Designing Agri-Environmental Schemes to cope with uncertainty

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Abstract

Agri-environmental schemes (AES) are part of the main tools used by decision makers to trigger a transition in agricultural practices but one of the factors that discourages farmers from enrolling is the uncertainty of the costs and benefits associated with the adoption of the new practices. In this study, we distinguish between the "internal uncertainty" that is related to the characteristics of the farmer and his/her parcels and "external uncertainty", which is related to the occurrence of external events. We propose three innovations to better account for uncertainty in AES design: the possibility to suspend the conditions of the contract for one year, an opt-out option after three years and the opportunity for farmers to share their experience in peer-groups. We test their attractiveness through a choice experiment and analyze our results using a mixed logit model. We find that proposing AES that allow suspending the conditions of the contract for one year enhances participation.

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1 Introduction

Reduced greenhouse gas emissions, a decrease in pesticide and fertilizer use, and biodiversity conservation pose major challenges for today's agriculture. Policymakers often attempt to trigger the adoption of new sustainable practices through voluntary contracts called agri-environmental schemes (AES). Those contracts propose to remunerate farmers if they adopt practices in favor of the environment (pesticide or fertilizer reduction, cover crops, grasslands, etc.). In the context of the European Common Agricultural Policy (CAP), AES last 5 years and payments are calibrated based on an estimation of the opportunity costs of the change in practices for the average or typical farm. However, evidence collected both in Europe (Hanley et al., 1999; Cullen et al., 2018) and the US (Yang et al., 2005) suggests that farmers are reluctant to participate in these programs. As recently highlighted by Chèze et al. (2020) and Lefebvre et al. (2020), one of the factors that discourages farmers from enrolling in AES is the uncertainty of the costs and benefits associated with the adoption of the new practices.[1] In this paper, we distinguish between what we call "internal uncertainty", which is related to the characteristics of the farmer and his or her parcels, and "external uncertainty", which is related to the occurrence of external events (e.g., random shocks such as weather shocks).[2]

Even if some general benchmarks exist, future costs and benefits of new practices are imperfectly known because they depend on the farmers' ability to acquire new skills and adapt the new practices to the local context. We define "internal uncertainty" as the source of uncertainty related to the characteristics of the farm and the farmers. When making the decision to enroll in AES, the farmer possesses incomplete information regarding future costs and benefits, and additional information is only revealed after enrollment. For instance, regarding cover crops, the choice of

1. The literature in economics usually divides uncertainty into "risks", for which probabilities of the events are known, and "Knightian uncertainty", also called ambiguity. Ambiguity characterizes situation in which probabilities of the events are unknown to the decision makers (Ellsberg, 1961). In this paper, we use the general term "uncertainty" as it encompasses both types and in practice exact probabilities are not known.

2. Several classifications already exist in the literature. Lefebvre et al. (2020) for instance consider the distinction between foreground and background risk. The background risk can be defined as the uncertainty that cannot be avoided by the agents or insured (Eeckhoudt et al., 1996; Guiso and Paiella, 2008) and the foreground risk refers to the risks that are specifically linked to the AES commitment. In this paper we needed to distinguish between two kinds of uncertainty to which the farmer is exposed when committing to an AES. The same problem arose when looking at the concepts of inherent risks defined as "*the component of environmental uncertainty which derives from the stochastic nature of an ecosystem's behavior*" (Torres et al., 2017) or non-embedded risks defined as the risks beyond the control of the farmers (Dorward, 1999; Ridier et al., 2016). In both concepts, the risk is defined as a part of uncertainty that cannot be reduced or controlled for. For this reason, we choose to offer a new distinction between internal and external uncertainty.

the type of cover needs to be adapted to the soil and weather conditions; and growing a cover requires the acquisition of new skills for farmers. Given this uncertainty, farmers are expected to demand a compensation not only for the foregone income due to a change in practices but also for an uncertainty premium related to the lack of information regarding the future costs and benefits associated with enrollment.

Moreover, the adoption of environmentally-friendly practices can increase exposure to weather shocks and increase yield variability as shown in the case of organic farming (Knapp and van der Heijden, 2018). To take another example, reduced herbicide use increases the risk of weeds competing with the grapevines for water in the case of droughts (Winter et al., 2018). We define "external uncertainty" as the source of uncertainty related to the external shocks, and especially weather shocks, to which the farmer is exposed. Risk-averse farmers would thus likely enroll only if AES payments covered, not only the foregone income due to the change in practices, but also a risk premium to compensate for the "external uncertainty" linked to future weather shocks.

The appropriate management tool to help farmers cope with uncertainty differs according to the type of uncertainty present. In the case of internal uncertainty, the farmer is missing some relevant information to choose between enrolling and not enrolling. After a few years of enrollment, part of the missing information is revealed as the farmer experiments the new practice. The lack of information is a crucial element of uncertainty that affect a farmer's decision of whether or not to enroll in AES. On the other hand, the farmer's external uncertainty is not lessened after enrollment since the probability of weather shocks remains the same but the farmer may suffer larger losses if a shock occurs. In that case, the farmer needs risk management tools to deal with such random shocks. We propose three innovations to deal with these two sources of uncertainty.

First, we propose including in the contract an opt-out option after three years to deal with internal uncertainty. AES contracts under the CAP are generally five-years long and it is costly to break them (the farmer has to reimburse all payments received from year one). However, the internal uncertainty is significantly reduced after a few years of enrollment as the farmer acquires the relevant information regarding the costs and benefits of the implementation of the new practices on his own parcels using his own skills. In the presence of an opt-out option, the commitment only concerns the first three years of the contract. In other words, we propose a five-year contract with a three-year break clause. Therefore, the farmer is free to end the contract after three years if he observes that the actual costs and benefits make the practices unprofitable. If the practices prove beneficial, the farmer can then choose to continue the contract for another two years. This option should reduce the premium asked by the farmer to deal with internal uncertainty.[3]

Second, we propose introducing the possibility for the farmer to suspend the conditions of the contract for one year (of his choice) out of five and still receive the payment for the full five years. We call this option the "wild-card" option in our survey. We hypothesize that this option provides the farmer a risk-management tool if an exogenous random shock, such as a drought, occurs[4]. Indeed, the farmer can freely choose one year out of five, during which he would rather not fulfill the AES stipulations. Thus, the "wild-card" option should decrease the premium associated with external uncertainty. In our setting, the farmer still receives the payment if he uses the "wild-card" year for two reasons. First, for local stakeholders, suspending the payments seemed administratively tricky. Second, stable payments can decrease absolute risk aversion and encourage more risk taking in the adoption of new practices (Lastra-Bravo et al., 2015; Dessart et al., 2019). For these reasons, we propose a contract with five years of payments for only four years of actual commitment.

Third, we propose including the opportunity for farmers to share their experience in peer-groups. Peer-sharing can theoretically reduce the premium associated with both sources of uncertainty. It favors the diffusion of knowledge and skills to cope with the terms of the AES. It also provides information about how to cope with a random shock in order to improve the crop resilience.

These three innovations are tested on winegrowers in the South of France though a choice experiment (CE). The contracts proposed were designed with local stakeholders in order to address real-life conditions and the potential interest of farmers, and thus decrease the hypothetical bias inherent to choice experiments. Targeted practices are the reduction of herbicide use, to improve water quality, and the adoption of cover crops, which helps prevent soil erosion. Both practices also have positive effects on biodiversity conservation.

3. The choice of a threshold after three years has been proposed by local stakeholders. According to our local partners, it seemed long enough for the farmer to get familiar with the new practice and short enough to encourage enrollment. Moreover, contracts of one to two years may not be welcomed by those services given the costs linked to AES promotion and the associated administrative burden.

4. In our study, we only focus on weather shocks due to droughts since our field partners identified droughts as the main worrying external uncertainty faced by winegrowers (see Section 3.1). We acknowledge that this "wild-card" option may not be appropriate for other sources of external uncertainty linked, for instance, to variations in market prices that may last over multiple periods.

Our results on a sample of 172 farmers suggest that among the three innovations tested only the wild-card option significantly increases AES attractiveness. The amount that farmers are willing to forgo for an AES including the wild-card are superior to 20% of the total amounts of the payments. This suggests that the attractiveness of this innovation is not only related to the savings of extra costs that would be supported by the farmers to meet the conditions of a standard 5-years AES. We attribute this result to the fact that this option allows winegrowers to better deal with random shocks such as droughts. Section 2 reviews the literature regarding AES and uncertainty and innovations that have already been tested using CE. Section 3 introduces our methodology. Section 4 presents our results and Section 5 concludes.

2 Literature

2.1 AES and uncertainty

The literature on agri-environmental schemes has considered risk and uncertainty issues related to the implementation of conservation practices. [5] A large part of the literature, dominant in 2000's, considers the issue of risk with respect to asymmetric information (moral hazard and adverse selection), compliance and monitoring (Choe and Fraser, 1999; Ozanne et al., 2001; Fraser, 2002, 2004; Ozanne and White, 2007, 2008; Yano and Blandford, 2009, 2011). Other articles tend to show that AES have been used as a risk management tool by risk-averse farmers when uncertain production (e.g. price volatility) is managed though subsidized production with lower but risk-free revenues (Vollenweider et al., 2011; Lastra-Bravo et al., 2015; Arata et al., 2017).

