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Who are the Loss-Averse Farmers? Experimental Evidence from Structurally Estimated Risk Preferences

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Abstract

Even though recognized to be of increasing importance, robust estimations of European farmers' risk preferences are still scarce, likely owing to field and technical constraints. We conduct an incentivized field experiment with farmers, free of learning-bias, to structurally derive parameters of risk preferences based on Cumulative Prospect Theory. The sector studied is the apple and pear sector in Flanders, Belgium. Farmers are found to be highly risk-averse and to distort probabilities by overweighting small probability of desirable outcomes. However, contrarily to previous studies, we do not find evidence of loss aversion on average. Moreover, we investigate heterogeneous effects and show that some farmers significantly differ from the representative agent by still being extremely loss-averse. The results of this piece of research induce the need for considering heterogeneity across and within sectors when it comes to assessing risk preferences.

1 Introduction

The understanding of risk preferences has been at the core of agricultural economics for decades and is likely to regain interest because of the increasing exposure of farmers to market and climatic risks. This is particularly true for Europe where gradual market liberalisation have increased farmers' risk exposure (FAO et al., 2011; Haile et al., 2016). Even though risk preferences are recognized to be important factors for understanding farmer's decision-making, serious caveats still prevail in the literature.

First, most experiments tested models of risk preferences characterized by one parameter measuring the curvature of the utility function, the most common one being Expected Utility Theory (von Neumann and Morgenstern, 1947). Even though the latter presents the advantage of being practically easy to test, violations of its axiomatic properties have been systematically found in experimental data (Allais, 1953). Moreover, researchers trying to estimate risk preferences with multi-parameters models, i.e. considering rank-dependent and sign-dependent specifications, have concentrated on low-income countries (Tanaka et al, 2010; Liebenehm and Waibel, 2016; Liu, 2013) or involved students (Harrison and Rutstorm, 2005) and only few studies focus on farmers in high-income countries (Reynaud and Couture, 2012; Bocquého et al, 2014; Bougherara et al, 2017; Rommel et al., 2019). This may be due to the difficulty of collecting data in Europe, which is mainly hampered by farmers' time constraint and high opportunity cost. As risk preferences influence many aspects of farmers' decision making, characterizing the farmers' population on this dimension is key to the design of relevant and effective agricultural policy. Moreover, risk preferences vary across sectors and regions because of differences in agricultural policy and in the farming activities themselves. Hence the necessity to systematically investigating the distribution of farmers' risk preferences across and within sectors to deliver relevant risk management policy. Second, experimental designs and estimations methods of risk preferences have evolved tremendously during the last decades. Structural estimations have been shown to deliver more robust estimations (Harrisson and Rutström, 2008). However, experimental designs and estimation methods still vary tremendously across studies and only a few rely on robust structural estimations. Third, the state of current research in multi-parameter modelling does not enable to conclude on individual drivers of risk preferences because of the lack of analysis of heterogeneous risk preferences.

This paper builds on laboratory and field experiments applying prospect theory to measure risk attitudes, that is, involving rank- and sign-dependent specifications. There have been studies estimating risk aversion, loss aversion, and probability weighting by estimating the three parameters in a recursive way (Tanaka et al, 2010; Liu, 2008) (midpoint technique), but only few robust structural estimations (see Appendix, Table 8 for a review) and to our knowledge, only two studies have focused on high-income regions. First, Bocquého, Jacquet, and Reynaud (2014) have experimented with a sample of farmers in Bourgogne, France. Second, Bougherara, Gassmann, Piet, and Reynaud (2017) did a field experiment with farmers in the region of Champagne-Ardenne. Both regions have a rather diverse and similar agricultural production which includes cereal crops, livestock, market vegetables, and wine. Both studies found farmers to be very risk- and loss-averse and to distort probabilities by overweighting small stakes of desirable outcomes[1].

Hence the contribution of this paper is three-fold. First, it extends the limited knowledge of farmers' risk preferences in high-income countries to low subsidized sectors by experimenting with very entrepreneurial and business-oriented producers of apples and pears in Belgium. Second, we test a method enabling to reduce stochastic errors done by subjects in evaluating lotteries and show that it significantly influences the parameters' estimates. Third, we show the importance of estimating heterogeneous effects for understanding factors of risk preferences, and in particular loss-aversion. While there is a consensus on the fact that subjects tend to be rather risk-averse and to overweight extreme events, previous studies find very different measures of loss aversion. The latter observation call for a more rigorous analysis of heterogeneous effects associated with loss-aversion.

To do so, we use primary data collected within a sample of farmers producing mainly apples and pears. The innovation of the data is that it is free of learning bias so that choices made for binary lotteries at the beginning of the series do not systematically suffer from subjects' lack of experience with the tasks at hand. Choices were also incentivized by substantial real cash payments, asked sequentially and monotonous switching was not enforced. The parameters are structurally estimated using a homogeneous and then a heterogeneous model, that is further explored to characterized diverging sub-groups of farmers.

The main result is that the Belgian producers distort probabilities as much as the French producers do, on average. They are also equally risk-averse. However, the main difference with the previous studies is that we do not find evidence of loss-aversion, on average. However, the sample shows a high level of heterogeneity regarding loss-aversion, which is further investigated. Estimations show that even though the representative agent is not loss-averse, about 18% of the farmers completely deviate by being extremely loss-averse. We show that these are relatively young and relatively low educated farmers, having inherited a relatively small farm that they manage alone. In general, risk preferences are heterogeneous and correlated with specific individual characteristics.

The paper is organized as follows. Section 2 presents the conceptual framework and the associated methods are described in section 3. The data is described in the fourth section and the results follow in section 5. In section 6, we discuss the internal and external validity of the results. The last section concludes.

[1] Bourgherara et al. (2014) also investigated ambiguity aversion and show that farmers are ambiguity averse.

2 Conceptual Framework

The modelling of risk preferences is a central feature in agricultural economics for understanding differences in strategies and performances to given risk exposure and identifying adequate policies to support farmers. The dominant theory so far has been the Expected Utility Theory (EUT). Despite its advantages in terms of practical implementation (Just and Peterson, 2010), EUT has received little empirical support. Indeed evidence has accumulated whereby individuals systematically violate its basic assumptions, gradually dismissing the theory as an adequate description of individuals' choices under risk (Allais, 1953; Kahneman and Tversky, 1979). First, very large outcomes are usually preferred by individuals, even when they are associated with a very small probability. Second, when it comes to losses, people often focus on trying to reduce the probability of any loss rather than on the expected outcome, which is translated into a loss aversion phenomenon.

To integrate the findings of the laboratory experiments, Kahneman and Tversky (1979) have developed an alternative theory of choices under risk, named Prospect Theory (PT). The main contribution of this theory is the two-part utility function that captures the difference in behavior in the two outcome domains. However, separable PT violates first-order stochastic dominance. Hence Quiggin (1982) developed the idea of decision weights involving cumulative probabilities instead of single probabilities, which was further integrated by Kahneman and Tversky into Cumulative Prospect Theory (1992).

In Cumulative Prospect Theory, the power utility function is defined separately over gains ($x \geq 0$) and losses ($x < 0$) (Tversky and Kahneman, 1992) as follows:

$$u(x) = \begin{cases} x^{\sigma} & \text{if } x \geq 0 \\ -\lambda(-x)^{\sigma} & \text{if } x < 0 \end{cases} \tag{1}$$

where σ is the parameter controlling the utility curvature[2] and λ is the coefficient of loss aversion which reflects how much the distance to the reference point looms higher for losses than for gains. If $\sigma < 1$ the utility function is concave in the gain domain reflecting risk aversion and the closer the σ to zero the higher the degree of risk aversion. If $\lambda > 1$ the choices made by the subjects are characterized by loss aversion so that subjects are

[2]Originally when Tversky and Kahneman defined CPT in 1992, the utility curvature in the positive and in the negative was approximated by two distinct parameters. For simplification here we follow the common more recent practice whereby only one parameter is introduced to control for curvature in both domains (Wakker, 2010).

more risk-averse when it comes to losses than to gains.

