

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

Benoit Chèze, Maia David, Vincent Martinet*

May 2, 2017

Abstract

This article presents the results of a Discrete Choice Experiment (DCE) survey conducted among a hundred French farmers from June 2016 to February 2017. Respondents had to choose between conserving their actual farming practices or change towards a reduced use of pesticides. Thanks to this stated preference method, we analyze the factors influencing farmers' motivations to reduce -or not- their use of pesticides, we estimate the relative weight of these factors and we value the willingness to accept/willingness to pay for changes in each of these factors. Our contribution relies on including, besides other attributes, the role of the harvest-risk in farmers' decisions towards pesticides. Our results indicate that the most important attribute in the farmers' decisions making is the "*risk of poor harvest*" followed by the kind of "*administrative commitment*". Regarding the former attribute, farmers express high preferences for not bearing a risk of loss: they need to receive on average 100.89 euros (107.64 euros) per hectare and per year to compensate the utility loss associated with the risk of encountering one (two) additional year(s) of poor harvest.

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

*UMR Economie Publique, INRA-AgroParisTech, BP01, 78850 Thiverval-Grignon, France.
Tel: 33(0)1 30 81 53 37. E-mail: benoit.cheze@ifpen.fr; maia.david@agroparistech.fr; vincent.martinet@inra.fr.

1 Introduction

Reducing the use of pesticides has become a major challenge in developed countries' agriculture. 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 attempt to provide adequate incentives to change behaviors and boost research on this topic. Several farming practices have now proven efficient to maintain satisfactory yields while reducing the use of chemicals ((Lechenet et al., 2017)). Reducing pesticides could reduce farmers' costs, improve their health and environment and prevent resistance ((Wilson and Tisdell, 2001; Bourguet and Guillemaud, 2016)). However, up to now, results have been disappointing. Between 2008 and 2015, farmers' consumption of chemical inputs has increased in Europe (+10% in France over this period) and there is a lack of participation in agro-environmental schemes in this field. What are the main obstacles that prevent farmers from adopting low-pesticides 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 exploring the factors influencing farmers' choice to change their farming practices towards a reduced use of pesticides. Several socio-economic analyses have examined the motivations and obstacles to the adoption of environmentally friendly practices by farmers, using various methods. Contrarily to most of them, we use a quantitative approach, in order to estimate the relative weight of various decision factors and to provide 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 (see Hoyos (2010) for a survey). It is a stated preference method in which preferences are elicited through repeated fictional choices made by respondents. Compared to other non-market valuation methods, DCEs have the advantage of capturing the non-use value¹ 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 WTA/WTP as a contingent valuation would do. It is particularly useful to shed light on the trade-offs that occur in a problem or a decision-making. In our case, we wish to understand the factors influencing farmers' choice

¹The non-use value of non-market goods is the existence value or bequest value. It is for instance useful when valuing issues linked to biodiversity.

and the relative weight of these factors. We also wish to measure the WTA/WTP for changes in each of these factors. For these reasons, the DCE seems particularly appropriate to reach our objective.

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 article, the adoption of the alternative practice can occur within ((Khuffus et al., 2014; 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)) or independently of ((Beharry-Borg et al., 2013; Jaeck and Lifran, 2014; Birol et al., 2006; Vidogbena et al., 2015)) an agri-environmental contract with public authorities.

Regarding the specific issue of a reduced use of pesticides, to our knowledge, less than ten 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's flexibility is a major decision criteria. Khuffus 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 the commitments' flexibility and the potential administrative burden are two major components of farmers' decision to change their practices. However, only very 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. 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-pesticides farming strategies might be hampered by the uncertainty behind any deep change (...). Risk aversion may be a hindering factor".

Hudson and Lusk (2004) examines the role of the price-risk but the harvest-risk is even more at stake when considering the use of pesticides. Our analysis includes, besides other attributes, the role of the harvest-risk in French farmers' decisions to reduce -or not - their use of pesticides.

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 presents our main results and their interpretation. Conclusions and discussion are developed in section 5.

2 Methodology

The choice experiment approach relies on economic theory of consumer choice and non-market valuation. In a DCE survey, respondents have to make choices between 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 *satus quo*) and two fictional options. Respondents then choose their favorite option among these three. An option is defined by a set of attributes taking different values according to the option. 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 discrete choice modeling framework provides the advantage to vary simultaneously several attributes of the considered issue. By doing so, it reveals more detailed information than other stated preference methods such as contingent valuation. Especially, it allows to estimate the marginal rates of substitution between the different attributes. When one of the attributes is a cost (a price), these marginal rates of substitution can be interpreted as the WTP (or the WTA) for changes in the attributes' levels (see Section 4.3).

