Farmers' motivations to reduce their use of pesticides: a choice experiment analysis in France

Benoît Chèze[a, b, c], Maia David[b], and Vincent Martinet [b, c]

[a]IFP Énergies Nouvelles, 1-4 av. de Bois Préau, F-92852 Rueil-Malmaison, France.
[b]Economie Publique, AgroParisTech, INRA, Université Paris Saclay, F-78850, Thiverval-Grignon, France.
[c]EconomiX–CNRS, University Paris Nanterre, France.,
benoit.cheze@ifpen.fr maia.david@agroparistech.fr vincent.martinet@inra.fr

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Abstract

While reducing the use of pesticides is a major challenge in developed countries, dedicated policies did not yet result in a large adoption of low-pesticide agricultural practices. We analyze farmers' motivations to reduce -or not- their use of pesticides. We use a discrete choice experiment including, besides other attributes, the role of harvest-risk in farmers' decisions, whereas it has barely been studied in the quantitative literature. Our results indicate that risk is a strongly significant factor: farmers need to receive in average 79 euros per hectare and per year to compensate the risk of encountering one additional year of poor harvest out of ten. The administrative burden that may come along with a practice change also significantly affects farmers' decisions. Reducing health and environment impacts is a motivation only for a minority class of farmers: mainly those who have some sources of revenues from outside the farm.

Keywords: Discrete choice experiment; Pesticides; Farming practices.
JEL Classification: Q12, Q18, Q51, Q57, C35

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1 Introduction

Reducing the use of pesticides in agriculture has become a major challenge in developed countries. As shown by the recent extremely rapid growth of organic farming (+ 20% of sales in France in 2016), consumers are now aware and demanding on this issue.

Public policies have developed for the last ten years to provide adequate incentives to change behaviors and boost research on this topic. Several agricultural practices have now proven efficient to maintain satisfactory yields while reducing the use of chemicals (Lechenet et al., 2017). Reducing pesticides could possibly reduce farmers' costs, improve their health and environment and prevent pest resistance (Wilson and Tisdell, 2001; Bourguet and Guillemaud, 2016). However, up to now, results have been disappointing. From 2008 to 2015, farmers' consumption of chemical inputs has increased in Europe (+10% in France over this period) and there is a lack of participation in Agri-Environmental Schemes aiming at reducing pesticide use. What are the main obstacles that prevent farmers from adopting low-pesticide practices that could be win-win strategies? There is a demand from researchers in ecology and agronomy towards economists to understand the socio-economic factors that explain farmers' behavior.

Our work contributes to this question by measuring the relative weight of various factors that determine farmers' choice to reduce their use of pesticides. Several socio-economic analyses have examined the motivations and obstacles to the adoption of environmentally friendly practices by farmers, using various methodologies such as focus groups, qualitative surveys, role-playing games or agent-based models.[1] These methodologies are useful and complementary but we differ from them by adopting a quantitative approach, in order to estimate the weight of each decision factor, as well as farmers' willingness to pay (WTP)/ willingness to accept (WTA) for changes in these factors. Our methodology is based on non-market valuation, using a discrete choice experiment (DCE).

The DCE method has increasingly attracted the attention of environmental economists for the last ten years, as shown by their considerable recent use. It is a stated preference method in which preferences are elicited through repeated fictional choices made by respondents (Hoyos, 2010; Louviere et al., 2000). Compared to other non-market valuation methods, DCEs have the advantage of capturing the non-use value[2] and of taking into account several characteristics, or *attributes*, of the considered issue. It thus procures a WTP/WTA for each of these attributes rather than a global WTP/WTA as a contingent valuation would do. It is particu-

[1] Dumont et al. (2016); Malawska and Topping (2016); Greiner et al. (2009); Wilson and Tisdell (2001); Knowler and Bradshaw (2007).

[2] The non-use value of non-market goods is the existence value or bequest value. It is useful when valuing, for instance, issues linked to biodiversity.

larly useful to shed light on the trade-offs that occur in a decision-making. Among the main drawbacks of the method, DCEs may induce some cognitive difficulties (Hanley et al., 2002) as the questionnaire may be heavier than for a contingent valuation and it implies more complex econometric estimations. We kept vigilant on both these points.

The DCE approach has previously been used to examine farmers' choices to adopt environmentally friendly practices. Depending on the studies, the adoption of the alternative practice can occur within[3] or independently of [4] an agri-environmental contract with public authorities. However, regarding the specific issue of a reduced use of pesticides, to our knowledge, only few DCEs have been published. Christensen et al. (2011), for example, analyze Danish farmers' motivation to sign subsidy schemes for pesticide-free buffer zones. They show that the contract flexibility is a major decision criteria. Kuhffus et al. (2014) look into French wine-growers decision to sign an Agri-Environmental Scheme in which the payment is partly individual and partly based on a collective result (i.e. there is a bonus payment if the number of participants is above a given threshold). They show that farmers value positively the collective component of the contract. Jaeck and Lifran (2014) study rice-grower's choice to reduce their use of chemical inputs in Camargue (France) and show how targeted contracts are needed given farmers heterogeneity.

Globally, the literature shows that decisions flexibility and the potential administrative burden are two major components of farmers' decision to change their practices. However, only few contributions have looked into the role of risk in farmers' choices. Price-risk and harvest-risk are two factors that can drastically affect farmers revenues and their variability (Menapace et al., 2013; Kimball, 1988). In particular, a change in the use of pesticides can have major impacts on the stability of yields and many farmers actually use pesticides as a form of harvest insurance. As explained by Lechenet et al. (2017), "the transition towards low-pesticide farming strategies might be hampered by the uncertainty behind any deep change (...). Risk aversion may be a hindering factor". Hudson and Lusk (2004) examine the role of the price-risk but the harvest-risk is even more at stake when considering the use of pesticides. As we will see, risk is not an easy factor to be conceptualized as a DCE attribute that is convenient and easily understandable for respondents. Our analysis is a first attempt to include, besides other attributes, the role of the harvest-risk in 90 (75, at the end of the selection process) French farmers' decisions to reduce -or not - their use of pesticides.

[3]Kuhffus et al. (2014); Kuhfuss et al. (2016); Christensen et al. (2011); Broch and Vedel (2012); Espinosa-Goded et al. (2010); Ruto and Garrod (2009); Hudson and Lusk (2004); Peterson et al. (2015).

[4]Beharry-Borg et al. (2013); Jaeck and Lifran (2014); Birol et al. (2006); Vidogbena et al. (2015).

We first describe, in section 2, our methodology, including the experimental design and data collection. We then describe, in section 3, the econometric models associated to the DCE approach. Section 4 goes further in the econometric analysis by examining a Latent Class Model. Results and WTP/WTA estimates are presented in section 5. They show that farmers express high preferences for not bearing a risk of harvest loss as they need to receive in average 79 euros per hectare and per year to compensate the risk of encountering one additional year of poor harvest out of ten. Conclusions and policy implications are developed in section 6.

2 The choice experiment

The choice experiment approach relies on economic theory of consumer choice and non-market valuation. In a DCE survey, respondents have to make choices among several options defined by their attributes (*i.e.*, fundamental characteristics of the respondents situation). Several choice sets are typically presented to respondents, each composed of three options: the situation if nothing is changed (*i.e.*, the status quo) and two alternative options. The use of an opt-out option (status quo) is known to improve the realism of the choice cards (Adamowicz and Boxall, 2001; Kontoleon and Yabe, 2003). Respondents then choose their favorite option among these three. Each option is characterized by different levels of the attributes. One of these attributes usually represents the monetary contribution of the respondents. Other attributes can include environmental or social implications of the considered issue. See Louviere et al. (2000) for a detailed description of the method.

The DCE framework provides the advantage of taking into consideration several attributes of the considered issue, delivering more detailed information than other stated preference methods. Especially, it makes it possible to estimate the marginal rates of substitution between the different attributes. When one of the attributes is a cost, these marginal rates of substitution can be interpreted as the WTP (or WTA) for changes in the attributes levels.

In our case, respondents are farmers who choose between conserving their actual agricultural practices (status quo) or changing for practices with a reduced use of pesticides. The practice changes that were considered in our analysis were voluntarily quite general in order to fit different types of farms and soil-climate conditions. Precise examples were however exposed to make the options realistic and place respondents in a real-life framework.

2.1 Choice of the attributes and their levels

A first step in implementing our study was to choose the attributes composing the options, and their associated levels. Many factors are likely to influence farmers' choices to adopt low-pesticide practices: reducing input costs, improving their public image, entering a network of farmers, improving their quality of life and health, obtaining subsidies, an aversion to uncertain outcomes, routine behaviors, a lack of technical knowledge, etc. However, as explained by Hanley et al. (2002), the number of attributes must be limited so as to avoid the cognitive burden of making too complicated choices. The selection of the attributes was based on (i) the state of the literature, (ii) discussions with experts in agronomy, ecology and agricultural economics, (iii) focus groups with farmers and (iv) pre-tests on the choice sets. The focus groups and pre-tests revealed that the topic is very touchy among French farmers' community and we were very careful with the employed terms and their potential interpretation.

As shown in Table 1, the chosen attributes are:

1. The farmer's yearly **profit** (or gross margin) per hectare, expressed as a variation compared to the status quo. This average profit per hectare and per year, in euro, is the monetary attribute or cost attribute. The profit varies with a change of practice due to unspecified factors, including the impact on yields, on pesticide expenses, on public aids, on the sales price, etc. This attribute takes the following possible values: -50 €, +0€, +50€, +100€.

2. The **risk of poor harvest**, formalized as the number of years out of ten years for which the harvest is drastically and exceptionally reduced compared to a normal year (*i.e.*, reduced by at least 30%). This poor harvest is due to diseases, pests, weeds, etc. This attribute is expressed in additional years with poor harvest compared to the status quo: +0, +1 year, +2 years.