In line with the common findings in the literature, we hypothesize that farmers are risk-averse in the gain domain and risk-seeking in the loss domain so that u(x) is concave above the reference point and convex below it. Farmers are also hypothesized to be loss-averse so that the utility function would be steeper in the loss domain than in the gain domain. Then it is assumed that farmers subjectively convert probabilities of the lottery with a probability weighting function. This function follows the recommendations of Prelec (1998) and takes the following form:

$$w(p) = \frac{1}{exp(ln(\frac{1}{p}))^{\gamma}} \tag{2}$$

where γ is the parameter controlling probability weighting. If $\gamma < 1$, the function follows an inverse S-shape so that the smaller the γ, the more subjects overweight small probabilities of high payoffs and underweight high probabilities of relative smaller payoffs (Tversky and Kahneman, 1992). We hypothesize that farmers behave so.

Last but not least, the EUT model is nested into the CPT model because if risk aversion associated with losses is the same as for gains ($\lambda = 1$) and subjects do not distort probabilities ($\gamma = 1$) the CPT model reduces to the EUT one.

3 Methods

3.1 Recursive Method

Because the structure of the current experiment follows the design offered by Tanaka et al. (2010), raw measures of the parameters can be obtained by computing the mid-point values following the recursive approach developed by these authors. Indeed any combination of choices in the three series leads to a unique interval for the three parameters of CPT[3]. Switching points in series 1 and 2 serve to jointly determine σ and γ so that any combination of switching points can be rationalized by only one combination of the approximate value for (σ ; γ). Then the third series determines the loss aversion parameter λ, conditional on the value previously found for σ. Note that the parameters' values are approximated to the nearest 0.05 increments, and are thus rather imprecise (see Harrisson and Rutström (2008), for a detailed critic of the method).

[3]Tanaka et al. (2010) provides a detailed description of the method with predictions of parameters for all combinations of switching points.

3.2 Structural Estimations

Structural estimations of the fundamental parameters of preferences will be carried out by matching the observed choices with the model of Cumulative Prospect Theory [Harless and Camerer, 1994] [Nevo and Whinston, 2010]. The advantages of structural analysis as compared to a recursive construction of parameters are multiple. It is more robust as it allows the joint estimation of the three parameters of interest, namely σ for the utility curvature, λ for loss aversion and γ for probability distortion. This way it is also possible to evaluate and test the robustness of the theoretical model. Then the information contained in each parameter is mutually exclusive so that each parameter reflects a unique aspect of the preferences and parameters do not mutually inflate.

To estimate the parameters of the utility model, we follow the approach developed by Harrison and Rutström (2008). The prospective utility of agent i for the task j is written as:

$$U_i^j = PT_i^j(X_i; Z^j) + \epsilon_i^j \tag{3}$$

where $PT_i^j(X_i; Z^j)$ is the utility function under Prospect Theory and ϵ_i^j is the error term, which is assumed to be normally independently identically distributed.

$U_i^j(X_i; Z^j)$ is the utility obtained by respondent i from option A or B in decision task j. The utility value is known to the producer only, while the researcher can observe X_i, the respondent's characteristics, and has all information Z^j regarding the decision task j, which in this case is the participation fee and the probabilities.

It is assumed that respondents switch from A to B whenever $U_B > U_A$. The estimation of the parameters is done through the following latent index (called the Fechner index): $\Delta PU_i^j = (PU_i^{B;j} - PU_i^{A;j})$. The latent index PU_i^j is then linked to the observed binary choices made by the producer in the experiment through a standard cumulative distribution function $\Phi(\Delta U_i^j)$. The conditional log likelihood of choosing option B can be expressed as follows:

$$LnL_i(\sigma, \lambda, \gamma; X_i; Z^j; y_i^j) = \sum_{j=1}^{31} \left\{ [ln\Phi(\Delta U_i^j)/y_i^j = 1] + [ln\Phi(\Delta U_i^j)/y_i^j = 0] \right\} \tag{4}$$

The idea of maximum likelihood is to find the estimate(s) of the parameter(s) that maximizes the probability of observing the choices made by the group of producers surveyed. In other words, the maximum likelihood estimation is a systematic way of searching for the σ, λ and γ that maximize the probability of observing the data. In a first step, these parameters are estimated under the homogeneous model, assuming a representative agent. Because we are interested in the individual factors of deviation from the average risk preferences, the representative agent assumption is relaxed in a second step, by adding explanatory variables to the model (the X_i vector) and searching for deviation from the average estimates. A well-defined list of covariates will be included[4], the objective being to find a set of relevant explanatory variables that is jointly significant. We first test the correlation of the parameters by including the gender of the respondent ($resp\_male$), his age ($resp\_age$), a dummy variable taking value one if he owns the farm ($resp\_owner$) and finally a dummy taking value 1 if he has high education, that is beyond secondary school ($resp\_educsup$). The farm characteristics are further included on top of a farmer's characteristics. The former are characteristics that explain the farmer's risk preferences through his farming context. As per farm's characteristics we include the area currently cultivated with apples and pears ($area\_cultivated$) and dummies taking value one for the following aspects: cooperative's membership ($coop$), co-management of the farm ($co\_management$) and finally the fact that the farm has been inherited ($inherited$).

Hence this is done by jointly estimating the parameters as linear functions of the explanatory variables using maximum likelihood estimates of each parameter as follows (Nguyen and Leung, 2009):

$$\hat{\beta} = \hat{\beta}_0 + \hat{\beta}_1 resp\_male + \hat{\beta}_2 resp\_age + \hat{\beta}_3 resp\_educsup + \hat{\beta}_4 resp\_owner \tag{5}$$

$$+\hat{\beta}_5 area\_cultivated + \hat{\beta}_6 coop + \hat{\beta}_7 co\_management + \hat{\beta}_8 inherited \tag{6}$$

Finally, structural stochastic error will also be allowed for later on in the analysis through the following error specification (called Fechner stochastic error): $\Delta PU = \frac{PU_B - PU_A}{\mu}$ (Wilcox, 2008; Loomes, 2002). Concretely this factor of noise captures the error that individuals make by choosing a binary lottery for which their prospective utility does not exceed that of the alternative binary lottery. The robustness of the results will also be tested against the restriction of the sample to include consistent subjects only.

The structural models contained in this paper have always been estimated using four distinct optimization algorithms[5],[6].

[4]Remember that the method applied here rely on pooled data over individuals and it is thus implicitly assumed that the heterogeneity left unobserved after controlling for this set of covariates is random. An alternative is to run individual structural estimations of the parameters. However this requires having more observations per individuals than obtained in this experimental design, and thus more effort and time from farmers.

[5]We run 5 subsequent fits using "Newton-Raphson" (nr), "Davidson-Fletcher-Powell" (dfp), "Broyden-Fletcher-Goldfarb-Shanno" (bfgs) and finally "Berndt-Hall-Hall-Hausman" (bhhh) optimization algorithms.

[6]We developed the model specifications with help of the programming notes of Glen W. Harrison (2008) to user-written maximum likelihood models of utility functions in Stata and hence did not use any pre-packaged model specifications. Hence we control each step of the program.

The last key assumption regards the reference point subjects use to distinguish a loss from a gain. Expectations-based reference dependence has been supported by some studies (Loomes and Sugden, 1986; Bell, 1985; Koszegi and Rabin, 2006), while others estimate the reference point and do not find it to be significantly different from zero (Bougherara et al. 2011). In our case, it is reasonable to assume a reference point at zero as participants knew that there was a chance they would not be selected to play the game for real money. Hence this will be assumed as the pivotal reference point in the structural estimations.

4 Data and Descriptive Statistics

The survey was part of a large European project called SUFISA. The project encompassed the study of 23 case studies spread across 13 countries and for which a common questionnaire had been developed with the aim to study farmers' conditions, strategy and performances within Europe, across sectors and regions. The risk preferences elicitation task was developed for the Flemish apple and pear sector only and added at the end of the questionnaire.

4.1 The apple and pear sector

In 2016, Belgium counted 729 top fruit farms[7], of which 88% was located in Flanders, mainly around the capital town of the province of Limburg, Sint-Truiden (see Map 1 - part A). In 2014, the total fruit sector was worth 370 million euros, of which apples represented 74 million euros and pears 151 million euros, that is 60.8% of the total sector for the sum of both commodities (Department of Agriculture and Fisheries, 2016a). The Flemish farms specialized in this sector cover around 3% of the total agricultural land in Flanders. An important characteristic of orchard fruit production is the long rotation period of the trees, which is approximately 10-14 years for apple trees, while for pears it can run up to 25 years or even longer (Van Bogaert et al., 2012; Demeyer et al., 2013). This translates into high investment risk and high adjustment costs. The sector is in crisis partially because of the Russian ban on European F& V that has been applied since 2014[8]. In terms of market contraction pears were affected the most as in 2013, pears accounted for 30.1% of the agri-food exports to Russia while apples accounted for 5.6%. This resulted in a market contraction of 39.33%[9] for pears and 11.06% for apples.