In our case, respondents were farmers who had to choose between conserving their actual farming practices or changing their practices towards a reduced use of pesticides.

2.1 Choice of the attributes and their levels

A first step was to choose the attributes composing the options, and their associated levels. 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 the state of the literature, discussions with experts in agronomy, ecology and agricultural economists, focus groups with farmers and pre-tests of some choice sets.

As shown in Table 1, the chosen attributes are:

1. The farmer's yearly profit (or gross margin) per hectare: this attribute is given by the average profit per hectare and per year of the farm, in euro. This is the monetary attribute. The profit varies with a change of practice

due to several factors including the impact on yields, on pesticides' expenses, on public aids, on the sales price, etc. It is expressed as a variation compared to the status quo, taking the following values: -50 €, +0€, +50€, +100€.

2. The risk of poor harvest: given by the number of years out of ten years for which the farm's harvest is drastically and exceptionally reduced (i.e. reduced by at least 30%) compared to a normal year. This poor harvest is due to diseases, pests, weeds, etc. This attribute is expressed in additional years with poor harvest with the new practice compared to the status quo: +0, +1 year, +2 years
3. The administrative framework of the change of practice: describing whether the change is coming along with any administrative commitment. This commitment can imply a public aid or higher sales price (included in the margin, i.e. first attribute) but may also bring some administrative burden. This attribute is qualitative and is expressed as the additional commitments compared to status quo: "no additional administrative framework", "signing an agri-environmental contract with public authorities" (with specification), "joining a Charter" (inducing no contractual specification and a flexible commitment), "entering a certification process" (associated with a specification, controls and a green label).
4. Impact on health and the environment: this attribute indicates how the exposure to harmful substances for health or the environment is reduced with the change in practice. It can take the following values: -0%, -20%, -50% -80% compared to the status quo.

Attribute	Description	Levels
Profit	Variation in the average yearly gross margin per hectare	-50 €; + 0 € (SQ); +50€; +100€
Harvest Risk	Variation in the number of years with poor harvest out of 10 years	+0 year (SQ); +1 year; +2 years
Administrative framework	Administrative framework of the change in practice, if any	None (SQ); Chart; Contract; Certification
Impact on health and environment	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

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



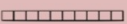





	Résultats pratique A	Résultats pratique B	Résultats pratique C
Marge annuelle par ha: Variation par rapport à aujourd'hui (les années normales) 	+100 euros par ha par an par rapport à aujourd'hui	+100 euros par ha par an par rapport à aujourd'hui	
Risque récolte: Hausse de la fréquence de pertes de grande ampleur avec le changement de pratique. Nombre d'années en plus sur 10 ans 	+0 année(s) avec ravages sur 10 ans 	+2 année(s) avec ravages sur 10 ans 	
Modalité du changement de pratique: En complément de vos engagements actuels 	Contrat	Aucune modalité supplémentaire 	
Impact sur l'environnement et la santé: Diminution de l'exposition aux produits phytosanitaires des Hommes et du milieu. 	Exposition aux produits phytosanitaires réduite de 20%	Exposition aux produits phytosanitaires réduite de 50%	
Cochez votre option préférée →	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
	SUIVANT 		

Figure 1: Example of a choice set

2.2 The experimental design

The aim of the experimental design is to select 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' choice. In order to choose the most relevant choice sets, that is those yielding maximum information on respondents' preferences, we use experimental design techniques (see Louviere et al. (2000) and Street et al. (2005)) and the dedicated *Ngene* software, which is a reference in this field. It provides a statistically optimal sub-set of the possible combinations using a Bayesian D-optimal design, in our case a fractional factorial efficient design².

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 represents an acceptable cognitive load.

²Details on the characteristics of the efficient design used and the associated program are available upon request.

2.3 Presentation of the questionnaire and data collection

The questionnaire was designed to last less than 20 minutes. A first part was dedicated to general questions regarding the farmer's activity, the size of the farm, the use of pesticides and the actual level of the attributes in the respondent's case. The aim of the survey was then shortly described using illustrated slides and describing in detail the four attributes. We were very careful so as to deliver an objective and neutral information.

The eight choice sets were then presented and the respondent was asked to pick his/her favorite option. The order of the choice sets was randomized so as to avoid having a potential declining concentration (last choices) always affecting the same choice set. The respondent could click on the icon (see Figure 1) in order to obtain additional explanations. In order to detect protest answers, farmers choosing unchanged practices in all choice sets were asked the reasons of their choice.

