Eliciting farmers' risk and ambiguity preferences in the loss and gain domain

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Abstract

Risk and ambiguity are pervasive in farming activities. Although agricultural economists have a long tradition of analysing risk, there is still a lack of understanding of farmers' risk and ambiguity preferences. We aim at structurally estimating these preferences. We use a model that combines a second order model for ambiguity and a model that allows for differences in utility in the gain and loss domains and probability distortion. Moreover, we allow for an endogenous reference point that we estimate. We collect responses from 197 farmers. We find (i) farmers are slightly risk averse in the gain and loss domains and have an inverse s-shaped probability weighing function for risk; (ii) farmers are slightly ambiguity averse in the gain domain and ambiguity neutral in the loss domain and have an inverse s-shaped utility function in the gain domain but do not distort probabilities in the loss domain; (iii) farmers have a positive reference point.

Key words: Risk Attitudes; Ambiguity; Field Experiment; Farmer;
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1 Background and motivation

Risk and ambiguity are pervasive in farming activities. Farmers must deal with random yields and prices. Agriculture has always been characterized by yield risks due to weather shocks. But, recently, farmers deal with yield variations due to rare and less predictable events (effects of global warming) and to environmental constraints (reduction of pesticides use for example). Price volatility is more and more a concern for farmers for several reasons. Globalization makes prices more influenced by supply and demand changes in other parts of the world. And also, governments provide less and less public support. Agricultural economists have paid a lot of attention to the impact of risk on farmers' activities and their risk management. Less attention has been paid to improving the elicitation of risk preferences. Most studies derive farmers' risk attitudes from deviations from a theoretically predicted optimal behavior. In such studies, risk attitudes are residuals that are not free from confounds such as anticipations for example. As for ambiguity, agricultural economists treat ambiguity as risk. In view of these limitations, there is a need to better assess farmers' risk and ambiguity attitudes. Indeed, in a review of the contributions of agricultural economics over the past century, Chavas (2010) mentions the challenges ahead of agricultural economics: "‘First, there is a need to refine our understanding of the role of risk/uncertainty in agriculture. For example, the current prospects for climate change raise the issue of how farmers will react to it. This can involve "‘rare events"’ that have not been observed before. It creates two significant challenges: (1) rare events are difficult to evaluate empirically (suggesting an important role for "‘ambiguity"’); and (2) the question is raised of the way decision makers (including farmers) should adjust their management strategies in response to this new uncertainty."’ In this paper, we aim at eliciting farmers' risk and ambiguity attitudes using an artefactual field experiment. We model farmers' utility using the model of Nau (2006) that is a discrete version of the smooth ambiguity model (Klibanoff, Marinacci, and Mukerji, 2009). This model enables to disentangle ambiguity from ambiguity attitudes. Besides, as Chakravarty and Roy (2009), we use a utility specification allowing for differences in utility in the gain and the loss domains and probability distortion. Moreover, we allow for probability distortion in the ambiguous situations and for an endogenous reference point that we estimate. We design a multiple price list protocol allowing for risky choices in the gain and loss domains and for ambiguous choices in the gain and loss domains. A total of 197 farmers were face-to-face interviewed. We find (i) farmers are slightly risk averse in the gain and loss domains and have an inverse s-shaped probability weighing function for risk; (ii) farmers are slightly ambiguity averse in the gain domain and ambiguity neutral in the loss domain and have an inverse s-shaped utility function in the gain domain but do not distort probabilities in the loss domain; (iii) farmers have a positive reference point. Our paper is organized as follows. In the next section (section 2), we describe the empirical models derived from structural models. In section 3, we describe the field experiment. In section 4, results are presented and discussed. Section 5 concludes.

2 Structural models

We follow the modeling strategy of Tversky and Kahneman (1992) and Klibanoff, Marinacci, and Mukerji (2005) to enable us to identify risk and ambiguity aversion parameters for the farmers in our sample.