3. The administrative framework of the change of practice, which describes whether the change is coming along with any **administrative commitment**. This commitment can be perceived positively as it may imply a public support, better valued products or the integration in a network; but it may also bring some administrative burden and thus be perceived negatively. This attribute is qualitative and is expressed as the additional commitments compared to status quo: "No additional administrative commitment", "Charter" (inducing no contractual specification and a flexible commitment), "Agri-environmental contract with public authorities" (with specification), "Certification process" (associated with a specification, controls and a green label).

4. The **health and environmental impacts**, indicating how the exposure to harmful substances for health or the environment is reduced with the change in practice. It includes local and global environmental quality (biodiversity, water quality,...) and farmers' health as well as the general population's health. This attribute can take the following values: -0% (status quo only), -20%, -50% -80% compared to the status quo.

Attribute	**Description**	**Levels**
Profit	Variation in the average yearly profit per hectare	-50 €; + 0 € (SQ); +50€; +100€
Risk of poor harvest	Variation in the number of years with exceptionally poor harvest out of 10 years	+0 year (SQ); +1 year; +2 years
Administrative commitment	Administrative framework of the change of practice, if any	None (SQ); Charter; Contract; Certification
Health and environment impacts	Exposure to harmful substance for health and the environment	-0% (only SQ); -20%; -50%; -80%

SQ: level in the status quo (but also possible in the other options)
only SQ: level only possible in the status quo option

Table 1: Attributes and levels

As mentioned before, the concept of risk is difficult to express as an attribute. Scientific terms such as variance or standard deviation should be banned as poorly understandable to the general public. After various tests, the formulation we propose seemed a good way to express yield variability in easy terms. This formulation is close to the one used in Jaeck and Lifran (2014). However theses authors express their risk attribute by the number of years for which the yield is beneath the mean yield. Having one year with a yield beneath the mean yield actually affects the mean yield and it is unclear in their article which mean yield is taken as a reference. We opted for a number of years with bad harvest, for a given mean profit (given by the first attribute). Our risk attribute represents the variability of the profit on ten years but not the mean profit on this period. As a consequence, the profit attribute and the risk attribute are independent. The exceptional and drastic character of the bad harvest seemed realistic regarding crop attacks that may occur without - or with low - pesticide use.

Regarding the "Health and environmental impacts" attribute, we initially set up a questionnaire using a chemical treatment frequency index used in France (the *Indicateur de Fréquence de Traitements phytosanitaires* (IFT)). Pre-tests, however, revealed that this indicator induced some misinterpretations and acceptability problems from farmers who then perceived this attribute as a technical objective to be achieved rather than a reduction of the impacts. Our wish was to capture here the environmental and health impacts of the agricultural practice independently from the constraints it implies, which are captured in the other attributes.

Figure 1 shows an example of a choice set (in French, as presented to respondents) where the first column gives the attribute's title and short definition, the three following columns represent three options among which the respondent must choose, the last column being the status quo.

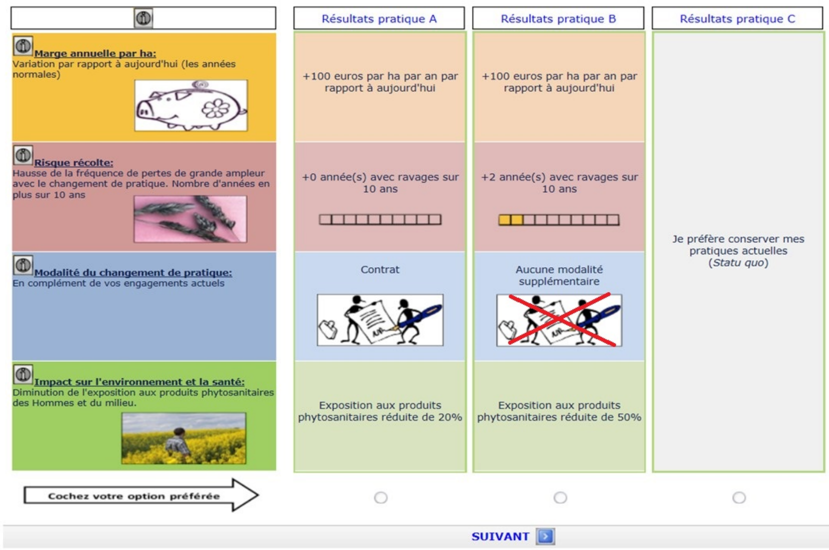

Figure 1: Example of a choice set

2.2 The experimental design

The aim of the experimental design is to construct the options (i.e. the combinations of attributes' levels) that are presented to respondents. With four attributes and three to four levels each, the questionnaire would be far too heavy if all the possible combinations of attributes' levels were submitted to respondents. In order to choose the most relevant choice sets to be presented, that is those yielding maximum information on respondents' preferences, we use experimental design techniques (see Louviere et al., 2000; Street et al., 2005) and the dedicated *Ngene* software, which is a reference in this field. By using a Bayesian D-optimal design, in our case a fractional factorial efficient design,[5] we obtain a statistically optimal

[5]Details on the characteristics of the efficient design used and the associated program are available upon request.

sub-set of the possible combinations. According to the literature, efficient designs have shown to lead to lower standard errors than orthogonal designs in particular when the sample size is small (Bliemer and Rose, 2010, 2011; Greiner et al., 2014; Rose and Bliemer, 2013).

This experimental design led to 16 different choice sets which were blocked into two groups in which respondents were randomly assigned, as is usual. As a result, the final questionnaire presented 8 choice sets to each respondent, which is an acceptable cognitive load, given what is done in the literature.

2.3 Presentation of the questionnaire, data collection and descriptive statistics

The DCE has been conducted among a set of French farmers (field crops, vegetable farming, wine-growers and mixed crop/livestock), excluding organic farmers which were considered as unable to reduce their pesticide use. The survey was held from June 2016 to May 2017, taking two forms: face-to-face interviews on the farms and a websurvey. We were careful to give very similar information in both types of interviews. We obtained in total 90 answers.

The questionnaire was designed to last less than 20 minutes. Respondents' were told that the questionnaire was designed by the French Institute for Agricultural Research (INRA) in order to implement better tailored public policies.[6] The issue addressed by our study was then shortly described with illustrated slides.

A first part of the questionnaire was dedicated to general questions regarding the farmer's activity, the size of the farm, the use of pesticides, as well as questions aiming at assessing the status quo level of each attribute for the respondents. The details of the four attributes and their implications were presented, delivering information in the most objective and neutral way. A set of qualitative questions was used to assess respondent's awareness on the interactions between agricultural practices, public policies and pesticide issues (see Appendix, Table 13).

The eight choice sets were then presented. For each choice set, respondents had to choose between conserving their actual practices, or selecting one of the two options associated with a reduced use of pesticides. The order of the choice sets was randomized so as to avoid potential declining concentration always affecting the same choice sets (last choices). During the choice sequence, the respondent could click at any moment on specific information icons (see Figure 1) in order to obtain additional explanations on each attribute. In order to detect protest

[6] The information delivered in this introductory part favors consequentiality, i.e. the fact that respondents believe there is a non-zero probability that their answers influence actual decisions, and that they may have to pay something in consequence. Consequentiality is a necessary (but not sufficient) condition for incentive-compatibility (see Johnston et al., 2017).

answers, farmers choosing the status quo in all choice sets were asked the reasons of this choice.

After the choice sets came some final questions on the socio-economic situation of the respondent (income level, gender, age, level of education) and on her understanding of the choice sets.

Some respondents were removed from the sample for various reasons: i) ten were removed for too short response time: those responding to the websurvey in less than eight minutes were considered as not reliable (see Börger (2016) for an analysis of the link between the response time and the quality of the answer) ii) five were removed for being identified as protest answers. We finally obtained 600 choices elicited from 75 respondents.

Table 2 and 3 present some descriptive statistics on this final sample. It is composed of 31% of women. The respondents' ages range from 23 to 68 years-old, with an average of 46 years-old. The mean size of their farm is about 117 hectares but there is a great disparity among them, as shown by the standard deviation (S.D in Table 2) of the yearly turnover and profit per hectare. Additional descriptive statistics regarding farms location and type are presented in the Appendix (Table 12), as well as statistics on respondents awareness (Table 13).

	Obs	Mean	S.D	Min	Max
Age	75	45.67	10.60	23	68
Size of the farm (ha)	75	116.68	103.18	0.1	500
Yearly turnover (€)	65	168113	151770	1	650000
Yearly average profit/ha (€)	32	1083	2545	0	12500

Table 2: Descriptive Statistics

In Table 4, we compare the main socio-demographic characteristics of our sample with the population of French farmers. A comparison with the population limited to non-organic French farmers would have been even more appropriate

	Nb	%
Number of farmers having some revenues from outside	39	52,0%
Number of farmers having suscribed to a harvest insurance	33	44,0%
Gender		
Women	23	30,7%
Men	52	69,3%
Education		
No formal qualifications	1	1,3%
Youth Training/BTEC First Diplo	13	17,3%
High School Diploma	25	33,3%
Bachelor	19	25,3%
Master's Degree	13	17,3%
PhD	1	1,3%
Other	3	4,0%

Table 3: Descriptive Statistics

but data was not available for this sub-population. As shown in Table 4, our sample is quite representative of the population regarding the age, sex ratio and the proportion of respondents having a high school diploma. There is however an over-representation of farmers having a higher education diploma (which is typical for websurveys) and the mean size of the farm is significantly larger in our sample than in the country.