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

The survey was held from June 2016 to February 2017, taking two forms: face-to-face interviews directly on the farms and a websurvey. We were careful to give very similar information in both types of interviews. We obtained in total 100 answers from French farmers whose location, activities and main socio-demographic characteristics are described in section 4.1.

3 The choice experiment approach and the different econometric models

The choice experiment modeling framework relies on the characteristics theory of value (Lancaster, 1966) and the random utility theory (McFadden, 1974). Different econometric models are used to analyze the discrete choice data, depending on the assumption made on the unobserved components of the random utility, *i.e.* the assumption on the distribution of its error terms.

3.1 Theoretical foundations of the choice experiment approach

Lancaster (1966) assumes that a good may be defined by its own 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 each attribute is associated with a utility level and that the (indirect) utility of

each respondent n for an alternative i in a choice set C , $V_{n,i}$ is derived from its K attributes, that is the sum of the utilities obtained from each of the K attributes. Typically the representative utility of an alternative i for respondent n is specified to be a linear-in-parameters function:

$$(1) \quad V_{n,i} = V(X_i, Z_n) = \sum_{k=1}^K \beta_{ik} x_{ik} + \sum_{a=1}^A \alpha_{an} z_{an} \quad \forall n \in \{1, \dots, N\}; \quad \forall i \in \{1, \dots, I\}$$

where $V_{n,i}$ is supposed to be a function of the observable i) K attributes of the alternative i , X_i , and ii) the A characteristics of the n -th respondent, Z_n .

For his part, McFadden (1974) proposes to consider that individuals make choices according to a deterministic part along with some degree of randomness. Combining theories of both Lancaster (1966) and McFadden (1974), we assume that the random utility of the i -th alternative for each individual n , $U_{n,i}$, is composed of a deterministic component, $V_{n,i} = V(X_i, Z_n)$, and a stochastic element, $\epsilon_{n,i}$:

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

where the error term $\epsilon_{n,i}$ is a random variable that captures the unsystematic and unobserved random element of individual n 's choice (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 utility level $U_{n,i}$ and choose the option that provides them with the greatest utility. It comes that an agent n will choose an alternative i from a finite set of alternatives C if its indirect utility of i , $U_{n,i}$, is greater than the indirect utility he could have derived from any other alternative j , $U_{n,j}$:

$$(3) \quad U_{n,i} > U_{n,j} \Rightarrow V_{n,i} + \epsilon_{n,i} > V_{n,j} + \epsilon_{n,j} \quad \forall j \neq i; \quad i, j \in C$$

The probability that an individual chooses alternative i is the same as the probability that the utility of alternative i is greater than the utility of any other alternative of the choice set (Adamowicz et al., 1998). Following Train (2009), the probability that an agent n chooses alternative i in a choice set C is:

$$(4) \quad P_{n,i} = P \{U_{n,i} > U_{n,j} \quad \forall j \neq i; \quad i, j \in C\}$$

$$(5) \quad \Leftrightarrow P_{n,i} = P \{V_{n,i} + \epsilon_{n,i} > V_{n,j} + \epsilon_{n,j} \quad \forall j \neq i; \quad i, j \in C\}$$

$$(6) \quad \Leftrightarrow P_{n,i} = P \{\epsilon_{n,j} < V_{n,i} - V_{n,j} + \epsilon_{n,i} \quad \forall j \neq i; \quad i, j \in C\}$$

3.2 The different econometric models

Different discrete choice models are obtained from different assumptions about the distribution of the random terms.

3.2.1 The conditional logit (CL) model

If we suppose that unobserved components, the error terms $\epsilon_{n,i}$, all independently, among the N agents and between the I alternatives, follow a standard Gumbel distribution³, 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 $\epsilon_{n,i}$:

$$(7) \quad P_{n,i}|\epsilon_{n,i} = \prod_{j \neq i} P \{ \epsilon_{n,j} < V_{n,i} - V_{n,j} + \epsilon_{n,i} \}$$

$$(8) \quad = \prod_{j \neq i} e^{-e^{-(V_{n,i} - V_{n,j} + \epsilon_{n,i})}}$$

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

$$(9) \quad P_{n,i} = \int \left(\prod_{j \neq i} e^{-e^{-(V_{n,i} - V_{n,j} + \epsilon_{n,i})}} \right) e^{-\epsilon_{n,i}} e^{-e^{-\epsilon_{n,i}}} d\epsilon_{n,i}$$

Calculations then lead this expression to simplify in

$$(10) \quad P_{n,i} = \frac{e^{V_{n,i}}}{\sum_j e^{V_{n,j}}}$$

where $P_{n,i}$ only depends on observable components.