Finally, some articles deal with the impact of risks associated with AES on the adoption of AES itself. Our article fits into this strand of the literature. Mante and Gerowitt (2009) collect data and seek to analyze participation of 865 arable farmers in an AES for field margins in Germany. They find that the risk of weed spreading is a major fear for farmers. Thus, the conditions of field margin implementation and management in AES contracts constitute strong determinants of participation. Wossink and Van Wenum (2003) conduct a contingent valuation on the adoption of a field margin conservation program via reduced chemical spraying and fertilizing on a sample of 250 arable farmers in the Netherlands and show that the perceived risk of field margins causing

5. There is a literature on the adoption of a variety of environmentally-friendly practices and the role of risk and risk attitudes. However we focus here on AES as a policy tool and not on individual practices.

more weed problems on the farm decrease both participation and the intensity of participation. As shown by Doerschner and Musshoff (2013) in a simulation exercise, risks associated with AES practices should be taken into account in the design of AES.

In this strand of literature, Chèze et al. (2020) and Lefebvre et al. (2020) focus on how risk and uncertainty explain, not AES enrollment, but changes in practices. Using a CE, Chèze et al. (2020) shows that the fact that a change in practice can increase the production risk is an important constraint to pesticide reduction. Moreover, Lefebvre et al. (2020) distinguishes two sources for the uncertainty: a foreground endogenous risk linked to AES adoption and a background exogenous risk that is the risk that subsists even after the adoption of an insurance. Their results, based on a framed field experiment, shows that in the presence of a background risk, the adoption of practices characterized by a higher foreground risk is less likely.

2.2 Innovation design in AES to cope with uncertainties

The literature on attractiveness of AES and policy innovations mainly relies on choice experiments (Mamine et al., 2020). A few studies focus on offering greater flexibility in AES contracts, either by proposing shorter contracts or by offering opt-out options. Seven studies suggest that the duration of the contract negatively impacts the attractiveness of agri-environmental contracts. In Denmark, Christensen et al. (2011) found that, in the context of pesticide-free buffer zones, farmers prefer shorter contracts and highly value the possibility to be released from contract without costs once a year. A recent paper regarding a contract for carbon sequestration offered to US farmers finds similar results (Gramig and Widmar, 2018). Results regarding the length of the contract or opt-out options have also been highlighted in the context of biofuel production (Krah et al., 2018) and of forest management, which often involves longer contracts of 10 to 20 years (Klosowski et al., 2001; Horne, 2006; Broch and Vedel, 2010, 2012). In a way our study combines both shorter contracts and the opt-out option, by providing the possibility of renewing the contract for two years at the end of the first three years.

To our knowledge, only one study has explored how the possibility of suspending the contract for one year can impact the attractiveness of AES. In a choice experiment dedicated to the analysis of the preferences of Australian pastoralists for biodiversity contracts, Greiner (2015) introduced the possibility for the farmer to negotiate a one-year suspension but only under exceptional circumstances. Her result suggests a strong preference of the farmers for this option. Our study differs from Greiner (2015), as the possibility of suspending the contract does not depend on exceptional circumstances and does not imply the suspension of the payment.

A number of recent papers have provided evidence that extension policies that seek to promote new technologies in developing countries could be improved by leveraging the power of peer influence, since farmers share personal information and feedback with each other (Beaman and Dillon, 2018; BenYishay and Mobarak, 2019; Nakano et al., 2018). Surprisingly, while many choice experiments have tested how the provision of technical assistance by extension services could improve enrollment in AES (Mamine et al., 2020), to our knowledge, none of them have proposed combining technical assistance with peer-sharing.[6] Among others, Espinosa-Goded et al. (2010), Christensen et al. (2011) and Blazy et al. (2021) found that farmers agree to be paid less if free technical assistance is provided by extension services. Kuhfuss et al. (2016), in a study targeting winegrowers in the South of France, also found a significant impact of technical assistance provision on the enrollment in an AES dedicated to pesticide reduction. However, our study differs from Kuhfuss et al. (2016) as we propose a new form of technical assistance based on peer-learning.

3 Survey framework

In this study, we test the attractiveness of innovative AES design to cope with uncertainties. We test the potential of these innovations in the context of a contract for herbicide use reduction and cover cropping in the French Mediterranean area. More specifically, we focus on the Languedoc-Roussillon wine growing region where about half of the cropland is dedicated to vineyards.

3.1 Weed management and cover crops

Historically, weeds have been an issue in agriculture because they exert pressure on resources (water, nitrogen, light) and produce a lot of seeds that perpetuate their growth. Weeds can potentially cause severe crop yield losses when not sufficiently controlled (Oerke, 2006; Storkey and Cussans, 2007; Tesic et al., 2007). Yet recent studies show that management options exist and

6. Several experimental networks in Europe propose combining peer sharing and technical assistance to help selected farmers to adopt green practices: DEPHY in France, LEAK in the UK, PESTIRED in Switzerland and GROEN in the Netherlands. Although it includes the same component, our policy innovation differs as we propose forming groups of farmers that can benefit from a few days of technical assistance a year, while in the aforementioned networks, the extension service worker can dedicate half his annual working time to working with the selected farms.

that the impact of weeds on yields can be quite negligible, which sheds light on the advantages of cover cropping and has begun to bring into question the use of herbicides (Gaba et al., 2020, 2016; Petit et al., 2015). Weeds provide habitat and resources: pollen for pollinators, seeds for birds and insects, and leaves for herbivores. Hence, it is important to reconsider how weeds are managed, not by systematically eliminating them, but rather by managing them to maintain both yields and biodiversity. In their meta-analysis, Winter et al. (2018) even show that, in comparison to intensive vegetation management (soil tillage, herbicide use), extensive vegetation management (vegetation cover, organic cropping system...) can favor various ecosystem services such as carbon sequestration, pest control and soil fertility. In addition, still in this meta-analysis no overall negative effect of inter-row vegetation cover has been found on grape quantity or quality. However, Winter et al. (2018) report that "nevertheless, in vineyards of dry climates without irrigation grape yields could decrease if vegetation is not carefully managed". This reserve may apply to our case study and shows that there is a potential risk associated with cover cropping.

Cover cropping can be spontaneous or crops can be sown. The cover can be permanent or temporary, in the row (the strip under the vine) and/or in the inter-row (the alleys) of the vineyard plot. Natural grass is usually preferred to sown crops since it is comparatively cheaper and easier to implement. Yet some plant species can have a positive impact on vines (better nitrogen fixation, lower water demand, pest repellent), which could motivate farmers to switch to sown crops. However, sowing crops is new to most winegrowers and the choice of seeds can be complex. The issue of cover crop destruction, using tillage or herbicides, and the date and extent of destruction also involve complex choices that impact ecosystem services production and yields (Tesic et al., 2007; Winter et al., 2018). Winegrowers need to experiment with different strategies for adapting and taking full advantage of their cover crops.

In order to avoid water competition in arid conditions, bare soil is the most common option in the vineyards of our study area (Celette and Gary, 2013). To be more specific, as shown by Fernández-Mena et al. (2021), for the area of our case study, most farmers keep a cover during the winter season but destroy it after the grapevine bud burst in March. However, over the long-run, cover cropping could improve soil quality and prevent soil erosion in a region marked by floods and droughts fueled by climate change. Therefore, the challenges for local stakeholders are to increase the number of inter-rows covered, delay the destruction of the cover until grapevine flowering in May, and avoid herbicide use.

3.2 Focus groups

We conducted six focus groups with local stakeholders, including winegrowers, extension services staffs, farmer associations, and farm-union bodies. The objective was, first, to identify the constraints associated with herbicide use reduction and cover cropping, and second, to discuss how innovative AES design could improve the adoption of these practices.

Farmers and other stakeholders specifically emphasized that herbicide reduction and cover cropping may cause substantial yield losses through water stress, especially as droughts become more frequent with climate change. The "wild-card" option, that is, the possibility to suspend the commitments one year out of five, emerged as a relevant solution to overcome this constraint and deal with climate shocks.

In relation with cover-cropping, winegrowers emphasized a need to experiment with different strategies for adapting and taking full advantage of their cover crops. They stressed that the impact on yields of cover cropping is uncertain and that, if the cover is not adapted to local conditions, it can induce considerable reductions in yields. Experimentation was described as requiring flexibility and learning opportunities. Winegrowers would need to learn more about new practices and would prefer enrolling over shorter period in order to acquire the relevant information. This was the basis for the inclusion of an opt-out option in our survey.

Some farmers also mentioned the importance of feedback from peers and suggested the development of peer-learning groups. In contrast, other farmers considered peer groups as a time-consuming constraint. For this reason, we test in our survey how an innovative form of technical assistance based on peer-learning can impact the acceptability of AES.

3.3 Attribute levels

In order to analyze the potential of our innovation for AES's attractiveness, we use a choice experiment (CE) survey. A CE is a stated-preference method used to assess individual *ex ante* preferences in hypothetical situations (Louviere, 2001). In particular, this method allows researchers to quantify preferences for different attributes of a good and is widely used to study farmer preferences regarding the contractual elements of AES (see Villanueva et al. 2017, Latacz-Lohmann and Breustedt 2019 and Mamine et al. 2020 for reviews). The entire survey is available upon request.