	Our sample	French farmers
Mean Age	45,7	50,6
Farm size (hectares)	117	56
Men / women ratio	69 % of men	68 % of men
Proportion having a high school diploma	33 %	21 %
Proportion having a higher education diploma	43,9 %	17 %

Table 4: Comparison of socio-demographic characteristics

3 A Random Parameter Logit model to account for farmers' heterogeneous preferences

3.1 Theoretical foundations of the choice experiment approach

The choice experiment modeling framework relies on the characteristics theory of value (Lancaster, 1966) and the random utility theory (McFadden, 1974). Lancaster (1966) assumes that a good may be defined by a set of characteristics. The value of a good therefore consists of the sum of the value of all its characteristics. Applying this theory in a choice experiment approach, this means that an alternative can be characterized by a set of characteristics, that we call attributes here, and that each attribute is associated with a utility level. The (indirect) utility $V_{n,i}$ of an alternative $i \in \{1, \dots, I\}$ for respondent $n \in \{1, \dots, N\}$, where I and N are given, possibly large, finite integers, is derived from the K observable attributes of the alternative, denoted as $X_i = (x_{i1}, \dots, x_{ik}, \dots, x_{iK})$, as well as of a set of A social, economic and attitudinal characteristics (socio-economic variables) characterizing the respondent, denoted as $Z_n = (z_{n1}, \dots, z_{na}, \dots, z_{nA})$:

$$V_{n,i} = V(X_i, Z_n) \quad \text{for } n = 1, \dots, N \text{ and } i = 1, \dots, I \ . \tag{1}$$

McFadden (1974) proposes to consider that individuals make choices according to a deterministic part along with some degree of randomness. Combining the two theories, we assume that the random utility of alternative i for individual n, $U_{n,i}$, is composed of the deterministic component $V_{n,i} = V(X_i, Z_n)$, and a stochastic element, $\epsilon_{n,i}$:

$$U_{n,i} = V(X_i, Z_n) + \epsilon_{n,i} \tag{2}$$

where the error term $\epsilon_{n,i}$ is a random variable that captures the unsystematic and unobserved random element of the choice of respondent n (Hanley et al., 2005; Holmes and Adamowicz, 2003; Louviere et al., 2000).

Assuming the rationality of individuals, respondents are thus supposed to associate each alternative i with a random utility level $U_{n,i}$ and choose the option that provides them with the greatest utility within a given choice set. It comes that an agent n will choose an alternative i from a finite set of alternatives S (with $card(S) \leq I$) if this random utility is greater than the random utility $U_{n,j}$ of any other alternative j in S:

$$U_{n,i} > U_{n,j} \Rightarrow V_{n,i} + \epsilon_{n,i} > V_{n,j} + \epsilon_{n,j} \ \ \forall\ j \neq i;\ \ i, j \in S \tag{3}$$

The probability that a respondent chooses alternative i is the same as the probability that the utility of alternative i is greater than the utility of any other alternative in the choice set (Adamowicz et al., 1998). Following Train (2009), this probability is

$$P_{n,i} = P\left\{U_{n,i} > U_{n,j} \quad \forall\, j \neq i;\ i,j \in S\right\} \tag{4}$$

$$\Leftrightarrow P_{n,i} = P\left\{V_{n,i} + \epsilon_{n,i} > V_{n,j} + \epsilon_{n,j} \quad \forall\, j \neq i;\ i,j \in S\right\} \tag{5}$$

$$\Leftrightarrow P_{n,i} = P\left\{\epsilon_{n,j} < V_{n,i} - V_{n,j} + \epsilon_{n,i} \quad \forall\, j \neq i;\ i,j \in S\right\} \tag{6}$$

3.2 Model specifications

According to equation (2), the random utility $U_{n,i}$ is composed of a deterministic component, $V_{n,i} = V(X_i, Z_n)$, and a stochastic element, $\epsilon_{n,i}$. Before estimating an econometric model, one needs to specify the deterministic part of the utility function, $V_{n,i} = V(X_i, Z_n)$. The linear specification is often chosen in the literature as it is the simplest to work with. We thus introduce the column vector of parameters $\beta_n = (\beta_{n1}, \ldots, \beta_{nK})'$, which are the coefficients quantifying the (linear) influence of the $K = 4$ attributes on utility, and may be specific to each respondent n.

We also introduce an Alternative Specific Constant (ASC) term to capture the effect of unobserved influences (omitted variables) on the utility function, which is a dummy variable taking the value 1 if none of the hypothetical alternatives is chosen (*i.e.*, the status quo alternative is chosen), and 0 otherwise. Thus, the ASC defines a situation with no variation of the farmer's profit, no additional years with poor harvest, no additional administrative commitment and no reduction of the health and environment impact. A positive and statistically significant coefficient η for the ASC dummy variable would indicate strong preferences for not moving from the current situation.

Hence, the model is specified so that the probability of selecting a particular farming practice scenario i is a function of attributes X_i of that alternative, of the alternative specific constant ASC, and of the socio-economic characteristics Z_n of the respondent n. As the utility $V_{n,i}$ is assumed to be an additive function, equation (2) becomes:

$$U_{n,i} = \left(\eta + Z_n \alpha^{ASC}\right) ASC + X_i(\beta_n + \alpha Z_n') + \epsilon_{n,i} \tag{7}$$

The column vector of coefficients $\alpha^{ASC} = (\alpha_1^{ASC}, \ldots, \alpha_A^{ASC})'$ captures the effect of the socio-economic characteristics on the status quo utility, and the matrix α of size (K, A) is composed of coefficients $\alpha_{i,a}$ capturing the cross-effect of socio-economic characteristic a on attribute i. In our case, $X_i = (x_{i1}, x_{i2}, x_{i3}, x_{i4})$ corresponds to the different levels taken by the attributes *"Profit"*, *"Risk of poor harvest"*, *"Administrative commitment"* and *"Health and environmental impacts"*, respectively.

Thus specified, the parameters $\beta_n = (\beta_{n1}, \beta_{n2}, \beta_{n3}, \beta_{n4})'$ quantify the influence that the various levels of the four attributes have on the utility respondent n

associates with the I different alternatives available, relative to the utility of the status quo option that appeared on every choice card.

Different econometric models, which rely on different assumptions on the distribution of error terms $\epsilon_{n,i}$, can be used to analyze the discrete choice data. In the same way, the attributes $X_i = (x_{i1}, x_{i2}, x_{i3}, x_{i4})$ can be treated as discrete or continuous variables, and it is possible to combine qualitative and quantitative attributes in the same model specification. Also, the interactions with socio-economic characteristics can be modeled in different ways. We now specify our modeling choices.

3.3 The Random Parameter Logit model

The Conditional Logit (CL) model, also called the multinomial logit model, is the workhorse model for analyzing discrete choice data and is widely used in DCEs. Its mathematical specifications are presented in Appendix 7.1. This model has however several well-known limitations. An important drawback is that it assumes homogeneous preferences across respondents, meaning that the probability that an agent n chooses alternative i in a choice set S, is considered fixed across all individuals ($\beta_n = \beta$ for all n), while we can expect the preferences to vary among the respondents. Two other important drawbacks are the hypothesis of the independence of irrelevant alternatives (*IIA*) and uncorrelated unobserved components. *IIA* implies that the relative probabilities of two options being chosen are unaffected by the introduction or removal of other alternatives. If the *IIA* property is violated[7] then the CL model does not fit the data. Results will be biased, leading to unrealistic predictions, and hence a discrete choice model that does not require the *IIA* property should be used.

Compared to the CL model, the random parameter logit (RPL) model, also called the mixed logit model, releases the *IIA* property by allowing the random components of the alternatives to be correlated, while maintaining the assumption that they are identically distributed (McFadden and Train, 2000; Greene, 2008). It provides a more flexible method for capturing heterogeneity of preferences by assuming that some parameters of the vector β are randomly distributed in the population rather than fixed as in the usual CL model. In the RPL, the preferences parameters β_n are thus allowed to vary across respondents.

Whenever the error term $\epsilon_{n,i}$ is assumed to be an independently and identically distributed Type I Extreme Value variable, the logit probability that respondent n chooses a specific alternative i for a given β conditional on the individual-specific parameters and error components can be expressed as follows:

$$P_{n,i}|\beta = L_{n,i}(\beta) = \frac{e^{V_{n,i}(\beta)}}{\sum_j e^{V_{n,j}(\beta)}} \tag{8}$$

[7]One can use the test proposed by (Hausman and McFadden, 1984) to test the *IIA* assumption.

The probability of choice unconditional on the error component is obtained by integrating over the error-component space. Following this, the unconditionnal choice probability of choosing alternative i is the logit formula in equation (8) integrated over all values of β weighted by the density of β:

$$P_{n,i} = \int L_{n,i}(\beta) f(\beta|\Omega) d\beta \tag{9}$$

where $f(\beta)$ is the density function for β, describing the distribution of preferences over individuals, and Ω is the fixed parameter of the distribution. Random parameters are generally supposed to be normally distributed in the RPL model because it is the most easily applied distribution allowing for both negative and positive preferences.

The choice probability in eq. (9) cannot be calculated exactly because the integral does not have a closed form solution in general. This integral is approximated through simulations. A value of β is drawn from its distribution. Using this draw, the logit formula in (8) is calculated. This process is repeated for many draws, and the mean of the resulting $L_{n,i}(\beta)$ is taken as the approximate choice probability yielding:

$$SP_{n,i} = \frac{1}{R} \sum_{r=1}^{R} L_{n,i}(\beta_r) \tag{10}$$

where R is the number of draws of β, and SP is the simulated probability that an individual n chooses alternative i.

3.4 Results

Table 5 presents the results for the RPL model when both the cost attribute (*"Profit"*) and the *"Health and environmental impacts"* attribute (which have quantitative levels) are specified as continuous variables but the two other attributes (*"Risk of poor harvest"* and *"Administrative commitment"*) are modeled as effect-coded dummy variables.[8] For robustness check, Table 10 in the Appendix presents the results for the CL (first column) and the RPL model (second column) when all attributes are specified as continuous variables. Table 5 also presents the results of the RPL extended model taking into account interactions with socio-economic variables (two columns on the right). We first present the results of the model without interactions, and then discuss the effect of socio-economic variables.