2.1 Modeling decisions in a risky environment

This section is motivated by the commonly observed phenomena of choice under risk: "losses loom larger than gains". Under cumulative prospect theory (Tversky and Kahneman, 1992), individuals display differing behaviours in the gain and loss domain. The value function writes:

$$v(x) = \begin{cases} (x - x_0)^{\alpha} & \textit{if} \quad x \geq x_0 \\ -\lambda. \left[(-x + x_0)^{\alpha} \right] & \textit{if} \quad x < x_0 \end{cases}$$

where α is the concavity of the utility function, x_0 is the reference-point parameter and λ is a loss aversion parameter. Usually the reference is supposed to be zero. In a first step, we will make such an assumption; in a second step, we will estimate the reference point and test whether it is actually null or not.

Under cumulative prospect theory, probabilities are transformed according to the following weighting probability function (Tversky and Kahneman, 1992):

$$\pi(p) = \frac{p^{\gamma}}{\left[p^{\gamma} + (1-p)^{\gamma}\right]^{1/\gamma}}$$

where γ is a parameter describing the shape of the weighting probability function. $\gamma < 1$ (resp. $\gamma > 1$) implies overweighting (resp. underweighting) of small probabilities and underweighting (resp. overweighting) of high probabilities. Note that the specifications used in this section collapse to the expected utility specification if $\lambda = 1$ and $\gamma = 1$.

2.2 Modeling decisions in an ambiguous environment

We base our model on Klibanoff, Marinacci, and Mukerji (2005) second order model and more precisely and the non continuous form presented by Nau (2006). The multiple prior model allows a separation between ambiguity, identified as a characteristic of the decision maker's subjective beliefs, and ambiguity attitude, a characteristic of the decision maker's tastes.

In the Nau (2006) modeling framework the state space can be represented as a Cartesian product, $\mathcal{A} \times \mathcal{R}$ where $\mathcal{A}$ are the finites set of J ambiguous elements and $\mathcal{A}$ is a set of K risky elements. An act is a mapping from observable states of the world to quantities of a single consumption good and will be denoted by a doubly-subscripted vector $\mathbf{x} = (x_{11}, x_{12}, \ldots, x_{JK})$. $x_{jk} \in \mathbb{R}$ are the payoff in state $A_j R_k$. Under four axioms detailed in Nau (2006) the preference relation under risk and ambiguity hold if and only if the utility function has the following form:

$$u(\mathbf{x}) = \sum_{j=1}^{J} (p_j) u(\sum_{k=1}^{K} q_{jk} v(x_{jk})) \tag{1}$$

where $\mathbf{p} = (p_1, \ldots, p_J)$ is a unique marginal probability distribution on ambiguity space $\mathcal{A}$, $\mathbf{q}_j = (q_{j1}, \ldots, q_{jK})$ is a unique conditional probability distribution on risky space $\mathcal{R}$ given $\mathcal{A}_j$, v is a strictly increasing state-independent first-order Bernoulli utility function unique up to positive affine transformations, and u is a strictly increasing state independent second-order Bernoulli utility function unique up to positive affine transformations given v. is a strictly increasing state independent second-order Bernoulli utility function unique up to positive affine transformations given v. $\mathbf{p}$ and $\mathbf{q}_j$ for $j = 1, \ldots, J$ are subjective belief. The probability distribution $\mathbf{p}$ can be interpreted as a distribution of the subject beliefs on the ambiguity. The function u is the ambiguity taste of the individual. The subjective beliefs on risky space $\mathbf{q}_j$ are made given the ambiguity context. Thus under this model the decision maker behaves as though she assigns probability $p_j q_{jk}$ to the state $\mathcal{A}_j \mathcal{R}_k$, and he bets on risky event as though his utility function was $u(v(w))$. The model follows the distinction of Klibanoff, Marinacci, and Mukerji (2005) between ambiguity with the distribution $\mathbf{p}$ and ambiguity attitude with the function u.