In CE, farmers are given a series of choice cards, on each of which they are asked to choose between various alternatives, usually two different hypothetical contracts and the status quo (i.e., their current situation). Each hypothetical contract is a package of attributes (e.g. contract payment, technical constraints, etc.) and each attribute offers different levels which vary between alternatives. The analysis of the contract choices provides information on how the relative levels of the attributes influence these choices, and the payments associated with the contracts allow us to estimate the willingness to accept (WTA) for each level of the attributes.

The attributes and their levels (Table 1) were adjusted in focus groups and through a pilot study.[7] Some characteristics are common to all of the proposed contracts: farmers have to use cover crops at the headlands (field boundaries) throughout the year and in every inter-row during winter time (from harvest until grapevine bud burst) on the enrolled acreage. These prerequisites were identified as acceptable by all the winegrowers present at the focus groups. The hypothetical contracts vary according to five attributes. Two attributes relate to the three AES innovations designed to manage uncertainty; two attributes concern the stringency of farming practices (herbicide use and cover crops); and one attribute outlines the payment levels.

The first attribute of interest for this study is *commitment flexibility* with three levels. Proposed contracts can last five years (no flexibility), or three years with an optional contract extension of two years, or five years with a "wild card" of one year, meaning that farmers are paid five years but are allowed not to fulfill the terms of the chosen contract during one year (of their choice). We expect both flexibility levels to increase the attractiveness of the contracts as they decrease the premium linked to uncertainty related to AES enrollment. The opt-out option allows the farmer to gather information before making a longer term commitment, and thus helps to buffer internal uncertainty. The "wild card" option provides a risk-management tool if a random shock should occur, and thus helps to mitigate external uncertainty.

Our second attribute of interest is the *peer-learning group*. Our hypothetical contracts can provide farmers with peer interaction and free collective technical assistance. Specifically, farmers have the possibility to share their experience within a group of four to eight winegrowers supported

7. As explained above, we conducted six focus groups with local stakeholders including winegrowers, extension services staffs, farmer associations, and farm-union bodies. We also conduct five face to face pilot surveys with winegrowers.

by a facilitator and, once a year, by an expert (in agronomy, in communication etc, depending on the group's needs). A peer learning group can theoretically help farmers to deal with both sources of uncertainty.

The other attributes include the *inter-row cover* which is the minimum number of inter-rows covered from grapevine bud burst until flowering on the enrolled acreage. Proposed contracts can require farmers to use cover crops on at least one of every three inter-rows, one of every two inter-rows, every inter-row, or none of the inter-rows (i.e., destroying the soil cover at the bud burst). We expect additional inter-row cover requirements to decrease farmers' willingness to participate in contracts.

Herbicide use on the enrolled acreage can be allowed, limited or banned. The constraint is partial when herbicide use is limited, allowing farmers to apply herbicides in the row only. Indeed, weed management is especially challenging in the wine row. Alternative practices to herbicides being more costly, we expect that the propensity of farmers to choose a contract will decrease as the constraint on herbicide use increases as in Kuhfuss et al. (2016).

Lastly, our monetary attribute is the annual *payment* per hectare which varies from 100 € to 600 €. The amounts were chosen based on actual AES payments offered for vineyards in the studied region [8] and following the study of Jacquet et al. (2019) on the costs of alternatives to glyphosate. The upper limit of these amounts enables us to assess the willingness to accept (WTA) of the most reluctant farmers. A higher payment is expected to have a positive effect on a farmer's propensity to subscribe to contracts.

To understand how the relative levels of the attributes influence the choice of contracts, we combine these levels in alternatives that constitute different contracts and then gather alternatives in pairs to form choice cards (as illustrated in Figure 1). The full factorial design of the CE, namely the number of unique choice cards that can be constructed from the selected number of attributes and levels, includes 186,192 choice cards. Using the Ngene software package (ChoiceMetrics, 2018), we selected an efficient design composed of 12 choice cards split into two blocks of six choice cards (each respondent being randomly assigned to one of the two blocks). [9]

8. Eliminate all herbicide use (EU PHYTO_02), 236 € /ha/year ; eliminate herbicide use in the inter-rows (EU PHYTO_10), 110 € /ha/year ; and maintain a permanent and sown inter-row cover (EU COUVER11), 110 € /ha/year .

9. Efficient design has been deduced based upon "priors". The reasonableness of the design priors has been determined using information obtained from previous work, focus groups and pilot interviews. We have selected

Table 1: Attributes and levels presented in hypothetical contracts

Attributes	Description	Levels
Commitment flexibility	Flexibility in contract length and in compliance with terms	5 years 3 years + 2 optional years 5 years incl. 1 "wild-card" year
Inter-row cover	Minimum number of inter-rows covered from grapevine bud burst until grapevine flowering	None 1 every 3 inter-rows 1 every 2 inter-rows All inter-rows
Herbicide use	Constraint on herbicide use	Allowed Allowed in the row only Banned
Peer-learning group	Opportunity to share experiences within a peer group supported by a facilitator and occasionally by technical advisers	Not included Included
Payment	Payment received by the farmer each year per enrolled hectare	100 €, 150 €, 250 €, 350 €, 450 €, 600 €

We added a status quo option to each choice card, which states "I prefer to keep my current practices". Note that current agricultural practices may vary from one winegrower to another and, if farmers choose to keep their current practices then the status quo should be defined according to individual current practices in order to take into account the fact that some farmers have already adopted these practices and are likely to maintain them. However, there is no *a priori* straightforward way to code the status-quo for the attribute regarding commitment flexibility. The variable "commitment flexibility" is coded 0 for the Status quo. In the main regression, the excluded level is the five year contract. We test the stability of our results to a change in the excluded category in the robustness test part.

Regarding the level of other attributes, our survey gives us information about herbicide use in the inter-row, but not in the row. Therefore, we assume that among the winegrowers who do not use herbicides in the inter-row, only organic winegrowers do not use herbicides in the row.

optimal efficient design by minimizing the D-error, the most commonly used measure of efficiency in experimental design practice.

Similarly, we have relevant information regarding the use of cover crops, but not for the number of inter-rows covered. Since we do not have such a precise level of information about farmers' cover practices, we decided to merge the two intermediate levels (one every three inter-rows and one every two inter-rows) into a single level called partial inter-row cover cropping. Then, from the attribute inter-row cover cropping, we create two variables: "Partial inter-row cover cropping" and "Cover crops on all inter-rows" [10]. If the farmer uses cover crops, the variable "Partial inter-row cover cropping" is equal to one and the variable "Cover crops on all inter-rows" is equal to zero.

Figure 1: Example of choice card

	Contract **A**	Contract **B**	
Commitment flexibility	**3 (+2) years**	**5 years incl. 1 wild-card year**	**I prefer to maintain my current practices**
Inter-row cover	**All inter-rows**	**1 every 2 inter-rows**	
Herbicide use	**Allowed in the row only**	**Banned**	
Peer-learning group	**Included**	**Not included**	
Payment	**€150**	**€250**	

3.4 Choice Modelling

The CE approach is in line with Lancaster's theory of consumer choice (Lancaster, 1966) and the econometric modeling is based on the behavioral framework of random utility theory (McFadden, 1974). It is assumed that a farmer chooses a contract if the net utility from that

10. Note that the fact that we merge two attributes should have only a very minor effect on the efficiency of our experimental design as we used linear priors for this attribute to generate the design. Indeed, we did not have precise information regarding the costs associated with the various levels of cover cropping when designing the choice cards.

contract is greater than either the other contract or the farmer's current situation. The utility that farmer n obtains from alternative i in choice card t can be written as:

$$U_{nit} = V_{nit} + \varepsilon_{nit} = V(X_{nit}) + \varepsilon_{nit}. \tag{1}$$

where X_{nit} refers to the vector of the levels of the x attributes. U_{nit} is composed of both an observed component V_{nit}, the deterministic part of the utility and a random unobserved component ε_{nit}, a stochastic error term.

If we assume the observable component of the utility to be a linear relationship of the levels of the attributes, we get:

$$U_{nit} = \sigma_n \sum_{k=1}^{K} \beta_{nk} x_{knit} + \varepsilon_{nit}, \tag{2}$$

where β_{nk} represents the marginal utility associated with the attribute level k (with K equal to the total number of attribute levels in our choice experiment,excluding the monetary attribute) for respondent n, and σ_n is a positive scale factor (Hensher et al., 2015).

We estimate coefficients β_{nk} using mixed-logit models which allow parameters to vary randomly across individuals, providing a continuous distribution of preferences (Boxall and Adamowicz, 2002). We allow the parameters to vary across individuals for all attributes, apart from the payment attribute in order to allow the computation of the willingness to accept (WTA). We assume a normal distribution for attributes coefficients. We also provide results using conditional logit model as a benchmark.

We also include in X_{nit} an Alternative Specific Constant (ASC) equals to one for the status quo alternative of not entering into any of the proposed contracts. The amount of payments received for each alternative is specified as a continuous variable. For the other attributes, we include one dummy variable for each level of the attribute described in Table 1 except one. This excluded level per attribute represents the reference level for each attribute.

The average marginal WTA for each attribute level is given by:

$$WTA_k = \frac{-\bar{\beta}_k}{\beta_{payment}}, \tag{3}$$

where $\bar{\beta}_k$ and $\beta_{payment}$ are respectively the estimated mean parameter for the coefficient associated with attribute level k and the estimated coefficient for the monetary attribute. WTA_k is the average annual payment per ha required by the farmer to accept the attribute level k of variable x compared to the reference attribute level of this variable.