[7] The target population is defined as specialised fruit farmers who cultivate at least one hectare of fruits, and grow apples and/or pears. Specialised fruit farmers obtain at least 50% of their total standard output from fruit farming.

[8] According to the Flemish monitoring network for agriculture (Landbouwmonitoringsnetwerk, 2017), fruit producers' level of satisfaction is the worst among all Flemish sectors.

[9] Which is calculated as 83.5% of 47.1%

Nevertheless, revenues of top fruit farmers are quite high: 75% of them earns more than 150,000 EUR a year while slightly more than 20% earn more than 500,000 EUR (Vervloet et al, 2015). However the sector is export oriented (around 70% of the production is exported) and hence exposed to market risk translated into price fluctuations at the farm level. The level of specialization is also very high as 50% of the farm sampled are fully specialized in top fruit and the ratio of top fruit income on total farm income is 87% on average. There is also a trend toward more specialization both at the individual and sectoral level as more and more farmers are shifting to pears (Demeyer et al., 2013; Department of Agriculture and Fisheries, 2016a) for reasons including higher prices, lower production risk and reduced competition on this market.

All in all, the fruit sector has never received high levels of protection under the CAP. Indeed, the Common Market Organization (CMO) for fruit and vegetables is a light market organization and as a result, the sector never received high levels of pillar I subsidies (direct payments). In the period 2007-2012, income payments received by fruit farms averaged about 1626euros per farm, or about 2% of farm income (Platteau et al., 2014; Department of Agriculture and Fisheries, 2016a). On the other hand, an important level of the European Common Agricultural Policy (CAP) for the fruits and vegetables sector is the support to cooperatives through subsidies for collective action and pooled risk management.

4.2 Sample description

All apple and pear farmers in Belgium were informed about the survey. The questionnaire had to be completed online. We opted for this mode of administration following farmer's demand during focus groups discussions; they required full-time flexibility and hence strongly opposed any phone or face-to-face interviews[10]. An online survey has the advantage of ensuring respondents' anonymity and proximity to the context in which they take daily decisions, hence the truthful revelation of preferences. Yet it might induce sample selection issues and affect data quality[11]. Given that the survey was mainly about institutional arrangements and advertised this way, sample selection, if any, is likely to be orthogonal to the risk task. The alternative sampling strategy that is commonly used by researchers would have been the use of a random list of farmers. However, often this strategy does not solve the sample bias because of the high level of attrition hampering the representativeness

[10] After individual consultation with farmers and focus groups, it became clear that the only viable option to collect answers was through an online questionnaire. Indeed, farmers in Flanders are not only very busy and entrepreneurial but they have also been frequently solicited (up to four times for a big share of them) in the year 2017. Hence some of them explicitly mentioned that they would only answer to an online survey, where they would be free to choose the exact timing of completion.

[11] One threat of online surveys is that data quality could be deteriorated by a farmer's low command of the online tool or by the fact that questions could not be rephrased across questionnaires to ensure each respondent's perfect understanding. To avoid such problems the questionnaire was tested through multiple pre-piloting interviews and short and clear comments were included to guide the respondents. Special care was given to the good understanding of the questions, the development of an exhaustive list of potential answers and the avoidance of redundancies. Our strategy has proven successful as the portion of inconsistent subjects is found to be very low (see section **??** for a detail discussion). Full-time assistance was also provided on phone or through email by one member of the team.

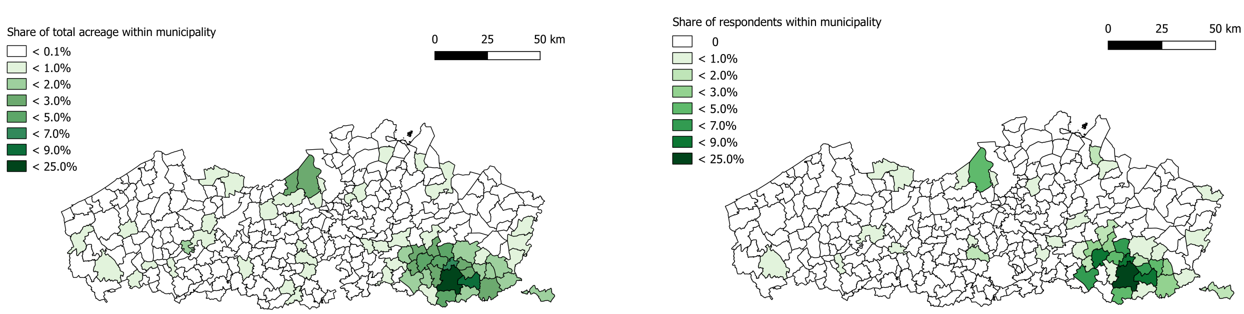
of the final sample obtained and questioning the reasons for the refusal of the missing farmers. Hence our target was to harvest as large as we could and make sure we could attract all types of farmers in representative proportions. The sample's representativeness will be discussed in section 4.2. Note that each subject had to complete an informed consent form at the beginning of the questionnaire and the risk task has received the favorable approval of the Social and Societal Ethics Committee of KU Leuven[12].

The data consists of 136 subjects making each 31 choices over the same set of pair lotteries, that is, 4216 observations. The sampling procedure aimed at representativeness and the ex-post comparison of sample and population statistics supports unbiasedness on three main dimensions: geography, age and farm size[13].

Figure 1: Geographical representativeness

(a) Population

(b) Sample



In particular, Figure 1, shows the geographical dispersion of the sample in panel A and of the total population of apple and pear farmers, in panel B. The comparison of both maps supports the representativeness of the sample as 85% of the farms sampled are located in the region of Sint-Truiden which is very close to the population statistics (86%). The targeted respondent was the farm's main decision maker, as being assumed to be the one whose risk preferences influence the most the farm's strategy. Descriptive statistics of the sample are reported in Table 3. In this sample, 93% is the farm owner, the others being farm managers. Respondents are 49 years old on average with 46% being younger than 50 years old and 3% being more than 65 years old (the legal age of retirement in Belgium). The proportion of females is only 5%. Farmers in Flanders are rather highly educated, which is reflected in our sample: only one farmer indicated to not have attended secondary education. For 50% of the sample, secondary education is their highest level of education, while 38% completed professional tertiary education (professional bachelor degree) and 11% even obtained an academic degree. This

[12]The protocol has been approved on November 14, 2018, and received the following dossier no. G-2017 11 1007. This approval is valid for four years.

[13]Unfortunately, the distribution of education cannot be assessed within this population because of missing data.

high level of education also helps to trust the ability of the respondent to handle the risk tasks.

In terms of farm characteristics, 53% of the farms have been inherited while 63% are co-managed in the sense that the respondent is not the only decision-maker. Usually, the second decision-maker is the wife of the farmer. The average farm revenue is 479 000 euros a year[14], while 50% have less than 300 000 euros a year. The area in production is on average 26 hectares, with a maximum at 245 hectares. On average, 87% of the farm income is from fruit production and only 5% have more than 50% from other income sources.

4.3 The experiment

The experimental design follows the adaptation to the European context made by Bocquého, Jacquet, and Reynaud (2014) of the risk tasks developed by Tanaka, Camerer and Nguyen (2010). It consists of three series of pairs of binary lotteries. The three series are reported in Table 2. Note that series 2 was shortened by two lines compared to the French experiment, which is unlikely to significantly affect estimates as the three last lines of this series were almost similar. The first two series involve only positive payoffs while the third one is a mixed lottery so that it always contains one negative payoff on both sides. The payoffs varied from choice to choice and from a lottery to lottery while probabilities were fixed per series. In the gain frame experiments, odds were 0.1, 0.3, 0.7 and 0.9 and always 0.5 in the loss frame. The three series are presented in Table 1. The series are rather simple and in particular, for series 2 and 3, three outcomes were invariant while the fourth one increased(decreased) sequentially from row to row.