2.3 The combined model

We combine the two specifications of the previous subsections distinguishing between the gain and the loss domains and allowing for a second order model.

$$u(\mathbf{x}) = \begin{cases} \sum_{j=1}^{J} \Phi^+(p_j) \left(\sum_{k=1}^{K} \Gamma^+(q_{jk}) x_{jk}^{\alpha^+} \right)^{\rho^+} & if \quad x_{jk} \geq x_0 \\ \sum_{j=1}^{J} \Phi^-(p_j) \left(\sum_{k=1}^{K} \Gamma^-(q_{jk}) (-\lambda(-x_{jk})^{\alpha^-}) \right)^{\rho^-} & if \quad x_{jk} < x_0 \end{cases}$$

Like previously $\mathbf{x} = (x_{11}, x_{12}, \ldots, x_{JK})$ is an act, x_{jk} is an outcome, x_0 is the reference point. We define the parameters as follows:

- α^+ (resp. α^-) the concavity of the utility function for risk in the gain domain (resp. loss domain)
- ρ^+ (resp. ρ^-) the concavity of the utility function for ambiguity in the gain domain (resp. loss domain)
- Γ^+ (resp. Γ^-) the weighting function on probabilities in the gain domain (resp. loss domain)
- Φ^+ (resp. Φ^-) the weighting function on the distribution of beliefs on ambiguity in the gain domain (resp. loss domain)

With the following weighting function:

$$\Gamma^+(p) = \frac{p^{\gamma^+}}{(p^{\gamma^+}+(1-p)^{\gamma^+})^{1/\gamma^+}} \quad \Gamma^-(p) = \frac{p^{\gamma^-}}{(p^{\gamma^-}+(1-p)^{\gamma^-})^{1/\gamma^-}}$$
$$\Phi^+(p) = \frac{p^{\phi^+}}{(p^{\phi^+}+(1-p)^{\phi^+})^{1/\phi^+}} \quad \Phi^-(p) = \frac{p^{\phi^-}}{(p^{\phi^-}+(1-p)^{\phi^-})^{1/\phi^-}}$$

For taking into account loss aversion, two commonly used hypothesis can be made. First, $\alpha^+ = \alpha^-$, $\rho^+ = \rho^-$, $\gamma^+ = \gamma^-$ and $\phi^+ = \phi^-$ but λ is supposed to be different from 1. In other words, all the loss aversion phenomena is represented by a single parameter λ. In this case λ perfectly describes how much "losses loom larger than gains". Second, we can only set $\lambda = 1$ in this case we suppose that both domains are separate and require two sets of preference functions. To identify the parameters of the combined model, we need one of these two hypotheses (Kobberling and Wakker, 2005). In this article, we will make each of these hypotheses and present the results.

2.4 The structural specification of individual decisions

In the experiment, farmers face series of lottery choices j where a choice has to be made between two lotteries A and B: $\{(p_j, y_H^A, y_L^A); (p_j, y_H^B, y_L^B)\}$. Lottery A (resp. B) offers a high outcome y_H^A (resp. y_H^B) with probability p_j and a low outcome y_L^A (resp. y_L^B) with probability $1-p_j$. In order to simplify the explanation we will collapse the distribution of the belief under ambiguity and real probability in the probability p_j in this section. We are able to do it since our protocol is similar to the protocol of Chakravarty and Roy (2009) enabling to distinguish risk from ambiguity.

For each individual and for a given lottery $k \in \{A, B\}$, the utility writes:

$$U^k = \pi\left(p_j\right).u(y_H^k) + \pi\left(1-p_j\right).u(y_L^k)$$

where π is the weighting function, u utility function and both are matching the corresponding risk/ambiguity and the domain gains/losses. For example, for a choice with no-risk and only ambiguity in domain of gain $\pi = \Phi^+$ and $u(x) = x^{\rho^+}$.

The difference in utilities between the two lotteries writes:

$$\Delta U = U^B - U^A$$

It provides the rule for the individual choosing lottery B. We model the decision as a discrete choice model. We consider a latent variable $y^* = \Delta U + \varepsilon$ that describes the decision to choose lottery B. We assume ε follows a standard normal distribution with zero mean and variance σ^2.

$$y^* = \Delta U + \varepsilon \text{ , with } \varepsilon \sim N(0, \sigma^2)$$

This is equivalent to:

$$\frac{y^*}{\sigma} = \frac{1}{\sigma}\Delta U + u \text{ , with } u \sim N(0, 1)$$

We do not observe y^* but only the choices individuals make so that:

$$\begin{cases} y = 1 \text{ if } y^* > 0 \\ y = 0 \text{ if } y^* \leq 0 \end{cases}$$

The probability to choose lottery B is:

$$Prob(\text{choose lottery B}) = Prob\left(\frac{y^*}{\sigma} > 0\right) = Prob\left(\frac{1}{\sigma}\Delta U + u > 0\right)$$

$$= Prob\left(u > -\frac{\Delta U}{\sigma}\right) = \Phi\left(\frac{\Delta U}{\sigma}\right)$$

where $\Phi(\cdot)$ is the standard normal distribution function.