4 Results

4.1 Descriptive statistics

We conducted an online survey that was sent out by our field partners to winegrowers in Languedoc-Roussillon in the spring of 2020. We collected the answers of 172 farmers (a response rate of about 10%), each completing six choice cards. Once protest answers have been dropped, we end up with 165 usable responses, equivalent to 2,970 observations (165 farmers x six choice cards x three alternatives).[11] Responses per block of choice cards are relatively balanced (47% for the first block, 53% for the second block). The average reading time for the description of the attributes is more than one and a half minutes and the farmers' reported degree of certainty in their choices is quite high (average rating: 7.6/10). This suggests that most winegrowers carefully responded to our survey and allows us to discard questionnaire-surfing.

Descriptive statistics of usable answers are presented in Table 5 in the Appendix. Wine growing is the principal activity for about 89% of the sample and the average land size is around 36 ha and an average of 72% of the farmers own their land. Almost 30% are engaged in organic farming and more than 20% are members of an Economic and Environmental Interest Group (EEIG), a group of farmers working together to adopt environmentally-friendly practices, suggesting self-selection of farmers already engaged in the agri-environmental transition. A high percentage (68%) of the

11. Among our 172 respondents, 21 (13%) always choose the status-quo, which may hide protest answers. Villanueva et al. (2017) distinguishes protesters who do not wish to engage in the trade-offs proposed by the contracts regardless of the payments and should be dropped in order not to bias the results, from very high takers that would enroll if higher payments were available. First, following their recommendations, by calibrating payments up to 600€/ hectares, we minimize the share of very-high-takers in our sample. This amount is superior to the amount of the most rewarding AES in our research area (approx. 300€/ha/year for conversion to organic farming), the costs for herbicide reduction estimated in a report by Carpentier et al. (2020) and the amount asked by the winegrowers for those constraints in our focus groups. Second, in order to further distinguish very high takers from protesters, we ask farmers to explain their choice each time they choose the status-quo. If respondents always choose the status quo and always explain that it was because they "refuse to be constrained on [their] practices whatever the monetary compensation", they are considered as protest respondents and removed from the sample (7 individuals out of the 172 respondents that is 4% of the sample). The other explanations include "the constraints on practices are too heavy" and "the payments are too low". Note that we provide results without excluding the 7 protesters in the robustness tests.

farmers are also past or current participants of AES, reflecting a certain awareness and concern with regard to environmental issues on the part of respondents. It also indicates that most of the farmers in the sample are familiar with the contracts presented in the choice experiment, thus ensuring a good level of confidence concerning the reliability of responses. We expected that more farmers with experience in cover cropping and herbicide use reduction would respond than others. Indeed, 68% of the respondents use cover crops and 60% do not use herbicides in the inter-rows. Among those who use cover crops, about 61% destroy the cover before the grapevine flowering (including a vast majority that destroy the cover around the grapevine bud burst). Note that these percentages are in line with the results by Fernández-Mena et al. (2021) who analyzed the management of cover crops in our study area.

Follow-up questions allow us to explain the behavior of the farmers in the choice experiment task (see Table 6 in the Appendix). Farmers report that the most important attribute in the contracts, on average, is the payment, followed by the herbicide use, and then the inter-row cover. About a third of our sample considered that commitment flexibility was important or very important in their choices. The greatest declared obstacles to implementing cover crops are first water stress, then yield loss, and lastly investment in machinery.

4.2 Main results

Table 2 displays the results of our main estimation using two models, a conditional logit in column (1) and a mixed logit in columns (2), (3) and (4), respectively, which display the estimation of coefficients β_k, the associated estimates of standard deviation and the WTA. Results in column (2) of the mixed logit estimation mostly confirm the results of the estimation of the conditional logit model displayed in column (1). In the mixed logit estimation, the four attributes other than the payment are considered as random parameters.

Table 2: Main results

Variables	Conditional logit	Mixed logit		
	Est. param.	Mean	SD	WTA (€)
	(1)	(2)	(3)	(4)
Payments (k €)	1.891***	4.603***		
	(0.434)	(1.027)		
ASC	0.099	-0.094		
	(0.160)	(0.371)		
3 years + 2 optional years	-0.041	-0.066	1.404***	
	(0.107)	(0.241)	(0.371)	
5 years incl. 1 "wild card" year	0.206*	0.524*	1.764***	-113.90
	(0.109)	(0.309)	(0.527)	[- 224.45 ; - 3.33]
Partial inter-row cover cropping	-0.220**	-0.315	1.778***	
	(0.094)	(0.250)	(0.286)	
Cover crops on all inter-rows	-0.475***	-1.389***	3.741***	301.74
	(0.126)	(0.441)	(0.785)	[144.06 ; 459.42]
Herbicides allowed in the row only	0.090	0.297	1.316***	
	(0.092)	(0.214)	(0.339)	
Herbicides banned	-0.362***	-1.497**	5.997***	325.11
	(0.103)	(0.750)	(1.506)	[57.24 ; 593.00]
Peer-learning groups	-0.043	-0.202	1.577***	
	(0.080)	(0.242)	(0.320)	
Observations	2,970	2,970		
Respondents	165	165		
AIC	2,119	1,660		
BIC	2,173	1,762		

*Note: Standard errors in parentheses; 10% confidence interval in brackets. WTA displayed only for significant variables. *** p<0.01, ** p<0.05, * p<0.1*

The coefficient associated with the payment is significant and of the expected sign, which means that an increase in the payment increases the probability that the farmer will enroll in the AES. The coefficient associated with the ASC variable is not significant. This can suggest that the obligations common to all contracts (permanent cover at the headlands and full inter-row cover during winter time) are on average not considered as a constraint by the farmers as advocated in the focus groups.[12] It also suggests that the administrative cost of entering an AES in on average negligible, which can be due to the fact that 68% of the sample are past or current beneficiaries of AES payments. Moreover, as explained by Hoyos (2010), the ASC captures unobserved sources

12. Moreover, cover at the headland is not a costly practice and inter-row cover cropping in the winter is fairly widespread among the winegrowers of the region.

of utility that are not included in the model so its non significance can also mean that the model estimated includes all the relevant attributes.

Banning herbicides and full inter-row cover cropping decreases the probability of enrollment in a contract in both specifications. According to column (4), farmers demand 325 €/year/ha on average to waive herbicide use. On average, an additional 302 € is required to convince the farmer to implement cover crops on every inter-row from bud burst to flowering. These last two attributes are associated with additional costs for the farmers, including initial investment in machinery, and additional time and labor. These practices are also associated with the need to acquire new skills, and the risks inherent in delaying the destruction of weeds or the banning of herbicides. It is important to note that these payment amounts are substantially higher than the payments offered in similar AES which compensate farmers 236 € to ban herbicides and 110 € to cover all inter-rows permanently.

The possibility to suspend the conditions of the contract for one year increases the probability of enrollment in the AES in both estimations. Farmers on average are willing to forgo 114 €/ha/year to get a five-year contract that includes a "wild-card" year. In such a contract, we could expect farmers to renounce about 20% of the payment (one yearly payment out of five), since they are only constrained for four years of foregone income out of five years of payments. Thus, the estimated WTA associated with the wild-card attribute should be assessed with respect to a 20% decrease in total WTA for the contract. Below a 20% decrease, the willingness to accept does not necessarily correspond to a decrease in the premium associated with uncertainty. In addition, remark that not adopting the practices for one year out of five is only an option, farmers can fulfill the clause of the contract for five years even if they have the option to use their "wild-card". In order to assess the significance of this result, we compare it to the WTA for the other attributes and the proposed payment levels in the CE.

If one considers that the only attributes that matter are the ones with a significant WTA, we can focus on cover-crops on all inter-rows (302 €/ha/year) and herbicides ban (325 €/ha/year). It leads to three potential constraints combinations, with: the cover crops, the herbicides ban or both. Given that we proposed six different prices in the CE, that leads to 18 potential contracts. They are presented Table 3 below.

Table 3: Example of a contract matrix

Payment (€)	Cover and herb. ban (WTA=627€)	Herb. ban (WTA=325€)	Cover (WTA=302€)
100	NA	NA	NA
150	NA	NA	NA
250	NA	**AW>20%**	**AW>20%**
350	NA	AA>20%	AA>20%
450	NA	AA>20%	AA>20%
600	**AW<20%**	AA<20%	AA<20%

Note: NA means the contract is never accepted, AA means the contract is always accepted, AW means the contract is accepted only if the Wild-card is proposed, $> 20\%$ *means the wild card WTA represents more than 20% of the payment,* $< 20\%$ *means the wild card WTA represents less than 20% of the payment.*

In this matrix, nine contracts are never accepted (“NA”), three are accepted if the Wild card is proposed in the contract (“AW”), and six are always accepted (“AA”). Among potentially accepted contracts, in six cases the 114€ of the Wild card would represent more than 20% of the payment (“$> 20\%$”), so in these cases farmers do not trade part of their subsidies to just be able to opt out of the contract constraints for one year, but they really show a WTP for flexibility.

This finding confirms that including a risk-management tool to account for external uncertainty in the design of AES can increase their attractiveness. This represents a very interesting result given the gap between the estimated WTA for herbicide banning and cover cropping and the common design of current AES.