An important drawback to this model is that β is considered fixed across all individuals, while we can expect the preferences to vary among the respondents. Two other important drawbacks are the hypothesis of independence of irrelevant alternatives (IIA) and uncorrelated unobserved components.

³The $\epsilon_{n,i}$ 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.

3.3 The random parameter logit (RPL) model

The random parameter logit model (McFadden and Train, 2000; Train, 2009), also called the mixed logit model, solves these three issues. In this model, the preferences parameters β are allowed to vary across individuals; only their distribution needs to be known. As such, for a given β we can define the logit probability :

$$(11) \quad L_{n,i}(\beta) = \frac{e^{V_{n,i}(\beta)}}{\sum_j e^{V_{n,j}(\beta)}}$$

If $f(\beta)$ is the density function describing the distribution of preferences over individuals, we get back to

$$(12) \quad P_{n,i} = \int L_{n,i}(\beta) f(\beta) d\beta$$

which is the probability of interest.

4 Results and interpretation

Recall that we want to analyze farmers' motivations to reduce their use of pesticides and to estimate the monetary value associated with the farmers' various decision factors. The DCE presented in the previous section has been conducted among a hundred farmers who had to choose between conserving their actual farming practices or changing their practices towards a reduced use of pesticides. After removing protest answers, we finally obtained 1992 choices elicited from 83 respondents. We first describe this sample in Section 4.1 and then analyze in Section 4.2.2 the discrete choice data collected by estimating two types of econometric models: the conditional logit (CL) and the random parameter logit (RPL).

4.1 Descriptive Statistics

Table 3 and Table 2 present some descriptive statistics for the final sample composed of 83 respondents (39% of women). The respondents' ages range from 23 to 68 years, with an average of 46 years. The mean area of their agricultural exploitations is about 117 hectares but there is a great disparity among them, as showed by the standard errors of the annual turnover and gross margin per hectare. Some other descriptive statistics are presented in the Appendix.

4.2 Econometric models

The results of both the CL and RPL estimates for the sample are presented in Table 4 and Table 5. Before presenting these results in Section 4.2.2, we have to specify

	Obs	Moyenne	E.T	Min	Max
Age	83	45.67	10.60	23	68
Surface agricole utile (SAU)	83	116.68	103.18	0.1	500
CA de l'exploitation /an (€)	70	168113	151770	1	650000
Marge par ha / an (€)	30	1083	2545	0	12500

Table 2: Descriptive Statistics

	Nb	%
Autres revenus que ceux de l'exploitation	47	57%
Genre		
Femmes	32	39%
Hommes	51	61%
Niveau d'éducation		
Sans diplôme	1	2%
BEPC/CAP/BEP	12	15%
BAC	24	29%
BAC+2	23	27%
BAC +3/+5	17	21%
Doctorat	1	2%
Autre	4	5%

Table 3: Descriptive Statistics

the model specifications which have been retained to estimate the econometric models.

4.2.1 Model specifications

According to Eq. (2), the random utility of the i -th alternative for each individual n , $U_{n,i}$, is composed of a deterministic component, $V_{n,i} = V(X_i, Z_n)$, and a stochastic element, $\epsilon_{n,i}$. It has already been explained how the econometric models (CL and RPL) actually depends on the assumption on the distribution of error terms $\epsilon_{n,i}$.

Before estimating these models, one also need 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 most simple one to work with.

Moreover, an Alternative Specific Constant (ASC) term is included to capture the (systematic) effect of unobserved influences (omitted variables) on the utility function. The ASC is modelled as a dummy that takes the value 0 if one of the hypothetical alternatives is chosen and 1 if 'none of these', *i.e.* the status quo alternative, is chosen. Thus, the ASC defines a situation with "no variation of the farmer's yearly gross margin per hectare", "no additional years with poor harvest", "no additional administrative framework" and "no reduction of the exposure to harmful substances for health or the environment". A positive and statistically significant ASC would indicate strong preferences for no additional conservation. It would suggest the existence of some omitted variables that have a positive effect on the farmers' utility of choosing to keep their actual farming practices.

