*** (0.022)	1.210*** (0.251)	0.326*** (0.024)	2.825*** (0.188)
Mixed livestock dominated by grazing livestock	-0.303*** (0.021)	1.895*** (0.210)	0.518*** (0.029)	0.073 (0.234)
Mixed farming: field crops and grazing livestock, other combination of crops and livestock			Baseline	
Age (years)	-0.005*** (0.000)	0.061*** (0.002)	-0.017*** (0.000)	0.017* (0.003)
No general education	-0.382*** (0.013)	-0.825*** (0.107)	-0.545*** (0.018)	-0.368*** (0.165)
Primary school certificate	-0.473*** (0.013)	-1.344*** (0.113)	-0.543*** (0.019)	1.324*** (0.185)
Secondary education (short)	-0.319*** (0.010)	-1.828*** (0.089)	-0.309*** (0.014)	0.229+ (0.130)
Secondary education (long)	-0.277*** (0.010)	-1.584*** (0.087)	-0.237*** (0.014)	-0.205 (0.131)
Non-agricultural higher education			Baseline	
No agricultural education or training ≤120 h	-0.199*** (0.019)	-3.090*** (0.159)	0.072** (0.026)	4.018*** (0.236)
Primary agricultural education	-0.208*** (0.019)	-3.767*** (0.146)	0.043+ (0.025)	3.903*** (0.228)
Secondary agricultural education (short)	-0.234*** (0.018)	-2.845*** (0.135)	0.243*** (0.024)	2.409*** (0.204)
Secondary agricultural education (long)	-0.230*** (0.017)	-2.458*** (0.133)	-0.004 (0.023)	3.385*** (0.207)
Agricultural higher education (short)	-0.061*** (0.018)	-2.186*** (0.135)	0.105*** (0.024)	3.707*** (0.209)
Agricultural higher education (long)			Baseline	
Share of permanent grasslands	0.352*** (0.038)	-3.235*** (0.322)	-0.313*** (0.054)	-2.708*** (0.454)
Density of grazing livestock (LU/ha)	0.135*** (0.014)	-0.503* (0.243)	0.396*** (0.034)	0.308 (0.452)
Natura	0.414*** (0.009)	0.425*** (0.064)	-0.012+ (0.016)	2.443*** (0.138)
Organic certification	0.303*** (0.032)	-0.872*** (0.218)	1.208*** (0.024)	2.672*** (0.185)
Ile de France	0.504*** (0.032)	3.117*** (0.328)	2.421*** (0.055)	15.726*** (0.580)
Champagne-Ardenne	0.053+ (0.030)	-0.743** (0.280)	1.605*** (0.058)	7.043*** (0.601)
Picardie	0.410*** (0.030)	1.407*** (0.287)	2.326*** (0.054)	7.055*** (0.576)

(Continued)

Table A3.1. (Continued).