To better understand this interesting result, we solicited qualitative evidence to explain our finding through online surveys administrated during the feedback meeting with local stakeholders. Among a list of potential explanations, 73% of the local stakeholders [13] believed that the attractiveness of the wild-card option is related to the management of water stress. The wild-card allows winegrowers to deal with random climate shocks and especially droughts. Other sources of random shocks including unpredictable expenses, such as machine breakdowns, or life events (injuries, disease, etc.) were also mentioned, which confirms that the "wild-card" is understood as a risk-management tool. On the contrary, only 33% believed that the attractiveness is due to savings on the extra costs related to the change in practices that would not be supported during

13. Note that those local stakeholders are not winegrowers and did not respond to our surveys. However, most of them are technical advisors with a very good knowledge of the constraints faced by winegrowers.

the "wild-card" year. Therefore, we are confident that the attractiveness of the "wild-card" option can be explained by the fact that it would allow farmers to better cope with uncertainty.

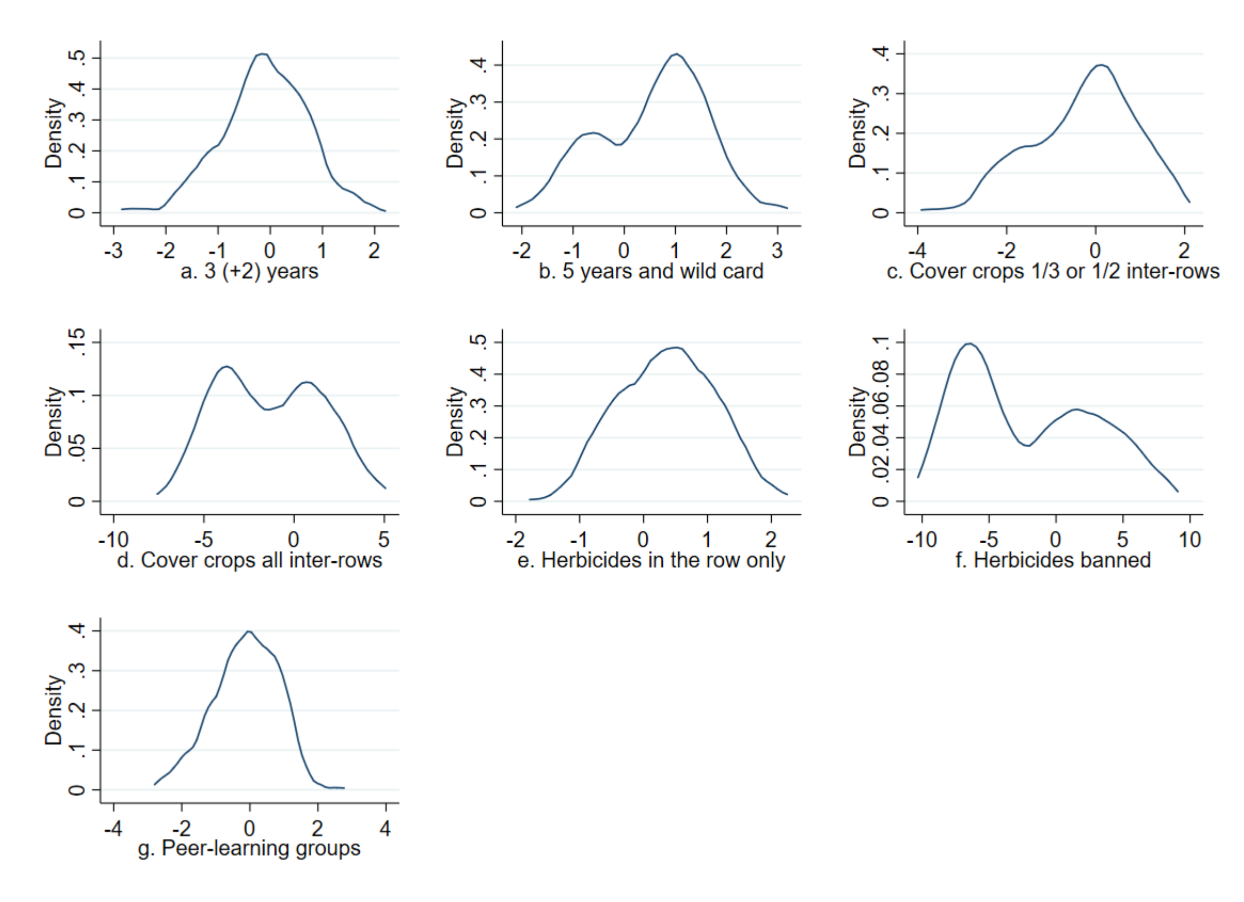
In contrast, the coefficient for the possibility to enroll for only three years with two optional years is not significant. In the previous sections, we explained why we proposed these two forms of flexibility to deal with two different types of uncertainty. According to our results, winegrowers are mainly interested in the possibility not to meet the contract commitment for one year. This suggests that, in our context and for our respondents, AES adoption is constrained by an external uncertainty linked to weather shocks. However, the fact that the possibility to enroll for only three years with two optional years is not significant does not mean the the choice to enroll is not constrained by internal uncertainty. As a matter of fact, it can also mean that our innovation is not suitable to address this uncertainty. AES enrollment involves a certain degree of irreversibility due to initial investment. Adopting a new practice can entail investment in machinery in order to deal mechanically with the cover and weeds and changes in the cropping system that would make it costly to go back to former practices. Even if the contract can be broken after three years, those costs would be supported by the farmer. Other explanations include the fact that farmers seek stable payments (Dessart et al., 2019) when using AES as a risk management tool, and that they have a preference for the 5-year contracts they are used to (Bougherara et al., 2021).

Regarding the possibility to join a group of peers, this form of technical assistance does not impact the probability to enroll in the AES in either specification. Among a list of possible explanations, 83% of the local stakeholders present at the feedback meeting considered that this result was due to the fact that wine-growers are too time-constrained.

4.3 Heterogeneity

Figure 2 displays interesting results regarding the distribution of the individual coefficients. As a matter of fact, we can see that the distribution of individual coefficients for cover cropping of all inter-row (2d) and for total ban of herbicides (2f) is bimodal. This suggests that a share of our sample is indifferent to this type of commitment but that another share, possibly different between the two attributes, is highly sensitive to this type of commitment. Figure 2 also suggests that the "wild-card" option increases the probability of enrollment for a specific share of our sample (2b).

Figure 2: Mixed logit: Individual coefficients. Kernel density estimates



Ai and Norton (2003) showed that in non linear model, the interaction effect may not be equal to the marginal effects of the interaction term [14]. Therefore, we explore heterogeneity using sub-samples rather than interactive variables.

We focus on three sources of heterogeneity: the fact that respondents are or are not past AES beneficiaries, risk aversion and organic farmers. According to the results displayed in Table 7, the possibility to enroll for only three years with two optional years remains non significant for both AES beneficiaries and non beneficiaries. Our result regarding the attractiveness of the contracts including a "wild-card" year is mainly driven by current or former AES beneficiaries. This suggests that the farmers who are more familiar with those contracts are the ones who favor the "wild card". Table 8 distinguishes between more and less risk averse farmers. We elicited risk preferences through a global assessment of farmers' willingness to take risks, as in Dohmen et al.

14. Ai and Norton (2003) showed that in non linear model, the "*magnitude of the interaction effect in nonlinear models does not equal the marginal effect of the interaction term and can be of opposite sign*". To our knowledge, solutions to this issue have been developed for some models, including ordered logit (Drichoutis and Nayga Jr, 2011), but not for mixed logit.

(2011) [15] and classified farmers as more (less) risk averse if their response was strictly below 6 (strictly above 5). Given the small sample sizes of those sub-samples, we're unable to conclude which farmers favor the "wild-card" but more risk-averse farmers value very negatively contracts requiring cover crops on all inter-rows. This suggests that these practices are considered as risky for the farmers. Eventually, regarding organic vs non-organic farmers, the results displayed in Table 9 shows that organic farmers values herbicides ban and cover crops very positively compared to non organic. This is consistent with the requirements of organic farming. Moreover, Table 9 suggests that our results regarding the "wild-card" might be driven by organic farmers but the difference in the estimated coefficients for the contracts including a "wild-card" between organic and non-organic farmers remain rather small so we are unable to conclude on this matter.

Those results should be interpreted cautiously. As a matter of fact, the size of the sub-samples are small and confidence intervals often overlap for many coefficients between different sub-samples. Therefore, we sometimes can reject that the coefficients are significantly different from zero for one sub-sample and not for the other but we are often unable to reject that the coefficients are equal for the two sub-samples. Studying attribute non-attendance (ANA) below gives us further insights regarding the heterogeneity of our results.

4.4 Attribute non-attendance

A basic assumption in choice experiment is that individuals take into account all the information available to take their decisions. It implies that they make trade-off among all attributes to choose their preferred alternative (the continuity axiom, see e.g. Mariel et al., 2021). Empirical evidence suggests that individuals might not be completely rational when making decisions and use various information processing strategies such as common-metric aggregation, attribute threshold, or ANA (Lew and Whitehead, 2020). ANA occurs when individuals ignore attributes they do not value, or because they use simplifying choice strategies called heuristics in front of complex tasks (Heidenreich et al., 2018). This problem can bias parameter estimation and WTP estimates from CE studies (Lew and Whitehead, 2020). In their stated preference studies guidelines, Johnston et al. (2017) suggest that ANA should be as part of the data analysis.