[8] These attributes are encoded using *i)* two dummy-coded variables (*"+ 1 year"* and *"+ 2 years"*) for the *"Risk of poor harvest"* attribute and *ii)* three dummy-coded variables (*"Charter"*, *"Contract"* and *"Certification"*) for the *"Administrative commitment"* attribute. Thus defined, the excluded levels for each variable – which are tied to the ASC – are "no additional years with poor harvest" and "no additional administrative commitment", respectively.

As commonly assumed in the literature (Hensher and Green, 2003), the coefficient associated with the cost attribute is considered to be constant, in opposition to the other parameters of the RPL models, which are assumed to be normally distributed.[9] For these random parameters, distribution simulations are based on 1000 Halton draws to estimate their respective mean and standard deviation.

Regarding the results of the RPL estimations without interactions with socio-economic variables (Table 5, first columns), standard deviations of a majority of the coefficients are significant, indicating that a RPL provides a significantly better representation of the choices than a CL[10], capturing heterogeneity among respondents.

Except for the *"Health and environmental impacts"* attribute, all the coefficients of the RPL model are statistically significant and have the expected sign. Contrarily to what was expected following the focus groups, the coefficient of the *"Health and environmental impacts"* attribute is not statistically significant at the 10 % level. The reduction of exposure to harmful substances for health or the environment seems to have no significant effect on farmers' decisions, a question we shall discuss in Section 4.

The coefficient of the *ASC* is statistically significant at the 5% level and is negative, meaning that farmers value negatively the fact of staying in the status quo situation. The sign of the cost attribute coefficient (*"Profit"*) is statistically significant at the the 1% level. As expected, its positive sign indicates that a higher profit has a positive effect on respondents' utility.

All the dummy variables associated with the *"Risk of poor harvest"* and *"Administrative commitment"* attributes have statistically significant and negative coefficients, meaning that an increase in harvest risk or administrative commitments significantly reduces respondents' utility. Interestingly, respondents associate any additional administrative framework coming with a change of practice as a higher administrative burden rather than as a beneficial support. We further detail the economic interpretation associated to these coefficients when estimating the associated WTP/WTA in section 5.

Role of the interactions with socio-economic variables In the extended model (Table 5, last columns), we have tested the role of the socio-economic variables on the parameters associated to each attribute. Examining such interactions

[9] The normal distribution is symmetric and unbounded. It has the convenient advantage of making no a priori assumption on farmers' preferences: positive as well as negative parameter values may be taken, in order to capture the heterogeneity in the population. Fixing the cost attribute coefficient, on the contrary, ensures that all respondents have a positive valuation of profits, according to intuition.

[10] Recall that a CL assumes that coefficients are the same for all respondents. For robustness check, Table 11 in the Appendix presents the results for the CL model.

	RPL Model		RPL Model with interactions	
	Coefficient (S.E)	Coeff. Std. (S.E)	Coefficient (S.E)	Coeff. Std. (S.E)
Attributes :				
.ASC	-0.786** (0.373)	2.648*** (0.361)	1.194 (0.806)	2.319*** (0.337)
.Profit	0.009*** (0.003)	- -	0.009*** (0.003)	- -
.Risk of poor harvest:				
+ 1 year	-0.718*** (0.230)	0.076 (0.338)	-0.707*** (0.241)	0.440 (0.339)
+ 2 years	-0.971*** (0.310)	0.626** (0.251)	-1.035*** (0.325)	0.892*** (0.279)
.Administrative commitment:				
Charter	-0.412* (0.245)	-0.828*** (0.292)	-0.424* (0.253)	-0.992*** (0.260)
Contract	-0.575** (0.252)	1.018*** (0.362)	-0.668*** (0.259)	1.039*** (0.337)
Certification	-0.757*** (0.266)	0.801*** (0.304)	-0.789*** (0.274)	0.833*** (0.282)
.Health & environ-mental impacts	-0.001 (0.005)	0.020*** (0.004)	-0.001 (0.005)	0.024*** (0.005)
. Outside revenues	-	-	-1.491*** (0.496)	-
. Awareness of environmental impacts	-	-	-0.719* (0.393)	-
. Cropland type :				
Market gardening	-	-	-1.889* (1.039)	-
Wine-growers	-	-	0.950 (0.775)	-
Mixed crop and livestock	-	-	3.991*** (1.134)	-
N (ind.)	75		74	
N (obs.)	1800		1776	
McFaden R^2	-		-	
Log Likelihood	-540.19		-529.07	

ASC: Alternative Specific Constant.
Dummy variable=1 if Statu Quo (SQ); 0 othherwise.

Table 5: Results of the RPL models without and with socio-economic interactions

helps to understand with more precision farmers' preferences towards each attribute. The coefficients of these socio-demographic variables are assumed to be constant, as is common in the literature.

Interactions with the following socio-economic variables have been tested: age, income, level of education, farm size, existence of sources of revenues from outside the farm, the farm type, whether the respondent thinks pesticides affect the environment (i.e. awareness of environmental impacts), whether the respondent thinks pesticides affect human health (i.e. awareness of health impacts), whether the respondent thinks maintaining yields is compatible with reduced pesticide use, whether the respondent initially knows her/his level of pesticides use, whether the respondent has subscribed an insurance contract.

We have tested individually the significance of the interaction between these variables and each attribute and have included the significant socio-economic variables in an extended model. The reduced model with significant interactions have been obtained using the backward elimination procedure. Only interactions with the *ASC* remain significant after this procedure. They are useful as they give information on which types of respondents are more willing to move away from the status quo, *i.e.*, willing to change their farming practices towards reduced pesticides.

All attributes parameters in the extended model are quite close to those in the model without interaction, showing that estimations are robust. They remain significant and have the expected signs, except for the *"Health and environmental impacts"* attribute which remains not significant, suggesting that the impact of pesticides on health and the environment is still not a major criteria in respondents' decisions.

Regarding the interactions of the socio-economic variables with the *ASC* (bottom part of Table 5), results show that farmers who have some revenues from outside the farm (*"Outside revenues"*) are significantly more willing to change their practices (as they have a stronger disutility staying in the status quo). This result confirms the idea that the behavior of farmers towards risk and the fear of having less stable revenues is an obstacle to the adoption of low-pesticide practices. Farmers who believe pesticides have a strong impact on the environment (*"Awareness of environmental impact"*) are also more willing to move from the status quo - that is to adopt practices that reduce their use of pesticides - which is consistent with intuition. The cropland types are coded as dummies, and their coefficients must be interpreted as differences with respect to field crops farms. Results indicate that vegetable farmers are significantly more willing to change their farming practices than field crops farmers whereas mixed crop/livestock farmers are less willing to do so than field crops farmers. There is no significant difference between wine-growers and field crops farmers' attitude towards leaving the status quo.

4 Exhibiting two populations through a Latent Class model

The fact that the *"Health and environmental impacts"* attribute is not significantly affecting the choice to adopt a practice reducing pesticide use is puzzling. In order to better understand farmers' preferences for the various attributes, especially this *"Health and environmental impacts"* attribute, we now try to determine whether we can identify some classes of farmers who have similar behaviors and how these classes can be defined.

4.1 A visual inspection as a starter

Using kernel density functions, Figures 2, 3 and 4 provide the distribution of the individual parameters for each attribute and the ASC estimated by the RPL model without interaction (similar distributions are obtained for the RPL model with interactions).

Regarding the *"Risk of poor harvest"* (Figures 2) and the *"Administrative commitment"* (Figure 3) attributes, farmers' preferences appear to be concentrated around a single value.

On the contrary, there seems to be at least two groups of preferences among respondents for the *"Health and environmental impacts"* attribute and the ASC (Figure 4). Note that the distribution of the parameter of the *"Health and environmental impacts"* attribute is clearly concentrated around a positive value and a negative (close to zero) value, which is not the case for the ASC coefficient (both values are negatives). This rather particular distribution of the *"Health and environmental impacts"* attribute may explain why its coefficient is not statistically significant in our results.

Though very useful and often revealing, inspecting graphs are always vulnerable to subjective interpretation and more objective statistical analysis is needed. The conclusions drawn from a simple visual inspection of the kernel density estimates argue for the use of a latent class model.

4.2 The Latent Class approach

Another way to take into account the heterogeneity in respondents' preferences is to analyze the sample with a Latent Class Model (LCM).[11] In this model, respondents are sorted into a number of classes C in which preferences are assumed to be homogeneous with respect to attributes. In contrast, preferences are allowed to be heterogeneous between classes partitioning the population.

[11]The LCM also relaxes the hypothesis of the independence of irrelevant alternatives (*IIA*).