For each series, subjects were presented with a first lottery pair randomly selected[15]. The subject was asked to make a choice between lottery A and B. According to the first choice made, the set of subsequent lottery pairs was given, one by one. If the respondent chose the safe (risky) lottery in the first place, he was then offered the riskier (safer) alternatives by going down (up) the series. In short, the risk preferences elicitation tasks were played sequentially, indifference was not allowed, nor monotonous switching was imposed for the tasks done. The difference in expected payoff was not shown as it might prompt subjects to consciously alter their preferences toward risk-neutral choices (Harrison and Rutström, 2008). The framing was neutral with amounts and probabilities displayed with numerics and highlighted in bold, as the population of farmers studied is used to make decisions in probabilistic settings. For negative amounts, we choose to frame them as "losing $x\ euros$" instead of "a payoff of $-x\ euros$" in order to reduce the risk that respondents would integrate the participation

[14] Note that we have this variable for x% of the sample

[15] The design used here is close to the *Random Lottery Pair Design* used by Hey and Orme (1994) which is argued by Harrison and Rutström, (2008) as having the advantage of being "extremely easy to explain to subjects, and the incentive compatibility of truthful responses apparent" (p.50).

fee when making their choice.

To ensure incentive compatibility, real rewards were provided in ranges that would trigger respondents' commitment[16]. This happened as follows. At the beginning of the experiment, subjects were informed that 20 of them would be randomly selected to play the game for real and would receive a pre-defined percentage of their payoffs (these range from -210 to 6000 euros). This percentage was fixed to be 10% and was revealed at the end of the game. Hence we preferred taking the risk of introducing background risk[17] in order to be able to offer substantial amounts and thereby minimize hypothetical bias (Rabin, 2000). Because of the ethical problem of inducing real losses for agents, a participation fee of 210 euros was offered at the beginning of the game. For each of the 20 randomly selected participants, one binary lottery was randomly selected and the respondent's preferred lottery was played out as the reward. The selected participant received 41 euros on average while 2 of them lost their participation fee and the luckiest one received 111 euros. Note that respondents could have won up to 621 euros. Money was sent by email in the form of a voucher to be spent on a local farm. The instructions given to the subjects are detailed in the appendix.

Randomization of the first choice to be made presents several advantages. First, the first lottery played likely artificially set the reference point so that other binary lotteries are evaluated as compared to the first one. By making it random, we control for the bias induced by such a phenomenon. Second, this ensures that if there is a learning process whereby choices made later on would better fit the subject's preferences, this one is randomly distributed across lottery pairs. In other words, the preferences at the sample level for a given lottery pair cannot be associated with the level of understanding of this lottery pair relative to the other rows. This is of crucial importance as learning effects might induce higher stochastic error for lines played earlier in each series which are also associated with lower levels of risk exposure and a higher level of potential losses in the third series. Third, randomization of the first lottery pair reduces the number of lottery pairs offered to the respondent and hence the fatigue and risk of unconsidered answers, still enabling the extrapolation of the choices over the whole series of lottery pairs. Hence the number of choice tasks performed by each individual, and the induced level of extrapolation required, were randomly allocated and thus orthogonal to an individual's characteristics. On average each individual had to perform 20 choice tasks[18].

[16] Rabin (2000) pointed that when offered too low rewards, subjects could play as if they were risk-neutral.

[17] Lusk and Coble (2008) when introducing background risk directly in the experiment found that it does not highly affect risk preferences. Cubitt et al. (1998) also provide evidence that it gives similar results as when each lottery is played for real rewards.

[18] Note that random choices by the whole sample would lead to an average of 31/2=15.5 lines played. The fact that we obtained a higher number of lines played is driven by the fact that agents are not risk neutral on average.

In most risk experiments, researchers chose to use the Multiple Price List (MPL) instead of sequentiality of the tasks[19]. Concretely, subjects are shown all choices in one table and asked to indicate at which level they would like to switch to option B. The alternative is the one we implemented, which is to offer subjects each binary lottery choice in a sequence. Both methods have advantages and disadvantages. The MPL has the advantage of being quicker, and maybe allows subjects of making more consistent choices (Harrison and Rustrom, 2008). However, MPL has been shown to induce a framing effect whereby subjects integrate the bounds of the series as references points and thus tend to artificially prefer row in the middle of the series (Harrison et al., 2005). We would also add another argument that is linked to the interdependence between the choices made in different lines. Indeed, it is likely that subjects weight payoffs in one line relative to the choices offered in other lines when they can see the whole series at once. This might be a non-negligible threat to parameters' unbiasedness, and in particular, it can increase the probability of observing loss aversion. Indeed, imagine a respondent is asked to consider the first line of series 3. Having to choose between the risk of "losing 310 euros" or that of "losing 310 knowing that he could loose only 160" by choosing to switch to option B a few lines down in the series, is very different. Hence MPL might inflate the estimate of loss aversion.

Then often researchers also choose to enforce monotonous switching[20]. By doing so, researchers loose the opportunity of assessing data quality by the identification of inconsistent subjects. Evidence has accumulated that subjects are not always consistent and sometimes do not understand the risk tasks at hand. The level of inconsistency depends on the level of education of subjects, their familiarity with probabilities and choices under uncertainty, their level of attention and the clarity of the instructions. Whether or not multiple switches reflect inconsistency or other phenomenons as the lack of commitment of the subjects or the lack of incentive to answer truthfully, being able to control for this phenomenon is important for the external validity of the experiment and the inferential conclusions. To the contrary of the MPL, the sequential list has the advantage of letting the researcher detect subjects switching back and controlling for their nature in the estimations. Robustness tests will be performed in the homogeneous and heterogeneous models to assess the potential bias induced by inconsistent agents in the parameters' estimates[21] and its effect on the parameters' estimates.

[19]see Table 8 in the Appendix for a review

[20]see Table 8 in the Appendix for a review.

[21]though as will be discussed in Section 5.2 there is a trade-off between the detection of inconsistent agents and the randomization of the first line to reduce stochastic bias.

5 Results

5.1 Mid-point technique

A simple look at the distribution of switching points associated with each series (Table 4) already provides information about the levels of risk and loss aversions characterizing the sample. An interesting observation is that the distributions of switching points in series 1 and 2 in our sample are similar with that of Bocquého et al. (2014) who applied the same risk preferences elicitation task within a sample of French farmers. However, the distribution in series 3, which involves negative outcomes, is very different as our respondents switch earlier than in the French sample (see Table 4), meaning that they have a stronger preference for more risky lotteries in the loss domain. This is the first evidence of a lower level of loss aversion.

In Table 1 the mean value and standard deviation of each parameter are reported. The parameter of utility curvature, σ, is 0.605, which is close to values computed with the same method by Tanaka et al. (2010), Liu (2013) and Bocquého et al. 2014[22]. The distribution is skewed toward risk-averse individuals, with a smooth decrease toward risk-seeking individuals who are less numerous. The loss aversion parameter λ is 2.643, hence lower than the value of 3.76 found by Bocquého et al. (2014)[23]. However, the distribution of this parameter reveals a high degree of dispersion with a portion of 18.4% of individuals being extremely loss averse ($\lambda > 9$). The remaining share of the sample is on average not loss averse, hence the heterogeneity in risk preferences. Finally, the average value of the parameter γ is 0.678, rejecting EUT in favor of an inverted S-shaped probability weighting.