15. To be precise, we asked: “Do you consider yourself as a person that is generally willing to take risks, or as someone who avoids risk as much as possible?" and use a Likert scale from 1 (not at all willing) to 10 (willing). A majority of farmers seems to be willing to take risks, with 66% reporting a risk tolerance above 5.

Early studies on the topic have focused on stated ANA information (individuals indicating whether they considered a specific attribute or not when making their choices, see e.g. Hensher et al., 2005). A second strand of the literature uses analytical models to infer the rules used by respondents. The workhorse of this literature is the equality-constrained latent class (ECLC) model, where each class represents a specific non-attendance decision rule (Scarpa et al., 2009; Hensher and Greene, 2010). In practice some respondents are allowed to belong (in probability) to latent classes with coefficient constrained to be equal to zero for selected attributes, while non selected attributes are constrained to have equal coefficients among classes. Latent class models works similarly to mixed logit models, except that the distribution of β-coefficients are assumed to follow a discrete rather than normal mixing distribution (Pacifico and Yoo, 2013). Coefficient constrained to be zero for some classes are labelled as class-specific, while the others are considered as class-fixed parameters.

A problem with the ECLC approach is that the number of potential classes ($= 2^x$) grows exponentially with the number k_x of attributes. A five attributes CE thus leading to 32 potential ANA rules. This leads to computational and interpretation issues. Thus, we combine stated and inferred ANA information. We estimate an ECLC model but use reported information on attributes importance in making decisions to specify the constraints on the latent classes to be estimated. Table 6 in the Appendix indicates that the commitment flexibility and peer-learning attributes are by far considered as less important than the other attributes by respondents (about 30% consider the attributes as important or very important against around 60% for the other attributes). Given the potential heterogeneity in attendance to the two levels of the commitment flexibility attribute, we apply attribute-level non attendance for this attribute as proposed by Erdem et al. (2015). We choose to estimate a model with total attendance in Class 1, non-attendance on the "3+2 years" attribute level in Class 2, non-attendance on the "wild card" attribute level in Class 3 and non-attendance on the "Peer group" attribute in Class 4. Results are displayed Table 4 below.

Table 4: Attribute non-attendance analysis based on Latent class model estimation

	Coeff. (1)	Conditional WTA (2)	Unconditional WTA (3)
Class-specific para.			
3 years + 2 optional years	0.062		
	(0.099)		
5 years incl. 1 "wild card" year	0.559***	-322.159	-234.854
	(0.140)	[-544.590 ; -99.728]	[-396.576 ; -72.702]
Peer-learning groups	-1.658***	956.039	259.087
	(0.292)	[344.708 ; 1567.370]	[93.416 ; 424.757]
Class-fixed para.			
Payments (k €)	1.735***		
	(0.476)		
ASC	0.025		
	(0.204)		
Partial inter-row cover cropping	-0.194*	111.675	
	(0.115)	[-19.890 ; 243.240]	
Cover crops on all inter-rows	-0.472***	272.282	
	(0.152)	[61.469 ; 483.095]	
Herbicides allowed in the row only	0.086		
	(0.110)		
Herbicides banned	-0.402**	231.685	
	(0.173)	[8.586 ; 454.785]	
Class shares			
TA	0		
NA on "3+2" years	0		
NA on "wild card"	0.271		
NA on "peer groups"	0.729		
Observations	2,970		
AIC	2,091		
BIC	2,163		

*Note: Standard errors in parentheses; 5% confidence interval in brackets. WTA displayed only for significant variables. *** p<0.01, ** p<0.05, * p<0.1*

Class shares in Table 4 inform us that none of the farmers used a total attendance strategy. Results indicates that 27.1% of the farmers ignored the wild card attribute level and 72.9% the peer-group attribute. Taking non-attendance into account affects magnitude, significance and WTA estimation of almost all parameters in the model. To compute WTA estimates, we follow Carlsson et al. (2010). In Column (2), we compute Conditional WTA by simply dividing the attribute's coefficient by the price's coefficient. In Column (3) we take into account the fact that some individual do not take some attributes into account, and that thus their WTA for these attributes is 0. The Unconditional WTA is thus computed by multiplying the conditional WTA by the class shares for the concerned attributes.

Regarding the attributes of interest, the mean wild card WTA is more than twice the one we found using the mixed logit estimation, even with the Unconditional WTA Column (3). The case of peer-learning groups is even more surprising, as among the small share of farmers that took it into account, it was more seen as a burden than a positive feature of the contract. The average compensation to accept to be part of a group is 259 euros €/ha/year. That result echoes what we noted during the focus groups, as mentioned in Section 3.2. The results concerning cover cropping are more aligned with the main results, except that partial inter-row cropping is now a statistically significant constraint. Finally, the ECLC analysis reveals that banning herbicides might be accepted for a lower compensation, 232 €/ha/year here against 325 €/ha/year in the main model.

According to information criteria, the ECLC model offers a better fit to the data than the conditional logit model (Column (1) Table 2), but a worse fit than the mixed logit model (Column (2) Table 2). Thus although the ECLC model results are informative, we do not consider them as our main results.

4.5 Robustness tests

4.5.1 Coding the status quo

Section 3.4 stressed that there is no *a priori* obvious or theory-driven way to code the status quo in order to estimate the impact of our two forms of flexibility. In our main estimation, the variable "commitment flexibility" is coded 0 for the Status quo and the excluded level is the five year contract. Table 10 in the Appendix displays the results excluding other levels. Columns (1) and (2) display the results when excluding the opt-out option. In column (3) and (4), we exclude the ASC but include the three dummies. In this latter option, the status-quo is coded zero for the three dummies. The coefficients and the WTA concerning the "wild-card" option are stable in both estimations. However, the coefficient is only significant with a p-value equals to 16% if we include the three dummies.

We also test how the fact that we merged two attributes affects our results. In Table 11, we display the results if we assume that the winegrowers that declared using cover crops cover one of every three inter-rows in column (3) and (4) and one in every two inter-rows in columns (5) and (6). In column (3), the coefficient associated with the use of cover crops one every three inter-rows higher in absolute terms than the one associated with one every two inter-rows. This suggests that the status-quo is not coded appropriately. In column (5), the coefficient associated with one every two or three inter-rows are highly similar which suggest that both attributes can be merged as we proposed. The estimated coefficient for our attribute of interest, the wild-card, remains significant but only at 20% level. Moreover, in column (7) and (8), we assume that all conventional farmers use herbicides in the inter-row. Our results remain robust.

4.5.2 Sample selection

To check whether estimates are robust to specification of the model, we apply several tests including those suggested by Johnston et al. (2017). Robustness checks are presented in Table 13 in the Appendix. If learning is involved in repeated choice tasks, responses to the first question may not provide the best estimates so we exclude responses to the first choice card seen (column 1) by respondents. In column (2), we exclude responses to the last choice card in order to check for a lassitude effect. Next, in column (3), we exclude respondents who indicate they are uncertain about their contract choices (rating strictly less than 5). Finally, we exclude respondents who read the description of attributes in less than thirty seconds. Results are fairly stable, even if the coefficient associated with the wild-card option is significant at only 15%. Note that the decrease in sample size increases the minimum effect size.

Moreover, we also estimate the model with and without excluding protesters. The results displayed in Table 12 confirm that our results are robust to the inclusion of protesters.

5 Conclusion

One of the factors expected to discourage farmers from enrolling in AES is the uncertainty of costs and benefits associated with the adoption of the new practices. This uncertainty can be related to the characteristics of the farmer and his/her parcels (internal uncertainty) or to the occurrence of external events (external uncertainty). In close collaboration with winegrowers and local stakeholders, we defined three innovations to account for these uncertainties in AES contracts and tested them on 172 winegrowers in the South of France using a CE. Environmental practices targeted were the reduction of herbicide use and the practice of cover cropping. The implications of our results are threefold.

First, the formation of peer groups animated by an environmental facilitator in order to share knowledge to both ease practice implementation (internal uncertainty) and share experience in response to weather shocks (external uncertainty) does not significantly improve AES attractiveness, probably due to the time consuming nature of these activities. According to our ANA analysis, it would even substantially decrease the probability to engage in contracts for about one fourth of the sample.

Second, the opportunity to commit to a contract for three initial years and then two optional years does not significantly impact the decision to enroll either. This innovation aimed at giving farmers the opportunity to experiment the practice, thus relieving the uncertainty of implementation costs given the farmer's parcel and his own skills (internal uncertainty).

Three years of enrollment may seem too long already to convince farmers in our survey. Indeed, it has been shown in the literature that shorter contracts or release options are usually highly valued by respondents. For example, in Denmark, Christensen et al. (2011) found that, in the context of pesticide-free buffer zones, farmers needed to be paid 128 € more /ha/year to accept a five-year contract rather than a one-year contract. Their study also reveals a strong preference for the option to break the contract (137 € /ha/year). This last option is much more flexible than ours since farmers can use it every year, not only at the end of the first three years. This may explain why our results are not significant. Besides, it might be related to the fact that initial investments are irreversible, capture a preference for stable payments (Dessart et al., 2019), or a preference for familiarity as farmers are used to 5-year contracts (Bougherara et al., 2021), which outweigh the willingness to have the opportunity to experiment over shorter time periods.