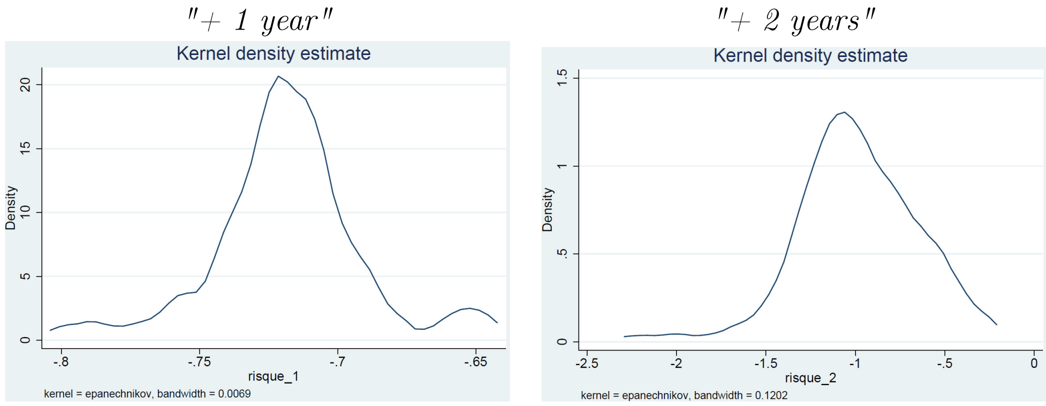

Figure 2: Distribution of the individual parameter for the two dummy-coded variables per level (*"+ 1 year"* and *"+ 2 years"*) for the *"Risk of poor harvest"* attribute using kernel density functions

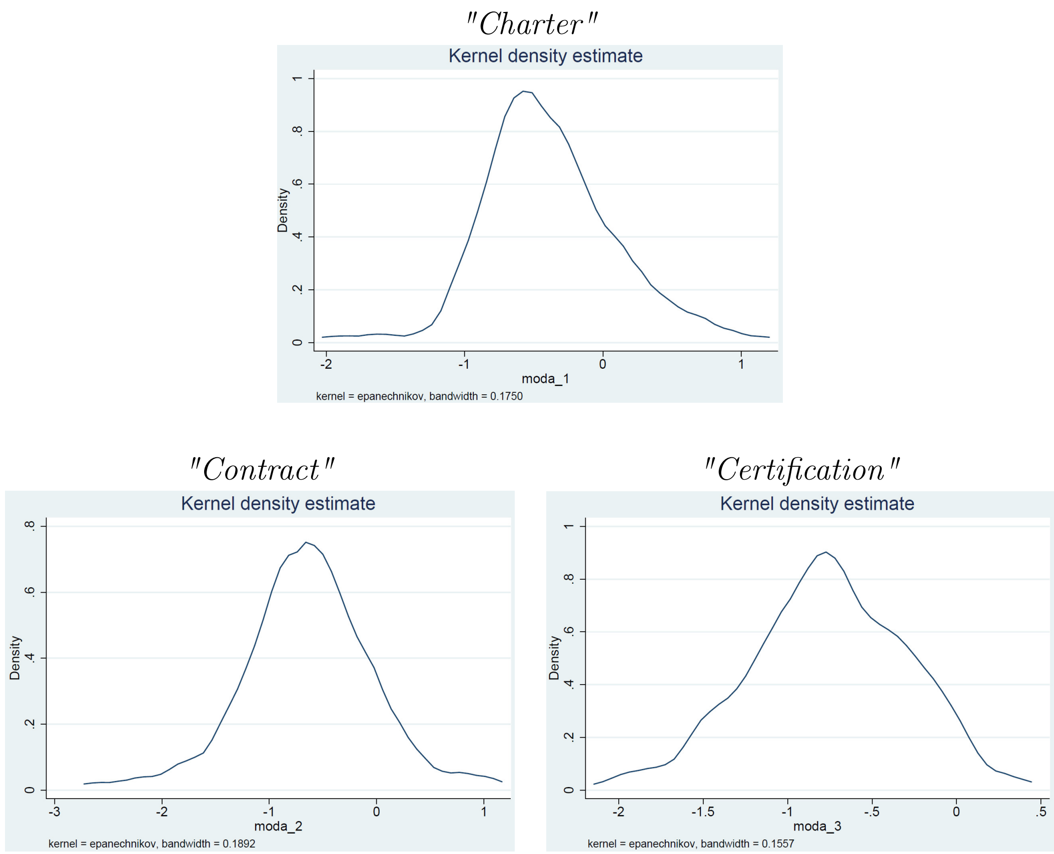

Figure 3: Distribution of the individual parameter for the three dummy-coded variables per level (*"Charter"*, *"Contract"* and *"Certification"*) for the *"Administrative commitment"* attribute using kernel density functions

"Health and environmental impacts" ASC (keep the current practice)

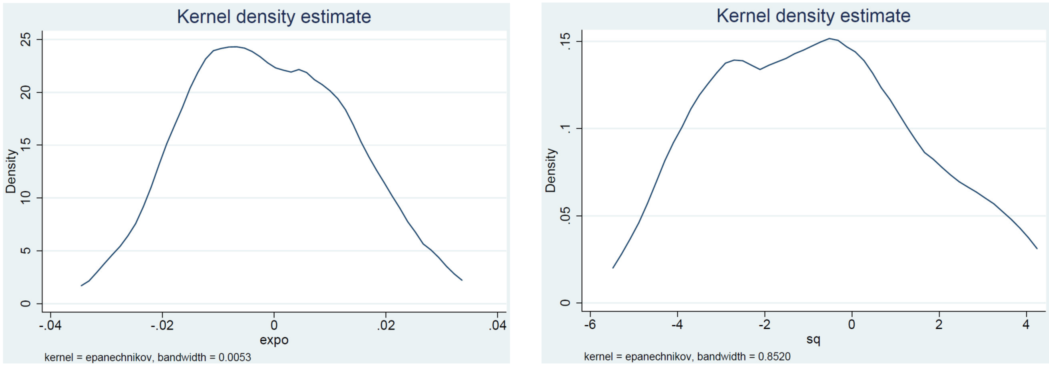

Figure 4: Distribution of the individual parameter for the *"Health and environmental impacts"* attribute and the ASC using kernel density functions

Compared to equation (8), the logit probability that respondent n prefers a specific alternative i over alternatives j is no more defined for a given β but becomes conditional on class c, as the β are now assumed to follow a discrete distribution and belong to one of C classes. The conditional probability that respondents who are members of class c choose alternative i is :

$$P_{n,i}|\beta_c = \frac{e^{V_{n,i}(\beta_c)}}{\sum_j e^{V_{n,j}(\beta_c)}}; \quad \forall c \in \{1,\ldots,C\} \tag{11}$$

where β_c is the vector of preferences parameters specific to class c, representing the average importance of each attribute for respondents belonging to c.

The unconditional probability of individual n selecting alternative i can be expressed as:

$$P_{n,i} = \sum_{c=1}^{C}(M_{n,c} \cdot P_{n,i}|\beta_c) = \sum_{c=1}^{C}(M_{n,c} \cdot \frac{e^{X_i\beta_c}}{\sum_j e^{X_j\beta_c}}) \tag{12}$$

where $M_{n,c}$ is the probability that respondent n belongs to class c. This probability is assumed to depend on the socio-economic characteristics Z_n as follows:

$$M_{n,c} = \frac{e^{Z_n\theta_c}}{\sum_{h=1}^{C} e^{Z_n\theta_h}} \tag{13}$$

the vector of parameters θ_c defining the effect of the various socio-economic variables on the probability to belong to class c (Boxall and Adamowicz, 2002).

The LCM model assumes that respondent's socio-economic characteristics affect choice indirectly through their impact on class membership. Note that θ_c includes $C-1$ class membership parameters with θ_C being normalized to zero for identification. All other coefficients are thus interpreted relative to this normalized class.

4.3 Model with two latent classes

The conclusion drawn from the kernel density visual inspection is confirmed by the results of the LCM with two classes. The 2-classes solution provides the best fit to the data, as shown in Table 6.

Number of classes	Parameters (P)	Log likelihood	AIC	CAIC	BIC
2	17	-563.62025	1161.2405	1217.6378	1200.6378
3	26	-553.72184	1159.4437	1245.6984	1219.6984
4	35	-523.06691	1116.1338	1232.2459	1197.2459
5	44	-510.51368	1109.0274	1254.9968	1210.9968

. AIC (Akaike Information Criterion) = -2LL + 2P

. CAIC (Consistent Akaike Information Criterion) = - 2LL + P[(ln N) + 1]

. BIC (Bayesian Information Criterion) = -LL + [P (ln N)]/2

Table 6: Criteria for determining the optimal number of classes

Table 7 presents the results of the LCM with two latent classes and respondents' socio-economic characteristics as *Segment function* (*i.e.*, determinants of class membership). These results indicate that our farmers sample can be divided into two main classes: *Class 1* comprises about 42% of the respondents, whereas *Class 2* comprises about 58% of them. Looking at *Class 1* results, the coefficient estimates are close to those estimated by the RPL models in Table 5, except for the *"Health and environmental impacts"* attribute which is now statistically significant and negative. Respondents belonging to *Class 1* value negatively exposure to harmful substances for health or the environment when choosing their agricultural practices. This class stands out from the majority of the respondents – *Class 2* farmers – who does not take into account health and environmental considerations (coefficient estimate is not statistically significant). Compared to *Class 2*, *Class 1* is also characterized by the significance and negative sign of the *ASC* coefficient, indicating that farmers in this class are more willing to leave the status quo, *i.e.*, to reduce their use of pesticides, than those in *Class 2*.

To understand the drivers of class membership, the second part of Table 7 (bottom of the first column) presents class membership coefficients, describing which socio-economic variables explain *Class 1* membership, the second class being normalized to zero. The positive and statistically significant coefficients of the variables *"Outside revenues"* and *"Awareness of environmental impacts"* indicate that farmers who have sources of revenues from outside the farm and who believe pesticides have a strong impact on the environment are more likely to belong to

	Latent class model with 2 latent classes and respondents' socioeconomic characteristics as segment function	
	Class 1 Coefficient (S.E)	**Class 2** Coefficient (S.E)
Attributes :		
.ASC	-2.798***	0.325
	(0.533)	(0.412)
.Profit	0.015*	0.006*
	(0.009)	(0.003)
.Risk of poor harvest:		
+ 1 year	-1.183**	-0.486**
	(0.465)	(0.268)
+ 2 years	-1.066*	-1.000***
	(0.570)	(0.369)
.Administrative commitment:		
Charter	-0.598**	-0.023
	(0.298)	(0.286)
Contract	-0.743**	-0.482
	(0.332)	(0.312)
Certification	-1.000**	-0.736**
	(0.435)	(0.342)
.Health & environ- mental impacts	-0.016*	0.006
	(0.009)	(0.006)
Segment function: *respondents' social and economic characteristics*		
. Constant	-2.165**	-
	(0.932)	
. Outside revenues	1.003*	-
	(0.542)	
. Awareness of environmental impacts	0,748*	-
	(0.433)	
. Awareness of health impacts	-0.299	-
	(0.405)	
. Awareness of profit impacts	0.719	-
	(0.433)	
N (ind.)	31	44
N (obs.)	744	1056
Class share (%)	40.9	59.1

ASC: Alternative Specific Constant.
Dummy variable=1 if Statu Quo (SQ); 0 oththerwise.