We estimate the parameters and the variance σ^2 using maximum likelihood. The log likelihood function writes:

$$\ln\left(L\left(\alpha_1, \gamma_1, \lambda, \alpha_2, \gamma_2, \rho_1, \phi_1, \rho_2, \phi 2 : y, \mathbf{X}\right)\right) =$$

$$\sum_i \left\{\left[\ln\left(\Phi\left(\Delta U/\sigma\right)\right)\right].\mathbf{I}(y_i = 1) + \left[\ln\left(1 - \Phi\left(\Delta U/\sigma\right)\right)\right].\mathbf{I}(y_i = 0)\right\}$$

where $\mathbf{I}(\cdot)$ is the indicator function, $y_i = 1$ when lottery B is chosen and $y_i = 0$ when lottery A is chosen, and **X** is a vector of individual characteristics.

3 The artefactual field experiment

We first describe the sample and then the protocol used in the artefactual field experiment.

3.1 Sample description

The field experiment took place during winter 2011-2012. We randomly chose farmers from a list of members of a big French cooperative, that ranked in 2011 in the top 20 of EU cooperatives according to a study by Price waterhouse Coopers) and offered them to particpate to a study on risk management. Farmers received a letter from the cooperative to inform them about our study, then we called them to fix a meeting for those who agreed to participate. Participants were face-to-face interviewed. Each interview lasted about 1 hour and a half. The questionnaire was composed of lottery choices followed by a survey on variables describing the farmer and the farm.

We collected questionnaires from 197 farmers. Table 1 gives some summary statistics regarding the individuals and their farms. The farmers produce mainly wheat. Farmers in the group, are mostly men, married with one child, and have relatively high education. Our sample contains farms with relatively large agricultural areas compared to the French national average (80 hectares). A majority of the farms are governed as a company[1](the farmer rents the capital from the company), few as a partnership[2] (the farmer offers his capital to the partnership) and the remaining are individual farms. They perceive their production activities as very risky in terms of output prices, input prices and weather-related events. Farming is perceived as risky in the sample. This consolidates the motivation of our survey.

[1]Stands for "Exploitation Agricole à Responsabilité Limitée" (EARL) or "Société Civile d'Exploitation Agricole" (SCEA) in France

[2]Stands for "Groupement Agricole d'Exploitation en Commun" (GAEC) in France.

Variables	Description	#Obs	Mean	SD
Describing farmers				
AGE	Age (in years)	197	48.56	10.16
SEX	=1 if farmer is a man =0 otherwise	197	0.97	0.15
HOUSEHOLD	Household size	197	2.89	1.35
EDUC	=1 if "baccalaureat" diploma or higher =0 otherwise	197	0.65	0.48
Describing farms				
UAA	Utilised Agricultural Area (hectares)	197	159.04	97.75
COMPANY	=1 if company and 0 otherwise	197	0.69	0.46
PARTNERSHIP	=1 if partnership and 0 otherwise	197	0.07	0.25
*Describing farmers' risk perception**				
RISKPPROD	Perception of output price risk	197	4.58	0.59
RISKPINT	Perception of input price risk	197	4.53	0.71
RISKCLIM	Perception of climatic risk (yield)	197	4.26	0.86
RISKCOM	Perception of output marketing risk	197	3.22	1.12
RISKPOL	Perception of risk related to policies	197	3.99	0.92
RISKTECH	Perception of technological risk	197	3.42	1.07

* Farmers were asked to grade their perception of the 6 types of risks related to their activity on a 5-level scale, from 1 ("not risky") to 5 ("very risky").

Table 1: Summary statistics

3.2 The lottery choices

For the lottery choice part, we used a multiple price list procedure where farmers made series of choices between two lotteries with varying probabilities and outcomes in the gain and loss domains. Choices were presented in the format of table 2.