Hence, the model is specified so that the probability of selecting a particular farming practice scenario i is a function of attributes of that alternative and of the alternative specific constant. We thus assume that the utility $V_{n,i}$ is an additive function. Eq. (2) becomes:

$$(13) \quad U_{n,i} = \eta ASC + \beta_{i,1}x_{i,1} + \beta_{i,2}x_{i,2} + \beta_{i,3}x_{i,3} + \beta_{i,4}x_{i,4} + \sum_{a=1}^A \alpha_{an}z_{an} + \epsilon_{n,i}$$

where $Z'_n = (z_{1n}, \dots, z_{an}, \dots, z_{an})$ represents the vector of the A socio-demographic characteristics of the n -th respondent. $x_{i,1}$, $x_{i,2}$, $x_{i,3}$ and $x_{i,4}$ correspond to the different level taken by the attributes "Gross margin", "Risk of poor harvest", "Administrative commitment" and "Health and environmental impacts", respectively. Note that in our case, "Gross margin" is the payment attribute. Thus specified, $\beta' = (\beta_{i,1}, \beta_{i,2}, \beta_{i,3}, \beta_{i,4})$ coefficients quantify the influence which the various levels of the four attributes exert over the utility that farmers associate with the I different alternatives available, relative to the utility of the "status quo" option that appeared on every choice card.

Regarding $X'_i = (x_{i,1}, x_{i,2}, x_{i,3}, x_{i,4})$, the attributes can be specified as discrete or continuous variables and it is possible to combine qualitative and quantitative attributes in the same model specification.

4.2.2 CL and RPL models results

Two models specifications has been chosen here. Table 4 presents the results for the CL (column (1)) and the RPL model (column (2)) when all attributes are specified as continuous variables whereas in Table 5, only the payment attribute (*Gross margin*) and the "*Health and environmental impacts*" attribute are modelled as a continuous variable. The two other attributes ("*Risk of poor harvest*" and "*Administrative commitment*") are modelled as effect-coded dummy variables.

	CL Model		RPL Model	
	Coefficient (S.E)	Coefficient (S.E)	Coefficient (S.E)	Coeff. Std. (S.E)
Attributes :				
.ASC	0.004 (0.182)	-0.471 (0.415)	-2.863*** (0.416)	
.Gross margin	0.003 (0.002)	0.006* (0.002)	-	-
.Risk of poor harvest	-0.196* (0.104)	-0.329** (0.143)	0.423*** (0.139)	
.Administrative commitment	-0.125** (.059)	-0.169** (0.074)	0.166 (0.141)	
.Health & environ- mental impacts	-0.001 (0.002)	-0.001 (0.004)	0.013*** (0.005)	
N (ind.)	83		83	
N (obs.)	1992		1992	
McFaden R ²	0.01		-	
Log Likelihood	-722.386		-596.833	
ASC: Alternative Specific Constant. Dummy variable=1 if Statu Quo (SQ); 0 otherwise.				

Table 4: Results of the CL and RPL models (first models specification)

In both Tables, the RPL model is preferred to the CL model according to its highest value of the log-likelihood function. Moreover, recent applications of the

	CL Model	RPL Model	
	Coefficient (S.E)	Coefficient (S.E)	Coeff. Std. (S.E)
Attributes :			
.ASC	-0.155 (0.204)	-0.777* (0.421)	2.885*** (0.466)
.Gross margin	0.003 (0.002)	0.006** (0.003)	- -
.Risk of poor harvest:			
+ 1 year	-0.409** (0.162)	-.0617*** (0.211)	0.020 (0.320)
+ 2 years	-0.350* (0.210)	-0.658** (0.293)	0.455 (0.439)
.Administrative commitment:			
Charter	-0.223 (0.162)	-0.431* (0.225)	-0.853*** (0.269)
Contract	-0.382** (0.170)	-0.527** (0.209)	0.385 (0.500)
Certification	-0.328* (0.182)	-0.519** (0.235)	0.659** (0.289)
.Health & environ- mental impacts	-0.001 (0.003)	-0.003 (0.005)	0.012* (0.007)
N (ind.)	83	83	
N (obs.)	1992	1992	
McFaden R ²	0.01	-	
Log Likelihood	-720.070	-593.123	

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

Table 5: Results of the CL and RPL models (second models specification)

RPL model have shown that this model is superior to the CL model in terms of overall fit and welfare estimates (Lusk et al., 2003). For all these reasons, we focus our interpretations on the results of the RPL models in both Table 4 and Table 5. According to McFadden and Train (2000), the RPL is a highly flexible model that can approximate any discrete choice model. Compared to the CL model, it relaxes the independence from irrelevant alternatives (IIA) hypothesis of the multinomial logit by allowing the random components of the alternatives to be correlated, while maintaining the assumption that they are identically distributed (Greene, 2008). Hence, some parameters of the vector β are assumed to be randomly distributed in the population rather than fixed as in the usual multinomial logit model.