Table 7: Results of the LC model with two classes and respondents' socio-economic characteristics as Segment function

the class that values negatively health and environmental impacts and that is more willing to reduce pesticide use.

Benefiting from additional revenues that are independent from the farm activity can be interpreted as a form of insurance through a diversification of the sources of revenues. The major role of the existence of outside revenues in farmers class membership confirms the significance of risk aversion to explain farmers' behavior. Those who can protect themselves from harvest risk by other means than pesticides are more willing to change their practices.

5 Willingness to accept estimates

As mentioned in Section 2, welfare measures can be determined in the form of marginal WTP/WTA by estimating the marginal rate of substitution between the considered attribute and income. The marginal utility of income is represented by the cost attribute's coefficient, β_{cost}, which is assumed constant as mentioned before. In our case, the non-monetary attributes are valued negatively by respondents, so we measure WTAs rather than WTPs. Estimates of the WTA values are obtained for each of the non-monetary attributes using the Wald procedure (Delta method).[12] Since utilities are modeled as linear functions of the attributes, the marginal rate of substitution between two attributes is the ratio between the coefficients:[13]

$$WTA_k = -\frac{dx_{cost}}{dx_k} = -\frac{dU/dx_k}{dU/dx_{cost}} = -\frac{\partial V/\partial x_k}{\partial V/\partial x_{cost}} = -\frac{\beta_k}{\beta_{cost}} \tag{14}$$

Estimates presented in Table 8 were calculated using the RPL models shown in Table 5. For attributes modeled as effect-coded dummy variables in Table 5, the WTA associated with each attribute k and each level l becomes:

$$WTA_k^l = -\frac{\beta_k^l}{\beta_{cost}} \tag{15}$$

where β_k^l are the estimated parameters, which measure the variation of utility associated with a variation of the attribute k from the status quo level to level l. WTA_k^l then represents the willingness to accept to move from the status quo level of attribute k to a level l.

[12]The Delta method stipulates that the WTA for a unit change of a given attribute can be computed as the marginal rate of substitution between the quantity expressed by the considered attribute and the cost attribute (Louviere et al., 2000).

[13]It should be noted that the derivative of the unobserved part of the utility function is supposed to be zero with respect to both attributes.

Since the RPL model assumes *i)* the cost attribute is a fixed parameter and *ii)* other attributes' coefficients are normally distributed, WTA are then normally distributed. We then have the convenient result that:

$$E[WTA_k] = -\frac{E[\beta_k]}{\beta_{cost}} \tag{16}$$

$$E[WTA_k^l] = -\frac{E[\beta_k^l]}{\beta_{cost}} \tag{17}$$

		Risk of poor harvest		Administrative commitment			Health & environmental impacts
		+1 year	*+2 years*	*Charter*	*Contract*	*Certification*	
RPL model with attributes modeled as dummy-coded variables	**Mean :**	**83.27**	**112.52**	**47.78**	**66.68**	**87.72**	-
	90% CI :	[38.15 ; 128.38]	[65.75 ; 159.30]	[1.02 ; 94.53]	[12.76 ; 120.61]	[37.09 ; 138.34]	-
RPL model with attributes modeled as dummy-coded variables and socio-economic interactions	**Mean :**	**79.11**	**115.72**	**47.42**	**74.73**	**88.17**	-
	90% CI :	[34.96 ; 123.25]	[67.10 ; 164.35]	[0.75 ; 94.08]	[18.45 ; 131.01]	[37.34 ; 139.00]	-

Table 8: WTA estimates for the Random Parameter Logit models

The estimated standard deviations and confidence intervals around the mean of the WTA estimates presented in Table 8 are obtained using the Krinsky and Robb parametric bootstrapping method (Krinsky and Robb, 1986). In calculating a WTA, it is important that both parameters used in the calculation be statistically significant, otherwise no meaningful WTA measure can be established. For this reason, no WTA were estimated for the *"Health and environmental impacts"* attribute with the RPL models.

As shown in Table 8, WTA estimates are similar using the RPL with or without interactions - which shows that estimates are rather robust - and we thus focus on the RPL with interactions in the results interpretation that follows.

Farmers in our sample need to receive 79 euros per hectare and per year (euros/ha/year), in average, to accept one additional year out of ten of poor harvest[14]. They need to receive 116 euros/ha/year to accept two additional years out of ten of poor harvest. The risk attribute seems to be a dominant criteria in our farmers decisions. Farmers express high preferences for not bearing a risk of loss as shown by the high amounts of the associated WTAs. We also note that this attribute is not linear in the sense that farmers need to receive much more for the first additional year of risk of poor harvest than for the second year. It is the fact of having

[14]Note that this attribute is measured for a given profit (which is the cost attribute) and thus only measures the variability of the harvest and not its level.

an increased risk of loss - rather than the extend of the risk increase - that seems to play most in their decision.

Regarding "*Administrative commitment*", farmers need to receive in average 47 euros/ha/year to accept to enter a charter, 75 euros/ha/year to accept to sign an agri-environmental contract with public authorities, and 88 euros/ha/year to accept to commit to a certification, all else being equal.[15] There is a hierarchical effect in the levels of the *"Administrative commitment"* attribute: respondents need to receive more to enter a certification process than an agri-environmental contract, which itself requires more compensation than a charter. This is consistent with intuition as a certification includes a rigorous specification and controls, contrarily to a charter. Signing an agri-environmental contract with public authorities, such as an Agri-Environmental Scheme, usually implies controls and specifications but that are less constraining than a certification associated to a label.

Table 9 presents WTA estimates for the LCM with two classes and respondents socio-economic characteristics as Segment function, which can help us to refine the previous interpretations based on the average values of the RPL model.

		Risk of poor harvest		**Administrative commitment**			**Health & environmental impacts**
		+1 year	*+2 years*	*Charter*	*Contract*	*Certification*	
Segment 1 *N (ind.) = 31*	**Mean :**	**75.19**	**67.70**	**37.96**	**47.17**	**63.56**	**1.03**
	90% CI :	[38.51 ; 111.86]	[43.59 ; 91.81]	[3.62 ; 72.30]	[10.52 ; 83.83]	[32.29 ; 94.83]	[0.65 ; 1.41]
Segment 2 *N (ind.) = 44*	**Mean :**	**84.41**	**173.84**	-	-	**128.00**	-
	90% CI :	[7.83 ; 161.00]	[47.26 ; 300.41]	-	-	[8.60 ; 247.39]	-

Table 9: WTA estimates for the latent class model with two classes and respondents' socio-economic characteristics as Segment function

The farmers of *Class 2* (covering 58% of our sample) are even more averse to risk than the estimates for the whole sample. Risk has an almost linear effect for them, with a WTA for "*+2 years*" equal to twice the WTA for "*+1 year*", while the effect seemed to be marginally decreasing when considering the whole sample. These farmers also seem to be highly reluctant to "*Certification*" (high WTA for this attribute) and not to the other forms of "*Administrative commitment*". Last, they do not account for the "*Health and environmental impacts*", in line with the RPL estimations for the whole sample.

[15]That is, if the contract/charter does not imply extra-costs, reduced yields or any other consequences on profit. In other words this WTA is only to compensate for the administrative and control burden - or any potential disturbance - of signing a contract/charter/certification.

Looking at WTA estimates for *Class 1* (covering 42% of our sample), we can see that the farmers belonging to this class are slightly less reluctant to "*Administrative commitment*" than the average of the whole sample (the mean values and the higher bounds of the confidence intervals of their WTA for these attributes are lower than that of the whole sample in the RPL model). Their attitude towards risk is also milder than the average of the whole sample. In particular, they value "*+1 year*" and "*+2 years*" of "*Risk of poor harvest*" the same way,[16] meaning that they treat the increase of risk "qualitatively," notwithstanding the number of additional years of poor harvest.

The main difference is that, for this class, a WTA for the "*Health and environmental impacts*" attribute can be estimated, as the coefficient for this attribute is significant for this class in the LCM. According to this result, respondents in *Class 1* need in average to receive 1 euro/ha/year to accept a 1% increase in the health and environment impacts of their agricultural practices. In other words, they are ready to loose 1 euro/ha/year to reduce the impact of their practices by 1%, which means that, everything else being equal, they could accept a profit loss of 20 (resp. 50 and 80) euro/ha/year for a 20% (resp. 50% and 80%) reduction of the "*Health and environmental impacts*" of their practices.

These results on the WTA for different attributes confirm the conclusions that the studied farmers sample, and possibly farmers population, can be sorted out in two groups: the first one (our *Class 2*) being reluctant to changes in risk increase and commitment, and insensitive to the health and environmental impacts of pesticides, while the second group (our *Class 1*) is willing to leave the status quo, sensitive to the health and environmental impacts of pesticides, and moderately averse to harvest-risk increase.[17] The farmers in this latter group are more likely to adopt agricultural practices that reduce pesticide use than those in the former group.

6 Conclusion and policy implications

This article investigates farmers' motivations and obstacles to reduce their use of pesticides. We use a quantitative approach based on a discrete choice experiment to measure the relative weight of various factors influencing farmers' practices. Our survey is the first of this kind on 90 French farmers.

[16] Although the mean WTA for two additional years of poor harvest is slightly lower than the mean WTA for one additional year of poor harvest within this class, we can see looking at the confidence intervals that the difference is not significant. The WTAs for one or two additional years of poor harvest can thus be considered as equivalent for *Class 1* in the LCM.

[17] Their limited aversion to the harvest-risk may be explained by the fact that farmers pertaining to this class more often have sources of revenues from outside the farm (as shown by the class membership probabilities in the previous section).