Third, the possibility of not meeting the term of the contract for one year out of five while still receiving the full payment however significantly improves AES attractiveness for farmers. This goes beyond the possibility of having a free lunch one year out of five as farmers on average accept a reduction in payments of more than 20% if the contract includes this option. Given the design of our wild-card option and the exchanges with local stakeholders, it appears that the wild-card option particularly alleviates the external uncertainty that predominates in our case, namely the uncertainty of a weather shock. In the context of pastoralists and graziers across north Australia's rangelands, Greiner (2015) also found that this type of flexibility in contractual arrangements increases voluntary participation in biodiversity conservation contracts. However, unlike our "wild-card" option, the one-year suspension of the contract in 'exceptional circumstances' proposed by Greiner (2015) needs to be negotiated and the farmer is not paid during that year.

Our sample is mainly composed of farmers who are already experienced with AES so one could question the external validity of our results. Given our results, it is likely that those farmers did not engage on the most demanding AES (herbicide banned and cover on all inter-rows). Therefore, we believe that our results provides valuable results for policy-making in order to enhance the attractiveness of AES.

Obviously, depending on the targeted practices, one has to ensure that the innovation in the AES design proposed is compatible with the environmental aim of the measure. Evaluating the expected environmental impact of an innovation such as the wild-card option is not an easy task. One should consider the increase in the number of farmers enrolling in AES but also the expected weed pressure given the expected weather. Besides, farmers have the opportunity to use the wild-card option but do not need to do so. The actual use of the option after contracting is an open question. The type of AES targeted for including the wild-card option should be carefully considered. Kuhfuss and Subervie (2018), when looking at the impact of various AES to reduce herbicides, showed that less restrictive AES reduce herbicide use only when weed pressure is high, while the more demanding AES decrease herbicide use whatever the year scrutinized. In that context, one must be careful when proposing a wild-card year in the design of an AES. Kuhfuss and Subervie (2018)'s results suggest it may be safer to offer the wild-card option only with demanding AES in order to ensure the measure achieves its environmental goal.

To conclude, given the reluctance of farmers to participate in AES contracts and the uncertainty surrounding costs and benefits in agriculture, especially due to the impact of weather shocks, increasing flexibility in AES design through a wild-card option could benefit both farmers and promoters of AES. It could help to enroll larger groups of farmers and begin the transition in practices in groups more reluctant than those that usually subscribe to AES.

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Table 5: Summary statistics: Sample

Variable	Description	Obs.	Mean
Farmer-level characteristics			
Gender	1 = male, 0 = female	165	0.83
Age			
18-34 years old	1 = yes, 0 = no	165	0.12
35-44 years old	1 = yes, 0 = no	165	0.29
45-54 years old	1 = yes, 0 = no	165	0.31
55-64 years old	1 = yes, 0 = no	165	0.24
Over 65 years old	1 = yes, 0 = no	165	0.04
Education			
No degree	1 = yes, 0 = no	165	0.02
Primary level	1 = yes, 0 = no	165	0.01
Secondary level	1 = yes, 0 = no	165	0.16
Upper secondary level	1 = yes, 0 = no	165	0.26
Undergraduate level	1 = yes, 0 = no	165	0.33
Graduate level	1 = yes, 0 = no	165	0.22
Farm-level characteristics			
Land size (LS)	Hectares	164*	36.37
Ownership	Share of land	165	71.39
Agricultural status			
Single household unincorporated farm	1 = yes, 0 = no	165	0.57
Jointly run farm	1 = yes, 0 = no	165	0.08
Private limited farming company	1 = yes, 0 = no	165	0.19
Other	1 = yes, 0 = no	165	0.16
Secondary activities			
Cereal crops	1 = yes, 0 = no	165	0.09
Vineyards	1 = yes, 0 = no	165	0.09
Market garden	1 = yes, 0 = no	165	0.02
Arboriculture	1 = yes, 0 = no	165	0.13
Livestock	1 = yes, 0 = no	165	0.02
No secondary activity	1 = yes, 0 = no	165	0.65
Vinification			
In cooperative cellar	1 = yes, 0 = no	161	0.66
In private cellar	1 = yes, 0 = no	161	0.24
Both	1 = yes, 0 = no	161	0.09
Production under PDO	1 = yes, 0 = no	165	0.68
Organic farming	1 = yes, 0 = no	165	0.29
AES	1 = yes, 0 = no	165	0.68
EEIG	1 = yes, 0 = no	165	0.21
DEPHY	1 = yes, 0 = no	165	0.08
Current farming practices			
Inter-row cover cropping	1 = yes, 0 = no	162	0.68
Temporary cover	1 = yes, 0 = permanent cover	110	0.62
Weeding before June	1 = yes, 0 = no	68	0.99
Inter-row herbicides use	1 = yes, 0 = no	162	0.14
Technical assistance	1 = yes, 0 = no	162	0.49

*Note: *We excluded an outlier farmer who reported a land size of 1,650 hectares.*

Table 6: Summary statistics: Follow-up questions

Variable	Unit	Obs.	Mean
Strongest barrier to cover cropping (N=151)			
Water stress	1 = yes, 0 = no	151	47.68
Nutrient competition	1 = yes, 0 = no	151	7.95
Yield loss	1 = yes, 0 = no	151	15.23
Unsuitable soil features	1 = yes, 0 = no	151	1.99
Unsuitable age of vines	1 = yes, 0 = no	151	1.99
Lack of workforce	1 = yes, 0 = no	151	7.28
Investment in machinery	1 = yes, 0 = no	151	15.89
Lack of information	1 = yes, 0 = no	151	1.99
Confidence in contract choices	1 = not sure at all to 10 = very confident	152	7.58
Influence of attributes on choices			
Commitment flexibility	% considering this attribute as important or very important	151	31.79
Cover cropping	% considering this attribute as important or very important	150	54.00
Herbicide use	% considering this attribute as important or very important	151	59.60
Peer-learning	% considering this attribute as important or very important	151	27.15
Payment	% considering this attribute as important or very important	151	61.59

Note: The number of respondents in this Table drops from 165 to approximately 150 due to missing answers, because follow-up questions were not mandatory in our survey.

Table 7: Heterogeneity: AES beneficiairies

	(1)	(2)	(3)	(4)	(5)	(6)
	Whole sample		AES beneficiaires		Non AES beneficiaires	
VARIABLES	Mean	SD	Mean	SD	Mean	SD
Payments (k €	4.603***		4.337***		5.841**	
	(1.027)		(1.174)		(2.335)	
ASC	-0.094		-0.388		0.800	
	(0.371)		(0.440)		(0.787)	
3 years + 2 optional years	-0.066	1.404***	-0.162	1.229***	0.011	1.690***
	(0.241)	(0.371)	(0.260)	(0.439)	(0.454)	(0.655)
5 years incl. 1 wild card year	0.524*	-1.764***	0.512*	1.134**	0.214	-3.710*
	(0.309)	(0.527)	(0.277)	(0.482)	(0.781)	(2.069)
Partial inter-row cover cropping	-0.315	1.778***	-0.293	1.698***	-0.214	1.066
	(0.250)	(0.286)	(0.278)	(0.402)	(0.422)	(0.666)
Cover crops on all inter-rows	-1.389***	3.741***	-1.273***	3.565***	-1.511*	3.304**
	(0.441)	(0.785)	(0.483)	(0.941)	(0.798)	(1.344)
Herbicides allowed in in the row only	0.297	1.316***	0.661***	0.892***	-0.307	1.894**
	(0.214)	(0.339)	(0.254)	(0.294)	(0.466)	(0.785)
Herbicides banned	-1.497**	5.997***	-2.196***	5.606***	-1.011	6.512***
	(0.750)	(1.506)	(0.750)	(1.006)	(1.620)	(2.430)
Peer-learning groups	-0.202	1.577***	-0.157	-1.283***	-0.164	1.786**
	(0.242)	(0.320)	(0.232)	(0.307)	(0.509)	(0.890)
Observations	2,970	2,970	2,016	2,016	954	954
Respondents	165	165	117	117	53	53

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Heterogeneity: Risk aversion

	(1)	(2)	(3)	(4)	(5)	(6)
	Whole sample		More risk-averse		Less risk-averse	
VARIABLES	Mean	SD	Mean	SD	Mean	SD
Payments (k€)	4.603***		3.000**		6.409***	
	(1.027)		(1.386)		(2.348)	
ASC	-0.094		-0.379		0.378	
	(0.371)		(0.535)		(0.675)	
3 years + 2 optional years	-0.066	1.404***	0.075	-1.389**	-0.333	-1.739
	(0.241)	(0.371)	(0.370)	(0.638)	(0.399)	(1.181)
5 years incl. 1 wild card year	0.524*	-1.764***	0.386	1.083*	0.686	1.573
	(0.309)	(0.527)	(0.380)	(0.581)	(0.777)	(1.625)
Partial inter-row cover cropping	-0.315	1.778***	-0.383	-1.618***	-0.245	2.854**
	(0.250)	(0.286)	(0.336)	(0.533)	(0.761)	(1.310)
Cover crops on all inter-rows	-1.389***	3.741***	-1.876***	2.839***	-0.567	4.976**
	(0.441)	(0.785)	(0.615)	(0.846)	(0.782)	(2.081)
Herbicides allowed in in the row only	0.297	1.316***	0.501	-1.016*	0.136	1.473*
	(0.214)	(0.339)	(0.317)	(0.611)	(0.384)	(0.820)
Herbicides banned	-1.497**	5.997***	-3.900***	5.538***	-0.285	6.874*
	(0.750)	(1.506)	(1.251)	(1.362)	(0.787)	(3.908)
Peer-learning groups	-0.202	1.577***	-0.010	1.427***	-0.049	1.617
	(0.242)	(0.320)	(0.306)	(0.494)	(0.385)	(1.111)
Observations	2,970	2,970	1,242	1,242	1,494	1,494
Respondents	165	165	69	69	83	83