Table 1: Parameters' value based on the midpoint technique

Variable	N	Mean	Std. Dev.	Min	Max
anti-index of risk aversion (σ)	136	0.605	0.425	0.13	1.5
loss-aversion (λ)	136	2.643	3.585	0.10	10
probability distortion (γ)	136	0.678	0.299	0.10	1.4

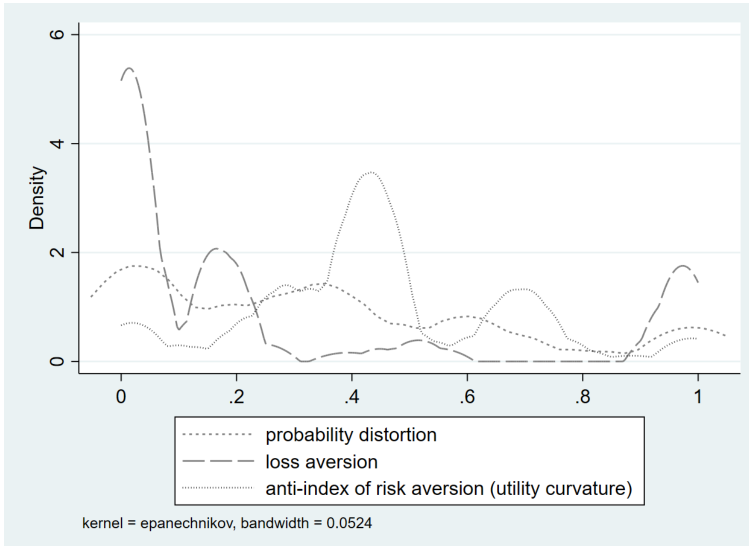
Interestingly, σ and γ display a rather homogeneous dispersion while λ does not. Figure 2 displays the distribution of the three parameters, after having been standardized for the sake of visual comparability. Contrarily to the two other parameters, λ clearly has two peaks at the extremes (long-dashed line), reflecting that the farmer's population is characterized by two groups: one not being loss-averse and the other being extremely loss-averse. Hence, so far, parameters for utility curvature and likelihood sensitivity are similar with values

[22] Tanaka et al. (2010) obtained an average estimated value between 0.59 and 0.63, Liu (2008) a value of 0.48 and Bocquého et al. (2014), an average value of 0.51 when using the mid-point technique

[23] Tanaka et al. (2010) found a similar value (2.63) and Liu (2008) a value of 3.47

found in other experiments while the loss aversion parameter would reflect rather low loss aversion.

Figure 2: Kernel distribution of standardized midpoint parameters



5.2 Homogeneous Model

To obtain robust estimates[24], we first run structural estimations of the CPT model as described in section 3, not considering any individual covariates. This means that in this model it is assumed that the representative agent's assumption holds so that every subject has the same preferences and behaves in accordance with CPT theory. Results are reported in Table 5.

In column 1, we first assume that the same error process applies for both lotteries when subjects form their preferences. The utility curvature coefficient, σ, is significantly lower than 1 which indicates concavity. Its value is 0.27 so that subjects are very highly risk-averse in the gain domain. The estimate of the probability weighting parameter, γ, is 1.8720. Hence choices of subjects seem to follow an S-shaped probability distribution distortion. The loss aversion parameter is estimated to be 1.14 and is not significantly different from one.

In column 2-5, we test the robustness of this estimates with respect to allowing subjects to make error in evaluating lotteries. Recall that the experiment of this article did not allow indifference, nor did it impose monotonous switching and rows were shown sequentially and played for real rewards for a random sub-

[24]The TCN procedure suffers from its recursive estimation structure which might lead to different inferences than the simultaneous estimation of the three parameters using maximum likelihood methods. When more than one parameters are involved, estimations through bounds are non-generalizable as they involved imposing a specific functional form of the utility function, which is not required in joint estimations.

sample. Even though the population studied here is highly educated and is familiar with probabilistic decisions, it was decided not to impose monotonicity in order to quantify inconsistent choices and their influence on parameters' estimates. 76% of the sample did not switch more than once in each series. Within the remaining group of subjects, 55% switched back and forth in adjacent lines only, indicating that they might be indifferent within an interval of outcomes. Hence this leaves the sample with 11% qualifying as being clearly inconsistent. However, it is important to understand that there is a trade-off between controlling for learning-effects and fully detecting inconsistent subjects. Indeed, the random process combined with the first choice made by each subject leads to an average of 20 choice tasks being actually performed per subject, which corresponds to 2/3 of the series. Hence we do not observe all individual choices and we are in a position to detect inconsistency in 66% of the choices. Still the proportion of subjects who consistently did the tasks is high, reflecting high data quality. We also control that this high proportion is not driven by subjects systematically clicking left or right in the online tool, as these would be considered as being consistent while actually, they did not consider their choices. The proportion of subjects always clicking left is 5.15% while the proportion of them clicking systematically left is 3.68%, which are too low proportions to drive the high level of consistency.

In column 2 of Table 5, we reduce the sample to consistent subjects only, which results in a contraction of about 11% of the set of observations. Both parameters measuring the utility curvature and the loss-aversion are not strongly affected by this reduction. However, γ becomes lower than one, meaning that the distribution distortion reverses. Hence, consistent farmers exhibit an inverse S-shaped function for probability distortion.

An alternative to control for errors subjects make in evaluating lotteries is to further extend the homogeneous model of CPT by allowing for some stochastic errors. The noise term μ is estimated as a normal probability with a standard deviation of 1.8042 and 2.1591, for the whole and the reduced sample respectively (Table 5, column 3 and 4). This specification leads to an increase in the estimate of the utility curvature (column 3 and 4)[25]. The parameter measuring probability distortion also appears to be more robust with a Fechner stochastic error specification. Moreover, comparing the estimates of λ between columns 2 and 4 and column 3 and 4, suggests that it is the consideration of inconsistency that significantly corrects the estimate of loss-aversion, while the Fechner stochastic error only captures a portion of the error that inconsistent agents make in evaluating mixed versus positive binary lotteries.

[25]This is diverging from Bougherara et al. (2017) whose model without error over-estimated the risk aversion parameter.

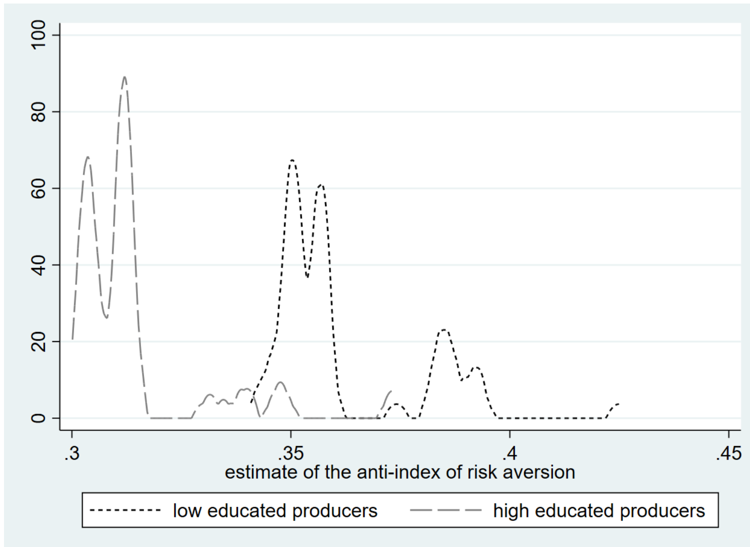
5.3 Heterogeneous Model

Unravelling heterogeneous preferences is done by estimating the three parameters of risk preferences against the list of socio-demographic variables described in section 3.2 using the structural model approach. Estimates are reported in Table 6. Note that a model including only farmer's characteristics leads to poor estimations since not jointly significant. Hence heterogeneity in risk preferences cannot be explained only by observable differences in farmers but requires to also consider differences in their farming context. Recall that the computation of the raw values using the mid-point technique indicated extreme heterogeneity in loss-aversion driven by some individuals (18%) being extremely loss averse. Hence even though the representative agent cannot be said to be loss-averse, the choices of some subjects might still be better approximated by a model allowing losses to loom higher in their decision-making process. Hence the importance of highlighting the socio-economic profile of those individuals.

Risk aversion

First, the anti-index of risk aversion is negatively correlated with the level of education so that farmers who have a higher level of education tend to be more risk-averse. This effect remains robust to alternative specifications (column 2-5). To evaluate the extent of this effect, we extract the individual predicted values of σ from the heterogeneous model. The distribution of σ for the subjects having reached high school against those who did not, is reported in Figure 3 and shows a clear shift toward a lower level of risk aversion for low educated farmers. The kernel density of the utility curvature for highly educated farmers (the grey long-dashed line) is centred around 0.26 while that of low educated farmers is centred around 0.31 (the black short-dashed line). Though the variable accounting for cooperative membership is significantly negatively correlated with σ, this effect is not robust to the reduction of the sample to consistent subjects only.

Figure 3: Kernel density of risk aversion, disentangling low and high educated producers



Probability Distortion

Next, the correlations between γ and the set of covariates are highly affected by the model specification. In line with the results of the homogeneous model for this parameter, it is the model with the Fechner stochastic error specification that is the most robust. The only correlation that resists to this specification is the one associated with co_management of the farm. In particular, farmers that jointly manage their farm with another manager have a stronger probability bias than the rest of the population. One plausible interpretation for this correlation is that there is a selection effect whereby people that need to associate with somebody else might do so because of difficulties to precisely assess the benefit of the different business strategies. By extracting the predicted values of γ from the heterogeneous model (column 4 of Table 6), we find a mean value of 0.66 for γ for farmers in co-management and 0.84 for farmers managing their farm alone.