We value farmers' WTP/WTA for several non market components of their decisions such as the administrative framework of a practice change, the impact of their activity on health and the environment, and the risk of harvest loss (for a given level of mean profit). Regarding the latter, using pesticides can be interpreted as an insurance behavior as it limits income variability by reducing harvest losses, without necessarily increasing the total mean income (Menapace et al., 2013). Farmers' behavior towards risk is therefore a potential major component explaining their willingness to reduce pesticides that had barely been examined by the quantitative literature on the topic.

We used two econometric models, namely a Random Parameter Logit allowing us to characterize the (average) preferences of the whole sample, and a Latent Class Model that identifies two classes of farmers.

We find that the administrative commitment that may come along with the agricultural practices change (charter, contract, certification) is not seen by farmers as an opportunity for support or integration in a network but rather as a burden. In particular, Agri-Environmental Schemes taking the form of a contract with public authorities are valued negatively. All else being equal, farmers would need to receive in average 75 euros/ha/year to accept signing such a contract.

Furthermore, the risk of poor harvest is a prominent obstacle for farmers' reduction of pesticides use. All else being equal, farmers need to receive in average 79/ha/year to accept one additional year of poor harvest every ten years. This amount is not very much higher (116 euros/ha/year) for farmers to accept two additional years of poor harvest every ten years, which shows how much this risk aversion corresponds here to an abstract fear rather than a rational behavior. There seems to be a psychological cost of harvest loss which is not necessarily correlated to the financial loss. The results of our Latent Class model, however, allows to distinguish the preferences on this attribute over two groups of farmers. Our *Class 2* farmers (58% of the sample) are more reluctant to an increase in risk (with a WTA of about 80 euro *for each* additional year of poor harvest) than the farmers of our *Class 1* (42% of the sample), which value an increase of risk at about 70 euros, irrespective of the number of additional years.

The impact of the agricultural practices on health and the environment does not seem to be a decisive factor for the interviewed farmers when analyzing the sample as a whole (RPL model). Our Latent Class Model, however, identifies that while the farmers of our *Class 2* do not take this attribute into consideration, those of *Class 1* value negatively health and environmental impacts of their practices. They are ready to give up 1 euro/ha/year to reduce these impacts by 1%. They are also more willing than the other class to change their practices towards a reduced pesticide use. Farmers who have sources of revenues from outside the farm are more inclined to pertain to this class. This confirms the role of risk aversion in farmers behavior: diversifying the sources of revenues is a form of insurance which seems to favor farmers change of practices.

Our results shed some light on the suitable agri-environmental policies to reduce the use of chemical inputs in agriculture. First, the WTA for an increased harvest risk can be interpreted as a risk premium, *i.e.*, as a minimum amount necessary for farmers to accept a risky practice change. The public subsidies implemented to encourage a reduction of pesticides should offer an amount at least as high as this risk premium, which varies according to the estimation of the risk magnitude (eg. one or two years of poor harvest every ten years). Public mechanisms to support risk-taking should also be considered, such as reliable and not too expensive public insurances.

Moreover, ours results unambiguously show that administrative commitments that may be necessary to reduce pesticides, for example to obtain a subsidy, are an obstacle. This result is consistent with the DCE literature on the adoption of Agri-Environmental Schemes. Authorities should set priority on improving the form of the offered contracts/charters/certifications so as to limit the administrative burden. Simplifying the formalities is probably a promising vector of improvement. Offering free assistance for administrative tasks should also be generalized.

Last, we have shown that the existence of outside revenues is determinant in farmers willingness to change practices. According to that result, lump-sum subsidies that are independent from farming activities could help farmers to adopt risky low-pesticide practices. Farmers with low, insecured income may be locked-in pesticide intensive practices.

Further research is needed in this field. In particular, complementary choice experiments among farmers could help to understand the weight of other factors such as the need for technical training on new practices, the role of network and neighborhood connexions, the impact of a practices change on work schedule, etc.

References

Adamowicz, V. and Boxall, P. (2001). Future directions of stated choice methods for environment valuation. *Choice experiments: A new approach to environmental valuation, London*, pages 1–6.

Adamowicz, W., Boxall, P. C., Williams, M., and Louviere, J. (1998). Stated preference approaches for measuring passive use values: Choice experiments and contingent valuation. *American Journal of Agricultural Economics*, 80(1).

Beharry-Borg, N., Smart, J., Termansen, M., and Hubacek, K. (2013). Evaluating farmers' likely participation in a payment programme for water quality protection in the UK uplands. *Regional Environmental Change*, (13):633–647.

Birol, E., Smale, M., and Gyovaii, A. (2006). Using a choice experiment to estimate farmers' valuation of agrobiodiversity on Hungarian small farms. *Environmental and Resource Economics*, (34):439–469.

Bliemer, M. and Rose, J. (2010). Serial Choice Conjoint Analysis for Estimating Discrete Choice Models. *in Stephane Hess , Andrew Daly (ed.) Choice Modelling: The State-of-the-art and The State-of-practice*, pages 137–161.

Bliemer, M. and Rose, J. (2011). Experimental design influences on stated choice outputs: An empirical study in air travel choice. *Transportation Research Part A: Policy and Practice*, 45(1):63 – 79.

Börger, T. (2016). Are fast responses more random? testing the effect of response time on scale in an online choice experiment. *Environmental and Resource Economics*, 65(2):389–413.

Bourguet, D. and Guillemaud, T. (2016). The hidden and external costs of pesticide use. *Sustainable Agriculture Reviews*, (19):35–120.

Boxall, P. C. and Adamowicz, W. L. (2002). Understanding heterogeneous preferences in random utility models: A latent class approach. *Environmental and Resource Economics*, 23(4):421–446.

Broch, S. W. and Vedel, S. E. (2012). Using choice experiments to investigate the policy relevance of heterogeneity in farmer agri-environmental contract preferences. *Environmental and Resource Economics*, (51):561–581.

Christensen, T., Pedersen, A. B., Nielsen, H. O., Mørkbakand, M., Hasler, B., and S.Denver (2011). Determinants of farmers' willingness to participate in subsidy schemes for pesticide-free buffer zones — A choice experiment study. *Ecological Economics*, 70.

Dumont, A. M., Vanloqueren, G., Stassart, P. M., and Baret, P. V. (2016). Clarifying the socioeconomic dimensions of agroecology: between principles and practices. *Agroecology and Sustainable Food Systems*, 40(1):24–47.

Espinosa-Goded, M., Barreiro-Hurlé, J., and Ruto, E. (2010). What do farmers want from agri-environmental scheme design? A choice experiment approach. *Journal of Agricultural Economics*, 61(2).

Greene, W. (2008). *Econometric Analysis*. Prentice-Hall, New Jersey, 6-th edition.

Greiner, R., Bliemer, M., and Ballweg, J. (2014). Design considerations of a choice experiment to estimate likely participation by north australian pastoralists in contractual biodiversity conservation. *Journal of Choice Modelling*, 10:34 – 45.

Greiner, R., Patterson, L., and Miller, O. (2009). Motivations, risk perceptions and adoption of conservation practices by farmers. *Agricultural systems*, 99(2-3):86–104.

Hanley, N., Adamowicz, W., and Wright, R. E. (2005). Price vector effects in choice experiments: an empirical test. *Resource and Energy Economics*, 27.

Hanley, N., Wright, R., and Koop, G. (2002). Modelling recreation demand using choice experiments: Climbing in scotland. *Environmental and Resource Economics*, 22(3):449–466.

Hausman, J. and McFadden, D. (1984). Specification tests for the multinomial logit model. *Econometrica*, 52.

Hensher, D. A. and Green, W. (2003). The mixed logit model: the state of practice. *Transportation*, 30(2).

Holmes, T. and Adamowicz, W. (2003). Feature based methods. In Champ, P. A., Boyle, K. J., and Brown, T. C., editors, *A primer on nonmarket valuation*. Kluwer Academic Publishers.

Hoyos, D. (2010). The state of the art of environmental valuation with discrete choice experiments. *Ecological Economics*, 69(8):1595–1603.

Hudson, D. and Lusk, J. (2004). Risk and transaction cost in contracting: results from a choice-based experiment. *Journal of Agricultural & Food Industrial Organization*, 2(1).

Jaeck, M. and Lifran, R. (2014). Farmers' preferences for production practices: a choice experiment study in the Rhone river delta. *Journal of Agricultural Economics*, (65(1)):112–130.

Johnston, R., Boyle, K., Adamowicz, W., Bennett, J., Brouwer, R., Cameron, T., Hanemann, M., Hanley, N., Ryan, M., Scarpa, R., Tourangeau, R., and Vossler, C. (2017). Contemporary guidance for stated preference studies. *Journal of the Association of Environmental and Resource Economists*, 4(2):319–405.

Kimball, M. S. (1988). Farmers' cooperatives as behavior toward risk. *The American Economic Review*, 78(1):224–232.

Knowler, D. and Bradshaw, B. (2007). Farmers' adoption of conservation agriculture: A review and synthesis of recent research. *Food Policy*, 32(1):25 – 48.

Kontoleon, A. and Yabe, M. (2003). Assessing the impacts of alternative 'opt-out'formats in choice experiment studies: consumer preferences for genetically modified content and production information in food. *Journal of Agricultural policy and Resources*, 5(1):1–43.

Krinsky, I. and Robb, A. L. (1986). On approximating the statistical properties of elasticities. *The Review of Economics and Statistics*, 68.

Kuhffus, L., Preget, R., and Thoyer, S. (2014). Individual preferences and collective incentives: what design for agri-environmental contracts? The case of wine-growers' herbicide use reduction. *Review of Agricultural and Environmental Studies*, (95(1)):111–143.

Kuhfuss, L., Préget, R., Thoyer, S., and Hanley, N. (2016). Nudging farmers to enrol land into agri-environmental schemes: the role of a collective bonus. *European Review of Agricultural Economics*, 43(4):609–636.