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Heterogeneity: Organic

	(1)	(2)	(3)	(4)	(5)	(6)
	Whole sample		Organic farmers		Non organic	
VARIABLES	Mean	SD	Mean	SD	Mean	SD
Payments (k€)	4.603***		5.053***		4.917***	
	(1.027)		(1.567)		(1.341)	
ASC	-0.094		0.249		-0.282	
	(0.371)		(0.601)		(0.471)	
3 years + 2 optional years	-0.066	1.404***	0.473	1.041*	-0.289	-1.734***
	(0.241)	(0.371)	(0.363)	(0.600)	(0.282)	(0.430)
5 years incl. 1 wild card year	0.524*	-1.764***	0.762*	1.254**	0.549	1.961**
	(0.309)	(0.527)	(0.451)	(0.558)	(0.366)	(0.811)
Partial inter-row cover cropping	-0.315	1.778***	0.074	1.364***	-0.530*	2.134***
	(0.250)	(0.286)	(0.439)	(0.483)	(0.306)	(0.622)
Cover crops on all inter-rows	-1.389***	3.741***	0.288	3.020***	-2.267***	3.364***
	(0.441)	(0.785)	(0.616)	(1.168)	(0.633)	(0.648)
Herbicides allowed in in the row only	0.297	1.316***	1.393***	-0.610	-0.017	1.484***
	(0.214)	(0.339)	(0.494)	(0.627)	(0.245)	(0.436)
Herbicides banned	-1.497**	5.997***	3.147***	2.055***	-5.466***	6.406***
	(0.750)	(1.506)	(0.758)	(0.621)	(1.143)	(1.588)
Peer-learning groups	-0.202	1.577***	0.152	1.431***	-0.347	1.272**
	(0.242)	(0.320)	(0.321)	(0.493)	(0.293)	(0.525)
Observations	2,970	2,970	864	864	2,106	2,106
Respondents	165	165	48	48	117	117

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Recoding the status quo: Flexibility

VARIABLES	(1) Mean	(2) SD	(3) Mean	(4) SD
Payments (K€)	4.851 ***		4.870***	
	(0.992)		(1.668)	
ASC	0.086			
	(0.340)			
5 years	-0.001	1.069***	0.056	-1.356**
	(0.231)	(0.413)	(0.405)	(0.586)
5 years incl. 1 "wild card" year	0.566**	-1.537***	0.544†	1.702**
	(0.274)	(0.481)	(0.396)	(0.702)
3 years + 2 optional years			-0.079	1.382***
			(0.389)	(0.395)
Partial inter-row cover cropping	-0.268	1.638***	-0.231	1.685***
	(0.235)	(0.320)	(0.252)	(0.638)
Cover crops on all inter-rows	-1.324***	3.397***	-1.503***	3.590***
	(0.418)	(0.574)	(0.506)	(0.802)
Herbicides allowed in the row only	0.373*	1.218***	0.356†	1.246**
	(0.220)	(0.309)	(0.248)	(0.544)
Herbicides banned	-2.041**	5.252***	-2.676**	5.468***
	(0.929)	(1.271)	(1.317)	(0.783)
Peer-learning groups	-0.208	1.436***	-0.265	1.445***
	(0.261)	(0.285)	(0.248)	(0.331)
Observations	2,970	2,970	2,970	2,970
Respondents	165	165	165	165

*Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1, † <0.2*

Table 11: Recoding the status quo: Practices

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Main results		SQ Inter-rows: 1/3		SQ Inter-rows: 1/2		Conventional uses herbicides	
VARIABLES	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Payments (K€)	4.603***		5.237***		5.793***		4.651***	
	(1.027)		(1.142)		(1.234)		(1.053)	
ASC	-0.094		0.160		0.204		0.083	
	(0.371)		(0.387)		(0.419)		(0.402)	
3 years + 2 optional years	-0.066	1.404***	0.041	-1.524***	-0.236	-1.509***	-0.098	1.429***
	(0.241)	(0.371)	(0.248)	(0.406)	(0.269)	(0.350)	(0.253)	(0.366)
5 years incl. 1 wild card year	0.524*	-1.764***	0.272	0.759+	0.396+	0.457	0.584*	-1.696***
	(0.309)	(0.527)	(0.307)	(0.569)	(0.280)	(0.869)	(0.312)	(0.548)
Partial inter-row cover cropping	-0.315	1.778***					-0.291	1.818***
	(0.250)	(0.286)					(0.255)	(0.311)
Cover crops 1/3 inter-rows			-0.630**	-1.117**	-0.274	-1.558***		
			(0.302)	(0.479)	(0.321)	(0.572)		
Cover crops 1/2 inter-rows			0.195	2.282***	-0.218	2.596***		
			(0.369)	(0.479)	(0.366)	(0.580)		
Cover crops on all inter-rows	-1.389***	3.741***	-1.511***	-3.235***	-1.661***	3.845***	-1.525***	3.904***
	(0.441)	(0.785)	(0.420)	(0.580)	(0.501)	(0.707)	(0.470)	(0.757)
Herbicides allowed in in the row only	0.297+	1.316***	0.154	1.343***	0.368+	-1.552***	0.514**	1.568***
	(0.214)	(0.339)	(0.254)	(0.322)	(0.254)	(0.343)	(0.220)	(0.351)
Herbicides banned	-1.497**	5.997***	-2.591***	5.849***	-2.903***	6.094***	-1.460**	6.006***
	(0.750)	(1.506)	(0.956)	(1.049)	(0.778)	(0.916)	(0.578)	(1.307)
Peer-learning groups	-0.202	1.577***	-0.478*	1.547***	-0.118	1.738***	-0.194	1.738***
	(0.242)	(0.320)	(0.269)	(0.302)	(0.264)	(0.305)	(0.222)	(0.325)
Observations	2,970	2,970	2,970	2,970	2,970	2,970	2,970	2,970
Respondents	165	165	165	165	165	165	165	165

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1, + p<0.2

Table 12: Robustness to protest responses

VARIABLES	(1) Mean	(2) SD	(3) Mean	(4) SD
Payments (K€)	4.603***		4.874***	
	(1.027)		(1.054)	
ASC	-0.094		0.178	
	(0.371)		(0.389)	
3 years + 2 optional years	-0.066	1.404***	-0.165	1.370***
	(0.241)	(0.371)	(0.239)	(0.458)
5 years incl. 1 wild card year	0.524*	-1.764***	0.535*	1.334**
	(0.309)	(0.527)	(0.308)	(0.520)
Partial inter-row cover cropping	-0.315	1.778***	-0.565*	2.105***
	(0.250)	(0.286)	(0.302)	(0.385)
Cover crops on all inter-rows	-1.389***	3.741***	-1.514***	4.036***
	(0.441)	(0.785)	(0.428)	(0.892)
Herbicides allowed in in the row only	0.297	1.316***	0.323	1.282***
	(0.214)	(0.339)	(0.228)	(0.308)
Herbicides banned	-1.497**	5.997***	-1.815**	5.500***
	(0.750)	(1.506)	(0.724)	(0.903)
Peer-learning groups	-0.202	1.577***	-0.145	1.707***
	(0.242)	(0.320)	(0.243)	(0.379)
Observations	2,970	2,970	3,096	3,096
Respondents	165	165	172	172

*Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1, † <0.2*

Table 13: Robustness to sample selection

VARIABLES	(1) Without first card	(2) Without last card	(3) Without uncertain resp.	(4) Without fastest readers
Payment (K€)	5.059***	5.382***	4.960***	5.247***
	(1.185)	(1.289)	(1.146)	(1.196)
ASC	0.053	0.031	-0.173	0.073
	(0.452)	(0.404)	(0.399)	(0.421)
3 years + 2 optional years	0.009	-0.111	-0.183	-0.185
	(0.293)	(0.260)	(0.239)	(0.281)
5 years incl. 1 "wild-card" year	0.492††	0.488††	0.434††	0.546*
	(0.335)	(0.311)	(0.279)	(0.284)
Partial inter-row cover cropping	-0.237	-0.512*	-0.229	-0.275
	(0.281)	(0.282)	(0.260)	(0.331)
Cover crops on all inter-rows	-1.912***	-1.695***	-1.395***	-1.565***
	(0.587)	(0.506)	(0.433)	(0.585)
Herbicides allowed in the row only	0.610**	0.352	0.302	0.458*
	(0.285)	(0.247)	(0.236)	(0.267)
Herbicides banned	-2.135**	-2.185***	-3.161***	-2.501***
	(0.878)	(0.623)	(0.951)	(0.799)
Peer-learning groups	-0.101	-0.136	-0.100	-0.149
	(0.285)	(0.224)	(0.216)	(0.257)
Observations	2,475	2,475	2,826	147
Respondents	165	165	157	

*Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1, †† p<0.15*