Loss aversion

Loss-averse farmers are shown to be farmers who, above any other characteristics, have relatively small farms. Thus the bigger the farm, the lower the loss-aversion. Note that the farm size, being a proxy for wealth and capital, is not correlated neither with risk aversion, nor with the level of probability distortion. Empirical evidence exists that poorer households are more reluctant to invest in risky productive activities and is often presumed to be driven by a lower risk aversion, even though mixed evidence has been found between wealth and risk aversion. Here we show that owners of smaller farms are not more risk-averse, but are instead more loss-averse. This result is also in line with the positive correlation between mean village income and loss aversion found by Tanaka et al. (2010). Moreover, inconsistent subjects are also found to be about twice more loss averse on average than the rest of the sample.

To investigate further the heterogeneity in loss-aversion, we predict the estimated value of the parameter λ for each subject. The kernel density distribution of the estimates of λ predicted for the full sample (on estimates reported in column 2 of Table 6) and displayed in Figure 4 (short dashed line) shows that for 55% of the subjects, λ is higher than 1 and for 33% it is even higher than 1.5, those individuals being thus extremely loss-averse. When restricting the sample to consistent individuals only (long dashed line in Figure 4, predicted from column 3 of Table 6), a big portion of the extreme right tail of the density disappears, reflecting that extreme loss-aversion is partially driven by inconsistent individuals. Characterizing the extremely loss-averse portion of the sample can be done by performing simple t-tests of the differences in means of observables between this group of extremely loss-averse subjects and the rest of the sample (means and differences are reported in Table 7). In line with results of the heterogeneous model, extremely loss-averse individuals have a smaller area in production, reflecting a lower wealth and capital. They are also more likely to share the management of their farm with another farmer. The differences in means also show that the population of extremely loss-averse individuals is younger of 4 years on average than the not extremely loss-averse group. Being younger on average, the extremely loss-averse sample is also more likely to have pursued education after secondary school. This portion of the sample is also more likely to live in Sint-Truiden, the cradle of apple and pear production and is more likely to have inherited the farm. Hence a plausible interpretation is that these producers were less likely to themselves choose to start a new apple and pear business. Note that even though the inconsistent subjects inflate the loss-aversion parameter, extreme loss-aversion cannot be entirely attributed to these subjects. Indeed, inconsistent individuals are more likely to be extremely loss-averse, but they account for no more than 39.5% of the extremely loss-averse subjects ($\lambda > 1.5$).

Finally, it is interesting to note that, after controlling for the whole set of covariates jointly, the age of the farmer is not significantly correlated with any parameters. To sum up, we find that risk aversion is mainly linked to education, loss aversion is correlated with farm size on top of any other variables and probability distortion is mainly linked to joint management of the farm.

6 Discussion

In order to compare our results with those previously reported in the literature, we have reviewed papers previously published and selected those estimating risk preferences of Cumulative Prospect Theory. Estimates are reported in Table 8 in the Appendix. It must be pointed, however, that estimates are sensitive to experimental design and estimation methods, hence variations in estimates across studies must be interpreted with the greatest caution. When compared with estimates of others studies[26], our estimate of 0.27-0.38 for the utility curvature (Table 5, column 1) appear to be on the lower bound of what is usually found for this parameter. Regarding probability distortion, we also show that Belgian farmers exhibit an inverse S-shaped function and the estimates of about 0.70 are close to the majority of the values found in previous studies, ranging from 0.65 to 0.96[27]. However the estimates of loss aversion reported by the selected papers in the literature are much more dispersed than for the two other parameters. The lowest estimates are reported by Bougherara et al. (2017) and Liebenhem and Waibel (2014), who both used structural estimations and obtain estimates around 1.3, though with very different models.

Remember that once we exclude inconsistent subjects, our estimate significantly reduces. [28].

It is very tempting to compare our results further with the two previous similar studies run in Europe and done by Bocquého, Jacquet and Reynaud (2014) (abreviated BJR here-after) and Bougherara, Gassmann, Piet and Reynaud (2017) (abreviated BGPR). Interestingly the three samples are comparable with regard to age and sex ratio[29]. However, the farmers who make up our sample are more educated than the farmers of Champagne-Ardenne[30] and Bourgogne[31]. Regarding loss aversion, while BJR found a much higher estimate (2.275), the estimate we found for the full model with a Fechner stochastic error specification (Table 6 column 3) is 1.208 and hence rather close to the 1.3 estimated by BGPR who use the same error specification. Note however, that while BGPR observe an increase in λ when excluding inconsistent individuals, we observe a reduction in this parameter's estimate. Regarding the utility curvature, our estimate (0.272-0.381) is instead closer to BJR (0.280), while BGPR found an estimate of 0.614[32]. Finally, regarding probability distortion, the three studies obtain rather

[26]Note that there is systematic evidence that subjects are risk-averse when making choices in laboratory experiments (Harrison and Rutström, 2008).

[27]with the exception of Liebenhem and Waibel who found an estimate of 0.133, in a model containing also parameters of time preferences.

[28]Note that Bougherara et al. (2017) are the only researchers also able to exclude inconsistent individuals. When doing so, their estimate for loss aversion increased to about 1.4, contrarily to the findings in our sample.

[29]49 years old in Champagne-Ardenne (Bougherara et al, 2017) and 47.7 years old in Bourgogne (Bocquého et al, 2014), while the sample in Champagne-Ardenne is composed of 97% male and Bocquého et al. (2014) do not mention the sex ratio of their sample.

[30]Bocquého et al. (2014) report a percentage of 32% of farmers having at least secondary-school education level.

[31]They also operate much smaller areas as farm size is on average about 160 hectares in Bourgogne and Champagne-Ardenne (Bocquého et al., 2014; Bougherara et al., 2017). However the standard output per hectare of fruit is about 10times the one of common wheat, according to the standard output coefficients produced by Eurostat.

[32]Note that these authors allow probability distortion to differ in both domains.

similar estimates. Indeed, BJR obtained an estimate of 0.655, while BGPR found 0.785 in the positive domain and 0.844 in the negative domain, which is close to what we find in the robust part of our results (columns 2-4 of Table 6). Hence the results obtained by the three groups of researchers slightly differ to some extend but are also strikingly similar in specific aspects. In order to compare results across experiments, one needs to pay proper attention to design's artefacts and how could it affect inference. The main difference between the three experimental designs is that BJR enforced monotonous switching[33], while it was not the case in BGPR and in our study. Hence, the difference of the estimates of loss-aversion, yet to be done with caution, hint at the fact that MPL with enforcement of monotonous switching might lead to an overestimation of loss-aversion[34]. We also show that the exclusion of inconsistent subjects can significantly affect the estimate for this parameter.

In this paper we also show interesting and new correlations between socio-economic characteristics of farm and farmers and the three parameters of the Cumulative Prospect Theory. The heterogeneous model suggests that the socio-economic characteristics included in the model is linked to one parameter exclusively. However, our results must be interpreted with care as we are in a position to show correlations only and unravelling the sense of the causality would require further research. In particular, we find that more educated farmers are significantly more risk averse on average. However it might be that more intrinsically risk averse farmers prefer to stay longer on school benches to delay their entry into a risky professional career or to reduce their probability of a failure through the acquisition of more knowledge. Reversely, education might provide farmers with more accurate information about the risk associated with farming and as such reinforce their reluctance to take risk in general. Second, the level of loss aversion is mainly associated with farm size, so that farmers managing smaller farmers are also more loss averse. Here again, the sense of the causality would deserve further research to disentangle if loss averse farmers deliberately opt for smaller farms or if it is the reduced liquidity associated with small farmers that makes them more averse to losses. Third, probability distortion is mainly associated with organisational variables. Again, here the sense of the causality is unclear and would deserve further research.

Finally, the estimations run in this analysis hint at three important lessons, to be confirmed by further research. First, the results suggest that the randomization of the first line played by subjects is an easy and efficient instrument to reduce stochastic error, as when doing so the Fechner stochastic error specification did not significantly affect estimates. Second, the ability of detecting inconsistent agents might be key to obtain robust

[33]For the rest, we apply the same elicitation tasks as BJR and we rely on similar basic estimation methods and both experiments were done with real payoffs of the same size so that the induced perception of a loss is similar.