	AECM		OF support	
	Participation decision (D_i^*)	Acceptable farm-level payment (P_i^*) in 1,000€	Participation decision (D_i^*)	Acceptable farm-level payment (P_i^*) in 1,000€
Haute-Normandie	-0.127*** (0.031)	0.859** (0.301)	2.146*** (0.056)	4.871*** (0.582)
Centre	-0.061* (0.029)	3.680*** (0.284)	2.151*** (0.052)	8.162*** (0.560)
Basse-Normandie	-0.518*** (0.029)	2.688*** (0.275)	2.045*** (0.052)	4.771*** (0.551)
Bourgogne	-0.278*** (0.029)	0.501+ (0.277)	2.700*** (0.051)	7.443*** (0.548)
Nord Pas de Calais	0.203*** (0.030)	-0.874** (0.300)	2.212*** (0.055)	6.374*** (0.587)
Lorraine	0.018 (0.030)	1.760*** (0.300)	2.697*** (0.053)	13.271*** (0.559)
Alsace	-0.038 (0.033)	-0.703* (0.290)	2.524*** (0.054)	8.225*** (0.573)
Franche-Comté	-0.394*** (0.031)	-3.171*** (0.285)	2.284*** (0.054)	2.790*** (0.564)
Pays de la Loire	0.115*** (0.029)	4.436*** (0.274)	2.609*** (0.051)	5.287*** (0.546)
Bretagne	0.642*** (0.029)	4.699*** (0.278)	1.862*** (0.052)	4.997*** (0.559)
Poitou-Charentes	0.417*** (0.028)	2.938*** (0.271)	2.350*** (0.052)	8.691*** (0.554)
Aquitaine	-0.180*** (0.028)	-1.370*** (0.284)	2.490*** (0.050)	6.601*** (0.543)
Midi-Pyrénées	-0.450*** (0.028)	-2.529*** (0.282)	2.332*** (0.049)	7.353*** (0.536)
Limousin	-0.336*** (0.030)	-1.118*** (0.291)	2.448*** (0.054)	5.751*** (0.567)
Rhône-Alpes	0.066* (0.028)	-1.397*** (0.272)	2.553*** (0.050)	5.932*** (0.538)
Auvergne	-0.278*** (0.029)	-3.526*** (0.279)	2.410*** (0.052)	5.715*** (0.555)
Languedoc Roussillon	0.149*** (0.028)	0.914** (0.286)	2.176*** (0.050)	5.819*** (0.538)
Provence-Alpes-Côte d'Azur	0.458*** (0.029)	2.017*** (0.278)	1.756*** (0.051)	3.481*** (0.550)
Corse				Baseline
Observed participation in AECM in 2015	2.512*** (0.007)	-	-	-
Observed participation in OF support at t-1	-0.280*** (0.020)	0.017 (0.165)	-	-
Observed participation in OF support in 2015			-	1.407*** (0.010)
Observed participation in AECM at t-1			-	-0.236*** (0.023)
2016	-0.363*** (0.009)	-0.603*** (0.077)	-0.241*** (0.013)	0.684*** (0.207)
2017	-0.228*** (0.008)	-0.593*** (0.064)	-0.325*** (0.011)	-0.582*** (0.098)
2018	-0.171*** (0.007)	-0.164** (0.057)	-0.389*** (0.010)	-0.512*** (0.087)
2019				Baseline
ρ	-0.034*** (0.005)	-	0.133*** (0.011)	-
σ	-	5.581*** (0.013)	-	6.978*** (0.020)
Number of observations	28,967	2,442	28,967	1,657
Log-likelihood		-504,317		-318,531
AIC		1,008,948		637,376
Schwarz criterion		1,010,826		639,254
Pseudo-R2 (McFadden)		0.241		0.378

Significance levels: *** p-value <0.001, ** p-value <0.01, * p-value<0.05, + p-value<0.1. Standard errors in parentheses.

AWU: annual work unit. LU: livestock unit.

Source: own elaboration.

Table A3.2. Generalised Tobit models estimation: marginal effects at the sample mean.