	Urn A		**Urn B**		Choice	
Chance	3/10	7/10	1/10	9/10		
S1-1	200 €	100€	270€	75€	A	B
S1-2	200 €	100€	280€	75€	A	B
S1-3	200€	100€	350€	75€	A	B
S1-4	200€	100€	390 €	75€	A	B
S1-5	200€	100€	430€	75€	A	B
S1-6	200€	100€	450€	75€	A	B
S1-7	200€	100€	480€	75€	A	B
S1-8	200€	100€	520€	75€	A	B
S1-9	200€	100€	600€	75€	A	B
S1-10	200€	100€	700€	75€	A	B
S1-11	200€	100€	900€	75€	A	B
S1-12	200€	100€	1200€	75€	A	B
S1-13	200€	100€	2200€	75€	A	B
S1-14	200€	100€	3000€	75€	A	B

Table 2: Example of lotteries set for risk in gain domain

The lottery choice part was composed of nine series. The order varied accross subjects (four modalities) to enable the study of order effects notably its impact on the estimated parameters. In one of the modalities, the five first series are a variation of the protocol of Tanaka, Camerer, and Nguyen (2010) (see 2 for the first one). The two first series of 14 choices are in the gain domain for risk only (series 1 and 2). This two series have different sets of probabilities, this way we can estimate the weighting function for risk in the gain domain. Series 3 involves 7 choices in both the gain and the loss domain under risk. Series 3 is build to estimate the loss aversion parameter λ. Series 4 and 5 contain both 14 choices in the loss domain under risk only. The four last series (6,7,8 and 9) are a variation of the protocol of Chakravarty and Roy (2009) (see for example series 6 in 3) for eliciting ambiguity preferences. Series 6 and 7 contain both 14 choices in the gain domain under ambiguity. This two series have different distribution of the subjective beliefs in the gain domain. Series 8 and 9 contain 14 choices in loss domain under ambiguity. This two series have different distribution of the subjective beliefs in the loss domain.

Choose which color you want to bet on: (circle you choice) WHITE RED

	Urn A 5 WHITES + 5 REDS		**Urn B** 10 Balls of same color (10 WHITES or 10 REDS)		
Condition	If you **don't** pick a ball of the colors you bet on	If you pick a ball of the color you bet on	If you **don't** pick a ball of the colors you bet on	If you pick a ball of the color you bet on	Choice
S6-1	0€	1000€	0€	100€	A B
S6-2	0€	750€	0€	100€	A B
S6-3	0€	500€	0€	100€	A B
S6-4	0€	250€	0€	100€	A B
S6-5	0€	150€	0€	100€	A B
S6-6	0€	110€	0€	100€	A B
S6-7	0€	100€	0€	100€	A B
S6-8	0€	90€	0€	100€	A B
S6-9	0€	70€	0€	100€	A B
S6-10	0€	50€	0€	100€	A B
S6-11	0€	40€	0€	100€	A B
S6-12	0€	30€	0€	100€	A B
S6-13	0€	20€	0€	100€	A B
S6-14	0€	10€	0€	100€	A B

Considering urn B, according to you what is the probability of appearance of the color you bet on? .....

Table 3: Example of serie for ambiguity in gain domain

Urn B is ambiguous but not risky. Once the distribution is known there is no random part for urn B. At the end of each series under ambiguity we add a question to reveal the distribution of subjective beliefs. For example in 3 all farmers logically answered $1/2$. No surprising responses was found for those questions.

The incentive of the experiment is controlled by randomly drawing one of the 119 choice situations. Then, in the randomly drawn choice situation, the lottery (A or B) chosen by the participant is played for earnings. All participants received a show-up fee (20€) to cover their expenses for coming to the experiment and to cover their potential expenses in the loss domain. All participants played for earning, that is each farmer received the show-up fee and his gains/losses according to his choices, that ensures a more homogeneous incentive for all farmers. Some studies prefer to randomly choose within the sample a set of farmer who will actually play the lottery for earning. For studies on risk and ambiguity preferences, we consider it is a better practice to have all subjects play the lottery they chose. We divided the payoff of each lottery by 50 for the financial feasibility of the experiment. In the whole experiment, the highest potential earning was 60€and the lowest was a loss of 20€.