[34]See section 4.3 for a discussion about the induced bias and framing effect

estimates in specific samples as controlling for their effect significantly affects estimates in this sample. Third, we show that heterogeneity matters and that even if the representative agent cannot be said to be loss-averse, an important proportion of the sample might still be extremely loss-averse. This suggests that heterogeneity should be investigated for sound policy recommendations.

7 Conclusion

We conduct a risk preferences elicitation task in the Flemish population of apple and pear producers to investigate risk preferences. We characterize choice behaviors by assuming that the decision process follows cumulative prospect theory. The experiment of this paper is likely to provide reliable estimates because of the structural estimations method but also thanks to the high educational level of subjects, the rather simple and short task and the incentives to respond truthfully.

The estimation of the prospective structural model of choices[35] provides evidence that farmers in this sample are very risk-averse and exhibit an inverse S-shaped function for probability distortion. However we do not find evidence that the representative agent is loss-averse. Nevertheless, some farmers are still found to deviate from the representative agent by being extremely loss-averse. Hence the behaviour of those farmers might differ when having to take decisions involving potentially significant losses and policies not accounting for this diversity might prove inefficient. In particular, we find that farmers owning or managing farms of relatively smaller size are not necessarily more averse to income fluctuation and do not distort probabilities more than other farmers, but instead seek to avoid losses relatively more than richer farmers. We also identify the demographic domains systematically associated with higher levels of loss aversion.

[35]We implicitly assumed that the data generating process result from one model of choice behavior, because the data do not allow us to run more heavy estimations whereby choices made by different individuals might be better described by different models. Still we allow for parameters to vary per subjects by introducing heterogeneity, and thus allow some subjects to have preferences which would better be supported by EUT, i.e. $\lambda = 1$ and $\gamma = 1$ instead of CPT.

TABLES

Table 2: Experimental Design

	Lottery A		Lottery B		E(A)	E(B)	E(A)-E(B)
Serie 1	30%	70%	10%	90%			
1	400	300	680	50	190	113	77
2	400	300	750	50	190	120	70
3	400	300	830	50	190	128	62
4	400	300	930	50	190	138	52
5	400	300	1060	50	190	151	39
6	400	300	1250	50	190	170	20
7	400	300	1500	50	190	195	-5
8	400	300	1850	50	190	230	-40
9	400	300	2200	50	190	265	-75
10	400	300	3000	50	190	345	-155
11	400	300	4000	50	190	445	-255
12	400	300	6000	50	190	645	-455
Serie 2	90%	10%	70%	30%			
1	400	300	540	50	390	393	-3
2	400	300	560	50	390	407	-17
3	400	300	580	50	390	421	-31
4	400	300	600	50	390	435	-45
5	400	300	620	50	390	449	-59
6	400	300	650	50	390	470	-80
7	400	300	680	50	390	491	-101
8	400	300	720	50	390	519	-129
9	400	300	770	50	390	554	-164
10	400	300	830	50	390	596	-206
11	400	300	900	50	390	645	-255
12	400	300	1000	50	390	715	-325
Serie 3	50%	50%	50%	50%			
1	250	-40	300	-210	105	45	60
2	40	-40	300	-210	0	45	-45
3	10	-40	300	-210	-15	45	-60
4	10	-40	300	-160	-15	70	-85
5	10	-80	300	-160	-35	70	-105
6	10	-80	300	-140	-35	80	-115
7	10	-80	300	-110	-35	95	-130

Table 3: Summary statistics

Variable	Definition	Obs	Mean	Std. Dev.	Min	Max
$resp\_owner$	the respondent owns the farm he is managing	136	.926	.262	0	1
$resp\_age$	the age of the respondent, in years	136	48.603	10.003	21	75
$resp\_male$	the respondent is a male	136	.949	.222	0	1
$resp\_educsup$	the respondent studied either at high school or university	136	.493	.502	0	1
$sint\_truiden$	the farm is located in Sint-Truiden	136	.846	.363	0	1
$inherited$	the farm has been inherited	136	.537	.5	0	1
$co\_management$	the respondent managed his farm jointly with another manager	136	.61	.489	0	1
$coop$	the farm (firm) is registered to a cooperative	136	.846	.363	0	1
$area\_cultivated$	the number of hectares cultivated with apple and or pear	136	25.636	26.547	1.45	245
$farm\_income$	the annual farm income, in 1000 euros	124	474.639	513.914	8	3415
$perc\_income\_topfruit$	the percentage of the farming income coming from top fruit production	122	85.955	22.601	0	100
$perc\_income\_farming$	the percentage of the farm income that is from farming	111	69.698	34.393	0	100

Table 4: Cumulative distribution of switching points in the French* and the Belgian sample

Switching Points	Series 1		Series 2		Series 3	
	Bourgogne	Flanders	Bourgogne	Flanders	Bourgogne	Flanders
1	15.0	23.5	26.2	19.1	10.3	30.9
2	17.8	24.3	28.1	22.1	17.8	52.9
3	18.7	30.1	29.0	20.6	31.8	61.0
4	18.7	30.9	29.0	25.0	44.9	75.0
5	21.5	34.6	31.8	31.6	69.2	76.5
6	29.0	38.2	33.7	33.8	73.9	78.0
7	43.0	42.7	36.5	39.7	77.6	81.6
8	44.9	50.7	44.9	49.3	-	-
9	49.6	52.2	49.6	51.5	-	-
10	58.0	56.6	53.3	50.7	-	-
11	59.9	58.8	56.1	56.6	-	-
12	61.8	60.3	62.6	64.0	-	-
13	-	-	62.6	-	-	-
14	-	-	67.3	-	-	-
Never Switched	38.3	39.7	32.7	36.0	22.4	18.4
Obs.	107	136	107	136	107	136

*: Switching points for the French sample obtained from Bocquého et al, 2014

Table 5: Estimates from the Homogeneous Model of Risk Preferences

	(1) Full sample	(2) Reduced sample	(3) Full sample Fechner stochastic error specification	(4) Reduced sample Fechner stochastic error specification
σ				
constant	0.2721***	0.2823***	0.3484***	0.3812***
	(0.0169)	(0.0112)	(0.0479)	(0.0482)
λ				
constant	1.1433***	1.1024***	1.2083***	1.0840***
	(0.1850)	(0.1464)	(0.1513)	(0.1481)
γ				
constant	1.8720***	0.7088***	0.7035***	0.7274***
	(0.0767)	(0.0316)	(0.0320)	(0.0344)
μ (Fechner error SD)				
constant			1.8042**	2.1591**
			(0.7273)	(0.8702)
Obs./nb of subjects	4216/136	3751/121	4216/136	3751/121
H_0: $\sigma = 1$	$Prob > chi^2$ = 0.0000	$Prob > chi^2$ = 0.0000	$Prob > chi^2$ = 0.0000	$Prob > chi^2$ = 0.0000
H_0: $\lambda = 1$	$Prob > chi^2$ = 0.4387	$Prob > chi^2$ = 0.4842	$Prob > chi^2$ = 0.1685	$Prob > chi^2$ = 0.5709
H_0: $\gamma = 1$	$Prob > chi^2$ = 0.0000	$Prob > chi^2$ = 0.0000	$Prob > chi^2$ = 0.0000	$Prob > chi^2$ = 0.0000

Standard errors in parentheses

Maximum Likelihood Estimations with standard errors clustered at the respondent level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Estimates from the Heterogeneous Model of Risk Preferences