Here, all the parameters except the payment attribute⁴ are specified to be normally distributed, and distribution simulations are based on 1000 draws to estimate their respective mean and standard deviation. The assumed normal distribution of the random parameters is one way to model heterogeneity in preferences. The normal distribution is symmetric and unbounded. So the use of this distribution means that we make a priori no 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 payment attribute coefficient, on the contrary, ensures that all respondents have a positive coefficient, in our case, so that the estimated WTA will be normally distributed (see Section 4.3 for more details).

Regarding the results of the RPL estimations, standard deviations of a majority of the coefficients are significant, indicating that a RPL provides a significantly better representation of the choices than a CL⁵ as it shows that there is heterogeneity among respondents around the mean. This indicates that the data supports choice specific unconditional unobserved heterogeneity for these attributes and some respondents might prefer lower levels of these.

Except for the "*Health and environmental impacts*" attribute, all the coefficients of the RPL model presented in both Tables 4 and 5 are statistically significant and have the expected sign. To our great astonishment, the coefficient of "*Health and environmental impacts*" attribute, even though negative, is not statistically significant at the 10 % level in both RPL models. The reduction of exposure to harmful substances for health or the environment seems to have no effect on the farmers' utility. The coefficient of the *ASC* is negative but not statistically significant in Table 4. In Table 5 however, its coefficient becomes statistically significant at the 10% level and remains negative. Combined with the latter result on the non-significance of "*Health and environmental impacts*" coefficient, it indicates that there are some variables that are not included in the model, which induce farmers to prefer to change their actual practices to reduce their use of

⁴And those associated with socio-demographic variables.

⁵Recall that a CL assumes that coefficients are the same for all respondents.

pesticides rather than conserving their actual farming practices.

In Tables 4 and 5, the sign of the payment attribute coefficient (*Gross margin*) in both RPL models is statistically significant at the 10% level and the 5%, respectively. Its positive sign was expected as it indicates that the effect on respondents' utility of choosing from a finite choice set an alternative with a higher average yearly profit per hectare is positive.

In the first model specification (Table 4), the "*Risk of poor harvest*" and "*Administrative commitment*" attributes are modelled as continuous variables. Both coefficients are negative, meaning that an increase in *harvest risks* or in *administrative commitments* reduce the respondents' utility. Interestingly, respondents associate any additional administrative framework coming with a change of practice as higher administrative burden rather than as a beneficial accompanying measure.

In Table 5 on the contrary, the two latter-mentioned attributes are modelled as dummy coded variables: attributes are encoded using *i*) two dummy-coded variables per level ("*+ 1 year*" and "*+ 2 years*") for the "*harvest risks*" attribute and *ii*) three dummy-coded variables per level ("*Charter*", "*Contract*" and "*Certification*") for the "*administrative commitments*" attribute⁶. All dummy variables are statistically significant and negative, confirming estimate results obtained for the first model specification (see Table 4). However, this second model specification tends to indicate that there are no linear effect in the "*administrative commitments*" attribute. In Table 5, the coefficients of "*Charter*", "*Contract*" and "*Certification*" correspond to the variation in utility due to an additional administrative framework taking the form of these three kinds of commitments, respectively, compared to the status quo situation, *i.e.* "no additional administrative framework". In absolute terms, the coefficient of "*Contract*" (−0.527) is superior to the "*Charter*" coefficient (−0.431) but inferior to the "*Certification*" one (−0.519). Curiously, "signing an agri-environmental contract with public authority", such as a *MAEC* contract, is actually perceived by respondents as worse than "entering a certification process" (yet associated with a specification, controls and a green label).

4.3 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 change in an attribute under consideration and the marginal utility of income represented by the coefficient of the payment attribute, β_{pay} . The latter is assumed

⁶Thus defined, the excluded levels for each variable – which are tied to the *ASC* – are "no additional years with poor harvest" and "no additional administrative framework", respectively.

constant as is common in the literature (Hensher and Green, 2003).