	AECM		OF support	
	Participation decision (D_i^*)	Acceptable farm-level payment (P_i^*) in 1,000€	Participation decision (D_i^*)	Acceptable farm-level payment (P_i^*) in 1,000€
Decoupled payments (100€/ha)	0.000 (0.000)	-0.093* (0.020)	-0.000 (0.000)	1.039*** (0.220)
Coupled payment for suckler cows (1,000€)	0.001*** (0.001)	0.041+ (0.009)	0.000 (0.000)	0.053 (0.011)
Fuel price (€/l)	0.041*** (0.039)	-0.105 (0.022)	0.007*** (0.013)	0.114 (0.024)
Land lease (100€/ha)	-0.000*** (0.000)	-0.007 (0.001)	0.000*** (0.001)	0.039+ (0.008)
Standard gross production (100,000€)	0.005*** (0.005)	-0.182*** (0.039)	-0.002*** (0.003)	-0.225*** (0.048)
Labour (AWU/ha)	-0.000* (0.000)	0.006 (0.001)	-0.019*** (0.037)	0.706 (0.149)
Utilised agricultural area (100ha)	0.025*** (0.024)	-0.316* (0.068)	0.018*** (0.035)	8.997*** (1.902)
Depreciation (10,000€/ha)	-0.002*** (0.002)	0.023 (0.005)	0.005* (0.009)	-8.106*** (1.713)
Share of rented land	0.006* (0.005)	1.322*** (0.283)	0.006*** (0.011)	-0.583* (0.123)
Less favoured area	-0.003*** (0.003)	-0.614*** (0.131)	0.005*** (0.010)	-0.071 (0.015)
Cereals, oleaginous, protein crops, other field crops	-0.046*** (0.044)	0.360*** (0.077)	0.001 (0.001)	0.906*** (0.192)
Vegetable gardening, horticulture	-0.109*** (0.105)	-0.015 (0.003)	0.006*** (0.010)	-0.045 (0.010)
Wine with quality label, other wine	-0.042*** (0.040)	-0.110 (0.023)	-0.004*** (0.008)	0.596*** (0.126)
Other permanent crops	-0.048*** (0.046)	0.716** (0.153)	0.030*** (0.057)	2.369*** (0.501)
Dairy farming	-0.009*** (0.009)	1.526*** (0.327)	0.015*** (0.028)	2.408*** (0.509)
Beef farming	0.004*** (0.004)	0.559*** (0.120)	0.010*** (0.019)	-1.370*** (0.290)
Mixed cattle farming	0.013*** (0.012)	1.059** (0.227)	0.008** (0.015)	0.135+ (0.029)
Sheep and goat farming	0.013*** (0.013)	0.437*** (0.094)	0.001* (0.003)	-0.409* (0.086)
Pigs and poultry farming, mixed livestock dominated by granivores	-0.030*** (0.028)	-0.260** (0.056)	0.008*** (0.015)	0.250** (0.053)
Mixed crops farming	-0.043*** (0.042)	0.951*** (0.204)	0.013*** (0.025)	2.363*** (0.499)
Mixed livestock dominated by grazing livestock	-0.027*** (0.026)	1.489*** (0.319)	0.021*** (0.040)	0.061 (0.013)
Mixed farming: field crops and grazing livestock, other combination of crops and livestock			Baseline	
Age (years)	-0.000*** (0.000)	0.048*** (0.010)	-0.001*** (0.001)	0.014*** (0.003)
No general education	-0.034*** (0.033)	-0.649*** (0.139)	-0.022*** (0.042)	-0.308*** (0.065)
Primary school certificate	-0.043*** (0.041)	-1.057*** (0.226)	-0.022*** (0.042)	1.107*** (0.234)
Secondary education (short)	-0.029*** (0.028)	-1.437*** (0.308)	-0.013*** (0.024)	0.191+ (0.040)
Secondary education (long)	-0.025*** (0.024)	-1.245*** (0.267)	-0.010*** (0.018)	-0.171 (0.036)
Non-agricultural higher education			Baseline	
No agricultural education or training ≤120 h	-0.018*** (0.017)	-2.429*** (0.520)	0.003** (0.006)	3.361*** (0.710)
Primary agricultural education	-0.019*** (0.018)	-2.961*** (0.634)	0.002+ (0.003)	3.264*** (0.690)
Secondary agricultural education (short)	-0.021*** (0.020)	-2.237*** (0.479)	0.010*** (0.019)	2.015*** (0.426)
Secondary agricultural education (long)	-0.018*** (0.018)	-1.932*** (0.414)	-0.000 (0.000)	2.831*** (0.598)
Agricultural higher education (short)	-0.005*** (0.005)	-1.718*** (0.368)	0.004*** (0.008)	3.101*** (0.655)
Agricultural higher education (long)			Baseline	
Share of permanent grasslands	0.032*** (0.030)	-2.543*** (0.544)	-0.013*** (0.024)	-2.265*** (0.479)
Density of grazing livestock (LU/ha)	0.012*** (0.012)	-0.396* (0.085)	0.016*** (0.031)	0.258 (0.054)
Natura	0.037*** (0.036)	0.334*** (0.071)	-0.000+ (0.001)	-2.043*** (0.432)
Organic certification	0.027*** (0.026)	-0.685*** (0.147)	0.049*** (0.093)	2.235*** (0.472)
Ile de France	0.045*** (0.044)	2.450*** (0.525)	0.098*** (0.187)	13.153*** (2.780)
Champagne-Ardenne	0.005+ (0.005)	-0.584** (0.125)	0.065*** (0.124)	5.890*** (1.245)
Picardie	0.037*** (0.035)	1.106*** (0.237)	0.094*** (0.180)	5.900*** (1.247)
Haute-Normandie	-0.011*** (0.011)	0.676** (0.145)	0.087*** (0.166)	4.074*** (0.861)
Centre	-0.005* (0.005)	2.893*** (0.619)	0.087*** (0.166)	6.827*** (1.443)
Basse-Normandie	-0.047*** (0.045)	2.113*** (0.452)	0.083*** (0.158)	3.990*** (0.844)
Bourgogne	-0.025*** (0.024)	0.394+ (0.084)	0.110*** (0.209)	6.225*** (1.316)