Lancaster, K. (1966). A new approach to consumer theory. *Journal of Political Economy*, 74(2).

Lechenet, M., Dessaint, F., Py, G., Makowski, D., and Munier-Jolain, N. (2017). Reducing pesticide use while preserving crop productivity and profitability on arable farms. *Nature Plants*, (3):170 08.

Louviere, J., Hensher, D., and Swait, J. (2000). *Stated choice methods : analysis and applications*. Cambridge University Press.

Malawska, A. and Topping, C. J. (2016). Evaluating the role of behavioral factors and practical constraints in the performance of an agent-based model of farmer decision making. *Agricultural Systems*, 143:136 – 146.

McFadden, D. (1974). Conditional logit analysis of qualitative choice behaviour. In Zarembka, P., editor, *Frontiers of econometrics*. Academic press, New York.

McFadden, D. and Train, K. E. (2000). Mixed MNL models for discrete response. *Journal of applied Econometrics*, 64.

Menapace, L., Colson, G., and Raffaelli, R. (2013). Risk aversion, subjective beliefs, and farmer risk management strategies. *American Journal of Agricultural Economics*, 95(2):384–389.

Peterson, J., Smith, C., Leatherman, J., Hendricks, N., and Fox, J. (2015). Transaction costs in payment for environmental service contracts. *Amercian Journal of Agricultural Economics*, (97(1)):219–238.

Rose, J. and Bliemer, M. (2013). Sample size requirements for stated choice experiments. *Transportation*, 40(5):1021–1041.

Ruto, E. and Garrod, G. (2009). Investigating farmers' preferences for the design of agri-environmental schemes: a choice experiment approach. *Journal of Environmental Planning and Management*, 52(5).

Street, D. J., Burgess, L., and Louviere, J. J. (2005). Quick and easy choice sets: constructing optimal and nearly optimal stated choice experiments. *International Journal of Research in Marketing*, (22):459–70.

Train, K. E. (2009). *Discrete choice methods with simulation.* Cambridge University Press, Cambridge, 2nd edition.

Vidogbena, F., Adegbidi, A., Tossou, R., Assogba-Komlan, F., Ngouajio, M., Martin, T., Simon, S., Parrot, L., and Zander, K. (2015). Control of vegetable pests in Benin - Farmers' preferences for eco-friendly nets as an alternative to insecticides. *Journal of Environmental Management*, (147):95–107.

Wilson, C. and Tisdell, C. (2001). Why farmers continue to use pesticides despite environmental, health and sustainability costs. *Ecological Economics*, (39):449–462.

7 Appendix

7.1 Mathematical details of the econometric models

Different discrete choice models are obtained from different assumptions about the distribution of the random terms. The RPL and LCM models have been presented in the main text. We present here the Conditional Logit (CL) model.

If we suppose that the unobserved components, the error terms $\epsilon_{n,i}$, all independently, among the N agents and between the I alternatives, follow a standard Gumbel distribution[18], we have specified a conditional logit model (or multinomial logit model).

Since the unobserved components are independent, we can multiply Eq. (6) to obtain the probability of individual n choosing alternative i, conditional on $\epsilon_{n,i}$:

$$P_{n,i}|\epsilon_{n,i} = \prod_{j \neq i} P\left\{\epsilon_{n,j} < V_{n,i} - V_{n,j} + \epsilon_{n,i}\right\} \tag{18}$$

$$= \prod_{j \neq i} e^{-e^{-(V_{n,i}-V_{n,j}+\epsilon_{n,i})}} \tag{19}$$

$P_{n,i}$ is then obtained with the integration of $P_{n,i}|\epsilon_{n,i}$ over the distribution of the unobserved components:

$$P_{n,i} = \int \left(\prod_{j \neq i} e^{-e^{-(V_{n,i}-V_{n,j}+\epsilon_{n,i})}} \right) e^{-\epsilon_{n,i}} e^{-e^{-\epsilon_{n,i}}} d\epsilon_{n,i} \tag{20}$$

Calculations then lead this expression to simplify in

$$P_{n,i} = \frac{e^{V_{n,i}}}{\sum_j e^{V_{n,j}}} \tag{21}$$

where $P_{n,i}$ only depends on observable components. Here the β' vector contains the β_{ik} parameters from Eq. (1), and vector X_i holds the attribute content of alternative i. The CL model is estimated using maximum likelihood procedures. This model assumes homogeneous preferences across respondents. In Eq. (21), the probability that an agent n chooses alternative i in a choice set C, β' is considered fixed across all individuals, while we can expect the preferences to vary among the respondents. The model also requires the hypothesis of independence of irrelevant alternatives (*IIA*), which implies that the relative probabilities of two options being

[18]The $\epsilon_{n,i}$ are supposed to be Independent and Identically Distributed (IID) and to follow a type I extreme-value distribution. Then the cumulative distribution function and the density function of each $\epsilon_{n,i}$ are $F(\epsilon_{n,i}) = e^{-e^{-\epsilon_{n,i}}}$ and $f(\epsilon_{n,i}) = e^{-\epsilon_{n,i}} e^{-e^{-\epsilon_{n,i}}}$, respectively.

chosen are unaffected by the introduction or removal of other alternatives. Indeed, according to Eq. (21), we have:

$$\frac{P_{n,i}}{P_{n,k}} = \frac{\frac{e^{V_{n,i}}}{\sum_j e^{V_{n,j}}}}{\frac{e^{V_{n,k}}}{\sum_j e^{V_{n,j}}}} = \frac{e^{V_{n,i}}}{e^{V_{n,k}}} \tag{22}$$

7.2 Robustness check: models comparison

In this subsection, we provide a comparison of the estimates of the CL and RPL models, in two different model specifications.

Table 10 presents the results for the CL (first column) and the RPL model (second column) when all attributes are specified as continuous variables.

	CL Model	RPL Model	
	Coefficient (S.E)	Coefficient (S.E)	Coeff. Std. (S.E)
Attributes :			
.ASC	-0.145	-0.603	-2.404***
	(0.192)	(0.397)	(0.358)
.Profit	0.005*	0.007**	-
	(0.002)	(0.003)	-
.Risk of poor harvest	-0.279**	-0.383***	0.396**
	(0.111)	(0.146)	(0.174)
.Administrative commitment	-0.171***	-0.234***	0.28***
	(.062)	(0.084)	(0.108)
.Health & environ- mental impacts	-0.001	0.001	-0.015***
	(0.003)	(0.005)	(0.004)
N (ind.)	75	75	
N (obs.)	1800	1800	
McFaden R^2	0.01	-	
Log Likelihood	-649.95	-547.41	

ASC: Alternative Specific Constant.
Dummy variable=1 if Statu Quo (SQ); 0 oththerwise.

Table 10: Results of the CL and RPL models when all attributes are specified as continuous variables

Table 11 presents the results for the CL model when both the payment (*"Profit"*) and the *"Health and environmental impacts"* attributes are specified as a continuous variable but the two other attributes (*"Risk of poor harvest"* and *"Administrative commitment"*) are modeled as effect-coded dummy variables

When comparing Tables 5 and 11, although estimates are similar in their order of magnitude, the RPL models are preferred to the CL models due to their higher value of the log-likelihood function.

7.3 Additional descriptive statistics and results of qualitative questions

	CL Model	CL Model with interactions
	Coefficient (S.E)	Coefficient (S.E)
Attributes :		
.ASC	-0.244 (0.215)	0.729** (0.311)
.Profit	0.004* (0.002)	0.005* (0.002)
.Risk of poor harvest:		
+ 1 year	-0.459*** (0.171)	-0.490*** (0.177)
+ 2 years	-0.530** (0.222)	-0.569** (0.229)
.Administrative commitment:		
Charter	-0.200 (0.170)	-0.215 (0.173)
Contract	-0.397** (0.179)	-0.416** (0.186)
Certification	-0.484** (0.194)	-0.514*** (0.198)
.Health & environ-mental impacts	-0.001 (0.003)	-0.001 (0.003)
. Outside revenues	-	-0.833*** (.171)
. Awareness of environmental impacts	-	-0.355*** (0.124)
. Cropland type :		
Market gardening	-	-1.041** (0.451)
Wine-growers	-	0.190 (0.320)
Mixed crop and livestock	-	1.658*** (0.415)
N (ind.)	75	74
N (obs.)	1800	1776
McFaden R^2	0.01	0.06
Log Likelihood	-608.82	-611.61

ASC: Alternative Specific Constant.
Dummy variable=1 if Statu Quo (SQ); 0 othherwise.

Table 11: Results of the CL models without and with socio-economic interactions

	Nb	%
French Region		
Ile de France	16	21,3%
Western Suburbs of paris	18	24,0%
Eastern suburbs of Paris	14	18,7%
North	1	1,3%
West	9	12,0%
East	4	5,3%
South West	3	4,0%
South East	7	9,3%
Mediterranean	3	4,0%
Cropland type		
Field crops	59	78,7%
Market gardening	5	6,7%
Wine-growers	7	9,3%
Mixed crop and livestock	4	5,3%

Table 12: Descriptive Statistics

	Nb	%
Do you see agri-environmental shemes as a constraint?		
Yes	57	76,0%
No	18	24,0%
Do you think reduced pesticides is compatible with constant yields?		
Yes	30	40,0%
No	39	52,0%
I don't know	6	8,0%
Do you think pesticides impact health?		
Not at all	5	6,7%
A little	17	22,7%
Significantly	33	44,0%
Very significantly	15	20,0%
I don't know	5	6,7%
Do you think pesticides impact the environment?		
Not at all	2	2,7%
A little	23	30,7%
Significantly	32	42,7%
Very significantly	17	22,7%
I don't know	1	1,3%

Table 13: Sensitivity to the administrative commitment and to health and environmental risk exposures