We designed the nine series so that the "‘neutral"’ switching point [3] varies for each serie; this way we can control the "framing effect[4].

[3]The switching point chosen by a risk or ambiguity neutral individual

[4]In the multiple price list design, subjects tend to focus more on the middle raw.

4 Empirical results

We estimate the parameters of the combined model under two hypotheses for identification reasons:

- In model (1), we assumer $\alpha^+ = \alpha^-$, $\rho^+ = \rho^-$, $\gamma^+ = \gamma^-$ and $\phi^+ = \phi^-$.
- In model (2a), we assume $\lambda = 1$.

In addition, we consider an exogenous reference point in models (1) and (2a) and an endogenous reference point in model (2b). Table 4 gives the maximum likelihood estimation results using clustering for individuals. We also estimate the variance controlling for each of the nine series with dummies that are omitted from display in table 4.

Hypothesis	(1)		(2a)		(2b)	
Estimated parameters	Coefficient (Robust SE)	P>|z|	Coefficient (Robust SE)	P>|z|	Coefficient (Robust SE)	P>|z|
σ						
constant	0.355	0.004	0.415	0.420	0.729	0.068
	(0.123)		(0.514)		(0.399)	
Risk	both domains		gain domain			
α^+						
constant	0.003	0.698	0.442	0.000	0.472	0.000
	(0.009)		(0.048)		(0.044)	
γ^+						
constant	1.003	0.000	0.334	0.000	0.329	0.000
	(0.007)		(0.032)		(0.031)	
			loss domain			
α^-						
constant			0.463	0.000	0.499	0.000
			(0.039)		(0.029)	
γ^-						
constant			0.384	0.000	0.409	0.000
			(0.031)		(0.024)	
λ						
constant	1.369	0.000				
	(0.202)					
Ambiguity	both domains		gain domain			
ρ^+						
constant	0.102	0.070	0.365	0.000	0.389	0.000
	(0.056)		(0.037)		(0.030)	
ϕ^+						
constant	0.270	0.256	0.623	0.000	0.598	0.000
	(0.238)		(0.039)		(0.047)	
			loss domain			
ρ^-						
constant			0.307	0.000	0.353	0.000
			(0.036)		(0.034)	
ϕ^-						
constant			1.049	0.000	1.435	0.000
			(0.250)		(0.263)	
x_0 : reference point						
constant					9.053	0.000
					(0.418)	
#Obs	23245		23245		23245	
Log likelihood	-12335.03 (N/A)		-11411.40 (N/A)		-11363.75 (N/A)	

Table 4: ML estimation of risk, ambiguity, probability weighting parameters and variance with clustering for individuals)

In model (1) the parameter of risk aversion for both domains and the weight on the distribution of subjective beliefs are not significantly different from 0. All others parameter are significant, but we need to compare them to 1. We made post estimation for equality to 1 for all parameters. We find that γ^+ is not significantly different from 1 ($Prob > chi2 = 0.694$). There is no distortion of probabilities. Moreover we find that α^+ is significantly different from ρ^+ ($Prob > chi2 = 0.050$), that is preferences for risk differ from preferences for ambiguity. And finally γ^+ is significantly different from ϕ^+ ($Prob > chi2 = 0.002$), the distortion for probabilities and for distribution of beliefs whatever the domain are different.