Table 6 reports the marginal WTA values for each of the attributes estimated in both RPL models using the Wald procedure (Delta method). 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 attribute in question and the payment attribute (Louviere et al., 2000). Since utilities are modelled as linear functions of the attributes, the marginal rate of substitution between two attributes is the ratio between the coefficients⁷:

$$(14) \quad WTA_k = -\frac{dx_{pay}}{dx_k} = -\frac{dU/dx_k}{dU/dx_{pay}} = -\frac{\partial V/\partial x_k}{\partial V/\partial x_{pay}} = -\frac{\beta_k}{\beta_{pay}}$$

When attributes are modelled as effect-coded dummy variables, but the payment attribute, the WTA associated with each attribute k and each level l becomes:

$$(15) \quad WTA_k^l = -\frac{\beta_k^l}{\beta_{pay}}$$

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

Since the RPL model assumes *i*) the payment attribute is a fixed parameter and *ii*) other attributes' coefficients are normally distributed, WTA are then normally distributed, as linear combinations of normal random variables. We then have the convenient result that:

$$(16) \quad E[WTA_k] = -\frac{E[\beta_k]}{\beta_{pay}}$$

$$(17) \quad E[WTA_k^l] = -\frac{E[\beta_k^l]}{\beta_{pay}}$$

For comparisons, estimates presented in Table 6 were calculated using both RPL models. The first lines correspond to WTAs computed from the RPL model estimates presented in Table 4 whereas the last lines correspond to WTAs computed from the RPL model estimates presented in Table 5. The estimated standard deviations and confidence intervals around the mean of the WTA estimates are obtained using the Krinsky and Robb parametric bootstrapping method (Krinsky and Robb, 1986).

⁷It should be noted that the derivative of the unobserved part of the utility function is supposed to be zero with respect to both attributes.

	Risk of poor harvest		Administrative commitment			Health & environmental impacts
Mean :	56.82		29.24			0.32
95% CI :	[17.57 ; 96.07]		[4.02 ; 54.46]			[-0.93 ; 1.57]
	+ 1 year	+ 2 years	Charter	Contract	Certification	Health & environmental impacts
Mean :	100.89	107.64	70.48	86.20	84.95	0.48
95% CI :	[32.15 ; 169.62]	[47.87 ; 167.40]	[-9.18 ; 150.14]	[9.86 ; 162.53]	[21.12 ; 148.78]	[-0.56 ; 1.51]

Table 6: WTA estimates

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. Recall that in both RPL models, the coefficient of "*Health and environmental impacts*" attribute is not statistically significant at the 10 % level. Not surprisingly, estimated coefficients and standard deviations lead to negative lower bounds of the confidence intervals for this attribute.

Regarding the other attributes, mean WTA estimates are systematically lower for the first model specification (Table 6, first lines) than for the second one (Table 6, last lines). Moreover, whatever the model specification retained, when the payment attribute is used as the normalizing variable, the most important attribute is the "*risk of poor harvest*" followed by the kind of "*administrative commitment*". Indeed, the mean WTA of the former and the latter attributes are respectively equal to 56.82 and 29.24 in the first model specification and are ranging from 100.89 to 107.64 and from 70.48 to 86.20 respectively in the second model specification.

Focusing on the second model specification, a second lesson is obtained from the comparison of the "*Risk of poor harvest*" attribute dummy coded levels. According to our results, farmers need to receive on average 100.89 euros per hectare and per year to compensate the utility loss associated with the risk to encounter one additional poor harvest. In the meantime, they need "only" to receive seven euros more than this amount (107.64 euros per hectare and per year) to compensate the utility loss associated with a risk multiplied by two. Actually, farmers express high preferences for not bearing a risk of loss. One or two additional year(s) out of ten of poor harvest are equivalent, meaning it is having a risk of loss that is important in their decision.

5 Concluding remarks and discussion

This article proposed to investigate farmers' motivations to reduce their use of pesticides and to evaluate the willingness to pay and/or to accept (WTP/WTA) to change their actual farming practice.

To better understand farmers' decision factors and the relative weight of these factors, we chose to apply a discrete choice experiment (DCE) approach. Globally, the literature shows that the flexibility of their decisions and the administrative burden are two major components of farmers' decision to change their practices. However, only very few contributions have looked into the role of risk in farmers' decisions. Price-risk and harvest-risk are two factors that can drastically affect farmers revenues. 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. Regarding the specific issue of a reduced use of pesticides, to our knowledge, very few studies proposed to examine the role of the risk in farmers' decision making. Our contribution offers to fill this gap by including, besides other attributes, the role of the harvest-risk in French famers' decisions to reduce -or not - their use of pesticides.

A DCE survey has thus been conducted among a hundred farmers from June 2016 to February 2017. Respondents had to choose between conserving their actual farming practices or changing their practices towards a reduced use of pesticides. After removing protest answers, we finally obtained 1992 choices elicited from 83 respondents. Each alternative of the choice set was a function of four attributes; namely "*Gross margin*", "*Risk of poor harvest*", "*Administrative commitment*" and "*Health and environmental impacts*".