(Continued)

Table A3.2. (Continued).

	AECM		OF support	
	Participation decision (D_i^*)	Acceptable farm-level payment (P_i^*) in 1,000€	Participation decision (D_i^*)	Acceptable farm-level payment (P_i^*) in 1,000€
Nord Pas de Calais	0.018*** (0.018)	-0.687** (0.147)	0.090*** (0.171)	5.331*** (1.127)
Lorraine	0.002 (0.002)	1.384*** (0.296)	0.109*** (0.209)	11.099*** (2.346)
Alsace	-0.003 (0.003)	-0.553* (0.118)	0.102*** (0.195)	6.879*** (1.454)
Franche-Comté	-0.036*** (0.034)	-2.493*** (0.534)	0.093*** (0.177)	2.334*** (0.493)
Pays de la Loire	0.010*** (0.010)	3.487*** (0.747)	0.106*** (0.202)	4.422*** (0.935)
Bretagne	0.058*** (0.056)	3.694*** (0.791)	0.076*** (0.144)	4.179*** (0.883)
Poitou-Charentes	0.038*** (0.036)	2.309*** (0.494)	0.095*** (0.182)	7.269*** (1.537)
Aquitaine	-0.016*** (0.016)	-1.077*** (0.231)	0.101*** (0.193)	5.521*** (1.167)
Midi-Pyrénées	-0.041*** (0.039)	-1.988*** (0.426)	0.095*** (0.180)	6.149*** (1.300)
Limousin	-0.030*** (0.029)	-0.879*** (0.188)	0.099*** (0.189)	4.810*** (1.017)
Rhône-Alpes	0.006* (0.006)	-1.098*** (0.235)	0.104*** (0.197)	4.962*** (1.049)
Auvergne	-0.025*** (0.024)	-2.772*** (0.593)	0.098*** (0.186)	4.780*** (1.010)
Languedoc Roussillon	0.013*** (0.013)	0.718** (0.154)	0.088*** (0.168)	4.867*** (1.029)
Provence-Alpes-Côte d'Azur	0.041*** (0.040)	1.585*** (0.339)	0.071*** (0.136)	2.911*** (0.615)
Corse	Baseline			
Observed participation in AECM in 2015	0.226*** (0.217)	-	-	-
Observed participation in OF support at t-1	-0.025*** (0.024)	0.013 (0.003)	-	-
Observed participation in OF support in 2015	-	-	0.057*** (0.109)	-
Observed participation in AECM at t-1	-	-	-0.010*** (0.018)	0.572*** (0.121)
2016	-0.033*** (0.031)	-0.474*** (0.101)	-0.010*** (0.019)	-0.141 (0.030)
2017	-0.021*** (0.020)	-0.466*** (0.100)	-0.013*** (0.025)	-0.487*** (0.103)
2018	-0.015*** (0.015)	-0.129** (0.028)	-0.016*** (0.030)	-0.428*** (0.091)
2019	Baseline			
ρ	-0.034*** (0.005)	-	0.133*** (0.011)	-
σ	-	5.581*** (0.013)	-	6.978*** (0.020)
Number of observations	28,967	2,442	28,967	1,657
Log-likelihood	-504,317		-318,531	
AIC	1,008,948		637,376	
Schwarz criterion	1,010,826		639,254	
Pseudo-R2 (McFadden)	0.241		0.378	

Significance levels: *** p-value <0.001, ** p-value <0.01, * p-value<0.05, + p-value<0.1. Standard errors in parentheses.

AWU: annual work unit. LU: livestock unit.

Source: own elaboration.