In model (2a), we find that farmers are risk averse for gains $\alpha^+ < 1$ ($Prob > chi2 = 0.000$) and for losses $\alpha^- < 1$ ($Prob > chi2 = 0.000$). We do not find a significant difference in the level of risk aversion in each domain $\alpha^+ - \alpha^- = 0$ ($Prob > chi2 = 0.392$). Farmers display an "inverse-s" shaped distortion of probabilities in gains $\gamma^+ < 1$ ($Prob > chi2 = 0.000$) and losses $\gamma^- < 1$ ($Prob > chi2 = 0.000$). Moreover, we find that the distortions in the gain and loss domains are significantly different (at 10%), $\gamma^+ - \gamma^- = 0$ ($Prob > chi2 = 0.095$). For risk we can see that preference differences between gain and loss domains are mainly due to difference on probability weighting functions. Farmers are ambiguity averse for gains $\rho^+ < 1$ ($Prob > chi2 = 0.000$) and for losses $\rho^- < 1$ ($Prob > chi2 = 0.000$). Preferences for ambiguity in the gain and loss domains are significantly different, $\rho^+ - \rho^- = 0$ ($Prob > chi2 = 0.011$). As for the probability weighting function on the distribution of subjective beliefs, we find inverse s-shaped distortion in the gain domain $\phi^+ < 1$ ($Prob > chi2 = 0.000$) and no significant distortion for the loss domain $\phi^- = 1$ ($Prob > chi2 = 0.845$). The weighting functions in the gain and loss domains are significantly different $\phi^+ - \phi^- = 0$ ($Prob > chi2 = 0.093$). We find significant differences in ambiguity preferences in the gain and loss domains. Furthermore, risk and ambiguity attitudes are significantly different ($\alpha^+ - \rho^+ = 0$, $Prob > chi2 = 0.034$; $\alpha^- - \rho^- = 0$, $Prob > chi2 = 0.000$; $\gamma^+ - \phi^+ = 0$, $Prob > chi2 = 0.000$; $\gamma^- - \phi^- = 0$, $Prob > chi2 = 0.007$). The difference between probability distortions in risk and ambiguity are often ignored. We find it matters.

In model (2b), the only difference with model (2b) is that the reference point is now endogenous. Results show that most parameters are almost unchanged. The main interest of model (2b) is the reference point. We find a positive reference point around 9 and significantly different from zero ($p.value = 0.000$). Farmers in our sample have a reference point significantly higher than 0. In our experiment, farmers are expecting gains and therefore may consider as a loss any amount under 9€.

5 Conclusion and discussion

In the context of increasing risks in agriculture, we designed an artefactual field experiment involving real payments to elicit farmers' risk and ambiguity preferences. We used two elicitation methods based on the protocols proposed by Tanaka, Camerer, and Nguyen (2010) and Chakravarty and Roy (2009). Our sample was composed of 197 French farmers. We estimated the parameters describing farmers' risk and ambiguity preferences derived from structural models. We find that farmers are risk and ambiguity averse in both domain gain and loss. We find that farmers display distortion in probabilities under the gain and loss domains for risk and only in the gain domain for ambiguity. Our results are coherent with previous studies. In the cumulative prospect theory framework, Tanaka, Camerer, and Nguyen (2010) found an α parameter around 0.60 (α^{+}=0.442 and α^{-}=0.463 in model (2a)), a probability weighting parameter γ around 0.74 (γ^{+}=1.003 in model (1); γ^{+}=0.334 and γ^{-}=0.384 in model (2)) and a loss aversion parameter λ around 2.63 (λ=1.369 in model (1)). Our study shows that, for our sample, farmers' behaviour (i) farmers' behaviour towards risk is different across domains, (ii) farmers' behaviour towards ambiguity is different across domains, (iii) farmers' behaviour towards risk and ambiguity is different. Model (2) fits our sample better than model (1). Behaviorial differences across domains, and risky and ambiguous situation cannot be neglected if the aim is to better understand farmers' decisions. We also found that the commonly assumed hypothesis of a zero reference point does not apply to our sample.

This study is a first step into a better understanding of farmers' behaviour towards uncertain (with both risk and ambiguity) situations using recent advances in experimental economics. Several characteristics of our study should be kept in mind however. The loss domain is not easy to implement in the field. Indeed, one cannot ask participants in the experiment to pay the experimenter if the lottery involves a loss. This was resolved here by the show-up fee. But, this fee in itself might play the role of an insurance mechanism. The MPL design also brings the problem of multiple switching points. The main limitations of this study are the chosen functional forms. Multiple models for risk and ambiguity exist. For risk most of them are well studied. However, for ambiguity lots of structural modeling are still developed and no consensus on the best fitting model arises. The choice of the second-order effect model can be discuss as Machina (2009) claims, but the aim of this paper was to introduce ambiguity analysis in agricultural domain and the second-order model offers an easy way to implement this first step. Future work aims at alleviating some of these limitations. This study is a preliminary work, more explicative variable will be introduced.

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