Two models specifications have been specified. In the first model specification, all attributes are specified as continuous variables. In the second model specification, only the payment attribute (*Gross margin*) and the "*Health and environmental impacts*" attribute are modelled as a continuous variable. The two other attributes ("*Risk of poor harvest*" and "*Administrative commitment*") are modelled as effect-coded dummy variables. Both model specification are estimated using Conditional Logit (CL) and Random Parameter Logit (RPL) econometric models.

Except for the "*Health and environmental impacts*" attribute, all the coefficients of the RPL models are statistically significant and have the expected sign. Regarding other attributes, both "*Risk of poor harvest*" and "*Administrative commitment*" attributes' coefficient are negative, meaning that an increase in *harvest risks* or in *administrative commitments* reduce the 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 accompanying measure.

When looking at the WTA estimates, the use of the payment attribute as the normalizing variable shows that the most important attribute in the farmers' decisions making is the "*risk of poor harvest*" followed by the kind of "*administrative commitment*". Regarding the former attribute, our results indicate that farmers express high preferences for not bearing a risk of loss. One or two additional year(s) out of ten of poor harvest are equivalent⁸, meaning it is having a risk of loss that is important in their decision.

Last but not least, to our great astonishment, the coefficient of "*Health and environmental impacts*" attribute is not statistically significant at the 10 % level in both RPL models. The reduction of exposure to harmful substances for health or the environment seems to have no effect on the farmers' utility. The coefficient of the *ASC* however, in the second specification estimated thanks to a RPL model, shows that there are some variables that are not included in the model, which induce farmers to prefer to change their actual practices to reduce their use of pesticides rather than conserving their actual farming practices. Combined with the latter result on the non-significance of "*Health and environmental impacts*" coefficient, it indicates that we have to go further in the analysis. One solution may be to include interactions of respondent-specific social, economic and attitudinal characteristics with choice specific attributes and/or with *ASC* in the utility function. Another solution would be to estimate a Latent Class Model as an alternative model for accounting for preference heterogeneity.

⁸According to our results, farmers need to receive on average 100.89 euros (107.64 euros) per hectare and per year to compensate the utility loss associated with the risk to encounter one (two) additional years of poor harvest.

References

- 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.
- Bourguet, D. and Guillemaud, T. (2016). The hidden and external costs of pesticide use. *Sustainable Agriculture Reviews*, (19):35–120.
- 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.
- Espinosa-Goded, M., Barreiro-Hurlé, J., and Ruto, E. (2010). What do farmers want from agri-environmental scheme design? A choice experiment approach. *Journal Agricultural Economics*, 61(2).
- Greene, W. (2008). *Econometric Analysis*. Prentice-Hall, New Jersey, 6-th edition.
- 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.
- 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.
- Khuffus, 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.
- Krinsky, I. and Robb, A. L. (1986). On approximating the statistical properties of elasticities . *The Review of Economics and Statistics*, 64.
- 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.
- Lusk, J. L., Roosen, J., and Fox, J. A. (2003). Demand for beef from cattle administered growth hormones or fed genetically modified corn: a comparison of consumers in France, Germany, the United Kingdom and the United States . *American Journal of Agricultural Economics*, 85 (1).
- 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.
- Peterson, J., Smith, C., Leatherman, J., Hendricks, N., and Fox, J. (2015). Transaction costs in payment for environmental service contracts. *American Journal of Agricultural Economics*, (97(1)):219–238.

- 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.

6 Appendix

	Nb	%
Région		
Ile de France	23	28%
Bassin Parisien Ouest	9	11%
Bassin Parisien Est	13	16%
Nord	2	2%
Ouest	12	14%
Est	6	7%
Sud Ouest	3	4%
Sud Est	9	11%
Méditerranée	6	7%
Type de culture		
Céréaliers	62	75%
Maraîchers	7	8%
Viticulteurs	7	8%
Autres	7	8%

Table 7: Descriptive Statistics

	Nb	%
Engagements de type MAE sont synonymes de contraintes supplémentaires:		
Oui	60	72%
Non	23	28%
Maintien des rendements est compatible avec une réduction des produits phytosanitaires:		
Oui	32	39%
Non	47	56%
Ne sais pas	4	5%
Les produits phytosanitaires ont un impact sur la santé:		
Pas du tout important	5	6%
Peu important	23	27%
Important	32	39%
Très important	19	23%
Ne sais pas	4	5%
Les produits phytosanitaires ont un impact sur l'environnement:		
Pas du tout important	3	3%
Peu important	29	35%
Important	31	37%
Très important	20	24%
Ne sais pas	20	24%

Table 8: Sensitivity to the administrative commitments and to health and environmental risk exposures