	(1) Full sample	(2) Reduced sample	(3) Full sample	(4) Reduced sample	(5) Full sample
			Controlling for inconsistent subjects	Fechner stochastic error specification	Fechner stochastic error specification
					Controlling for inconsistent subjects
σ					
resp_owner	-0.0114	-0.0425	-0.0053	-0.0330	-0.0275
	(0.0558)	(0.0399)	(0.0569)	(0.0409)	(0.0385)
resp_age	-0.0005	-0.0004	0.0001	-0.0000	0.0004
	(0.0018)	(0.0014)	(0.0018)	(0.0019)	(0.0012)
resp_educsup	-0.0731**	-0.0480**	-0.0681**	-0.0455*	-0.0476**
	(0.0336)	(0.0240)	(0.0345)	(0.0243)	(0.0233)
inherited	-0.0100	0.0103	-0.0099	0.0078	-0.0019
	(0.0313)	(0.0315)	(0.0342)	(0.0293)	(0.0351)
co_management	-0.0578*	0.0002	-0.0587*	0.0003	-0.0082
	(0.0314)	(0.0264)	(0.0315)	(0.0260)	(0.0238)
coop	-0.0727**	-0.0560	-0.0736**	-0.0360	-0.0391
	(0.0345)	(0.0424)	(0.0350)	(0.0657)	(0.0427)
area_cultivated	-0.0004	-0.0004	-0.0005	-0.0002	-0.0003
	(0.0006)	(0.0006)	(0.0006)	(0.0014)	(0.0010)
inconsistent			0.0056		-0.0554
			(0.0582)		(0.0379)
constant	0.4589***	0.4153***	0.4279***	0.4220***	0.3886***
	(0.1159)	(0.1040)	(0.1219)	(0.1163)	(0.0717)
λ					
resp_owner	0.4191	0.4611	0.5477	0.5079	0.5034
	(0.7577)	(0.5197)	(0.7712)	(0.5204)	(0.5356)
resp_age	-0.0239	-0.0267	-0.0226	-0.0245	-0.0206
	(0.0238)	(0.0181)	(0.0209)	(0.0178)	(0.0175)
resp_educsup	-0.0468	-0.1684	-0.2509	-0.1597	-0.1592
	(0.3980)	(0.3299)	(0.3882)	(0.3186)	(0.3225)
inherited	0.0446	0.1258	-0.0507	0.1116	0.0046
	(0.3635)	(0.3124)	(0.3619)	(0.2989)	(0.3079)
co_management	-0.6715*	-0.4151	-0.7079*	-0.4136	-0.5019
	(0.4031)	(0.3334)	(0.4086)	(0.3267)	(0.3306)
coop	-0.2091	-0.0592	-0.1219	-0.0098	-0.0627
	(0.4416)	(0.3785)	(0.4023)	(0.3916)	(0.3554)
area_cultivated	-0.0292***	-0.0191**	-0.0248**	-0.0179**	-0.0200**
	(0.0111)	(0.0083)	(0.0107)	(0.0083)	(0.0091)
inconsistent			2.0239**		2.1231**
			(0.8311)		(0.9687)
constant	3.1341**	2.7433**	2.7838**	2.5313**	2.5394**
	(1.5950)	(1.1384)	(1.3779)	(1.1829)	(1.1595)
γ					
resp_owner	-0.2336	0.1534**	-0.2001	0.1351*	0.1194
	(0.1980)	(0.0735)	(0.2164)	(0.0724)	(0.0787)
resp_age	-0.0006	0.0017	-0.0004	0.0010	0.0004
	(0.0086)	(0.0058)	(0.0088)	(0.0062)	(0.0069)
resp_educsup	-0.3267*	0.1339	-0.3603**	0.1113	0.1010
	(0.1746)	(0.1032)	(0.1688)	(0.1067)	(0.0851)
inherited	-0.1193	0.0158	-0.1455	0.0380	0.0215
	(0.1484)	(0.1033)	(0.1463)	(0.1070)	(0.0863)
co_management	0.1084	-0.2133**	0.1108	-0.1970**	-0.1909**
	(0.1497)	(0.1005)	(0.1492)	(0.0952)	(0.0871)
coop	-0.5684***	0.2069	-0.5462***	0.1750	0.1670
	(0.1612)	(0.1496)	(0.1653)	(0.1563)	(0.1254)
area_cultivated	-0.0063***	0.0027	-0.0051**	0.0021	0.0020
	(0.0022)	(0.0022)	(0.0025)	(0.0032)	(0.0019)
inconsistent			0.5294***		-0.2076
			(0.1676)		(0.2208)
constant	2.8883***	0.3555	2.7899***	0.4323	0.4860
	(0.4920)	(0.3660)	(0.5511)	(0.4264)	(0.4276)
μ (Fechner error SD)					
constant				1.5408	1.2432
				(1.1112)	(0.8576)
Obs./nb of subjects	4216/136	3751/121	4216/136	3751/121	4216/136

Standard errors in parentheses

Maximum Likelihood Estimations with standard errors clustered at the respondent level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 4: Kernel density of estimates of λ from the heterogeneous model on the full sample (short dashed) and on the reduced sample of consistent subjects (long dashed)

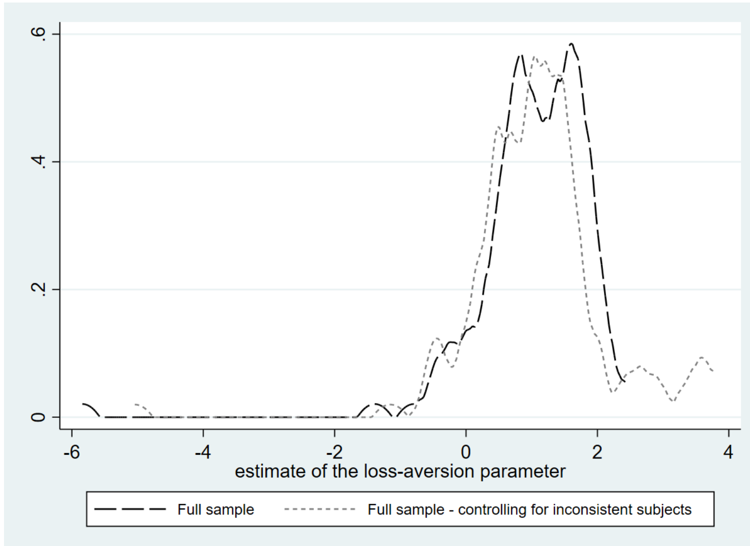


Table 7: Differences in means of observable characteristics between extremely loss-averse subjects and the rest of the sample

Variable	Group 1: Non extremely loss-averse		Group 2: Extremely loss-averse		Diff(Group 1-Group 2)	
	mean	st.dev.	mean	st.dev.	mean	st.err.
resp_owner	0.908	0.005	0.974	0.005	-0.066***	0.009
resp_age	50.265	0.166	44.316	0.310	5.950***	0.330
resp_male	0.959	0.004	0.921	0.008	0.038***	0.008
resp_educsup	0.439	0.009	0.632	0.014	-0.193***	0.017
sint_truiden	0.816	0.007	0.921	0.008	-0.105***	0.012
inherited	0.480	0.009	0.684	0.014	-0.205***	0.017
co_management	0.724	0.008	0.316	0.014	0.409***	0.016
coop	0.847	0.007	0.842	0.011	0.005***	0.012
area_cultivated	29.855	0.533	14.758	0.311	15.097***	0.878
farm_income	568.365	10.783	245.531	6.917	322.834***	17.431
perc_income_topfruit	85.971	0.452	85.917	0.611	0.054	0.803
perc_income_farming	74.346	0.643	57.150	1.192	17.196***	1.282
Obs.	98		38		136	

8 Appendix

8.1 Literature Review

Table 8: Literature Review

Authors	Journal	Year	Estimation method	Elicitation method	Parameters' estimates: risk aversion	Parameters' estimates: loss aversion	Parameters' estimates: probability distortion	Sample size	Context
Bougherara, Gassmann, Piet, Reynaud	European Review of Agricultural Economics	2017	SE	SL	0.614	1.374	0.785-0.844	197	France, farmers
Bocquého, Jacquet, Reynaud	European Review of Agricultural Economics	2014	SE	MPL	0.280	2.275	0.655	107	France, farmers
Liebenhem and Waibel[36]	American Journal of Agricultural Economics	2014	SE	MPL	0.112	1.351	0.133	211	Mali and Burkina Faso, cattle farmers
Liu	The Review of Economics and Statistics	2008	MPT	MPL	0.48	3.47	0.69	320	China, cotton farmers
Nguyen[37]	Journal of Risk and Uncertainty	2011	SE	MPL	1.012	3.255	0.96	181	Vietnam, fishermen
Nguyen and Leung	Journal of Agricultural and Resource Economics	2010	SE	MPL	0.62	2.05	0.75	103	Vietnam, livestock farmers
Tanaka, Camerer, Nguyen[38]	American Economic Review	2010	MPT	MPL	0.59-0.63	2.63	0.74	181	Vietnam, rural households

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