Expected Utility or Prospect Theory maximizers? Results from a structural model based on field-experiment data

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Abstract

We elicit risk preferences of French farmers in a field experimental setting under expected utility theory and cumulative prospect theory. We use two different estimation methods, namely the interval approach and the estimation of a random preference model. On average, farmers are risk averse and loss averse. They also exhibit an inverse S-shaped probability weighting function, meaning that they tend to overweight small probabilities and underweight high probabilities. We infer from our results that CPT explains farmers' behaviour better than EUT in the context of our experiment. We also investigate how preferences correlate with individual socio-demographic characteristics. We find that education and agricultural innovation are negatively linked with risk aversion. Our results also show that age, education, household size and the level of secured income tend to lower farmers' loss aversion. Finally, older farmers and farmers with large farms distort probabilities less than the others. These findings contribute to the literature which compares expected utility with competing decision theories. They also give important insights into farmers' behaviour towards risk, which is critical for relevant public policy design.

Keywords: risk preferences, field experiment, experimental economics, prospect theory

JEL Codes: C91; D81; J16; Q12

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1 Introduction

Risk and uncertainty play a significant role in almost every important economic decision. Since people differ in the way they take decisions involving risk and uncertainty, and since these differences are often described as differences in risk attitude, understanding individual risk preferences is a prerequisite to understand economic behaviour.

Numerous theories have been proposed to describe decision making under uncertainty, but expected utility theory (EUT) has dominated empirical research since its formulation by von Neumann and Morgenstern (1947). Indeed, most of the attempts to propose better representations of risky choices have not made it into mainstream economics. Though, prospect theory (PT) (Kahneman and Tversky 1979) is a notable exception. Supported by the growing evidence for probability weighting and loss aversion, today PT seriously challenges the standard EUT (Camerer 1998, Starmer 2000).

Moving forward the debate between EUT and competing theories of decision under risk has been one important objective of experimental studies for the last two decades. The seminal works by Harless and Camerer (1994) and Hey and Orme (1994) initiated the use of econometric methods to estimate decision models from observed behaviour and gave way to formal methods to compare theories.

In this paper, we propose to test EUT against PT after estimating preferences with formal econometric methods.

Whereas most of the literature on risk preference elicitation relies on lab experiments, we implement a field experiment using a systematic sample of French farmers. Harrison and List (2004) stressed the complementarity of both approaches to give sharper and more relevant inference on field behaviour. Experimental elicitation of farmers' risk preferences in the context of developed countries are rare (Pennings and Smidts 2003, Reynaud and Couture 2010) , and, to our knowledge, real money incentives have never been used in this context. Eliciting risk preferences on such a population is worth being undertaken from a public policy perspective. While agriculture is typically a risky activity, subject to uncertain climate and market environments, there is no consensus in the agricultural economic literature on the level of farmers' risk aversion. Thus, more investigations are needed to design adequate policy instruments.

The remainder of the paper is organized as follows. In Section 2, we survey studies that have formally tested decision weighting models against expected utility on a sample of farmers. Then, we describe our experimental protocol. The procedures for the estimation of preference parameters under EUT and PT are exposed in Section 4. The results are presented in Section 5.

2 Relevant Literature

The study of rational behaviour under uncertainty has been dominated by EUT (von Neumann and Morgenstern 1947) since 1947. Although empirical data quickly demonstrated the existence of systematic violations , its rigorous axiomatic base, simplicity of using, and normative appeal made EUT keep the primacy over alternative propositions during decades. Today, decision weighting theories constitute the main alternative to EUT. They have in common preferences over prospects that are non linear in probabilities, provided that subjects convert objective probabilities of individual outcomes into weights before they make choices. These weights involve some probability weighting function which is inverse S-shaped, meaning that individuals underweight high and overweight low probabilities. Among the decision weighting models, the best known can be classified as sign-dependent - e.g., separable prospect theory (SPT) (Kahneman and Tversky 1979) - or rank-dependent- e.g., rank-dependent expected utility theory (RDEUT) (Quiggin 1982). The cumulative prospect theory (CPT) (Tversky and Kahneman 1992) joins the most interesting features of SPT and RDEUT, namely outcome valuation relative to reference points and cumulative decision weights.

Field experiments with farmers leading to comparisons between decision theories are scarce. In most of them, model selection is not the core question. Harrison, Humphrey, and Verschoor (2010) and Galarza (2009) are noteworthy exceptions, the authors estimating mixture models with maximum likelihood methods among farmers in developing countries. Instead of estimating the parameters of each model assuming only one describes behaviour, in mixture models the coexistence of several theories is explicitly recognized. All preference parameters are jointly estimated, in addition to mixing probabilities which quantify the prevalence of each theory in the sample. Harrison, Humphrey, and Verschoor (2010) find mixing proportions for a EUT-SPT mixture model close to 0.5. Galarza (2009) estimate that 30% of the cotton producers from their sample exhibit EUT while 70% follow RDEUT.

A few other studies propose an elicitation of CPT parameters for rural people. Nguyen (2009) and Tanaka, Camerer, and Nguyen (2010) use the same experimental design with rural Vietnamese households (46% are farmers), as well as Liu (2010) but with Chinese cotton farmers. This design includes mixed lotteries, and this is the one we adapt in this paper. Whereas Tanaka, Camerer, and Nguyen (2010) and Liu (2010) infer intervals for parameters directly from responses, Nguyen (2009) estimates by maximum likelihood a random preference model. They all find that CPT describes their data better than EUT.

In the context of developed countries, we are not aware of any experimental paper estimating the parameters of some decision weighting model on a sample of farmers.

3 Experimental protocol

3.1 Experimental design and procedure

Our experimental design is adapted from Tanaka, Camerer, and Nguyen (2010) who elicit CPT parameters of Vietnamese rural households and correlate them with economic circumstances and individual characteristics. There are three series of questions which are variants of Holt and Laury's (2002) *multiple price lists*. Subjects are presented with a succession of pairs of binary lotteries, each pair being composed of a *safe* lottery (option A) and a *risky* lottery (option B), and they are asked to pick one at each row. In the first two series, payoffs are all positive whereas, in the third and last series, lotteries mix positive and negative outcomes. To enforce monotonicity, subjects are asked to pick the row at which they prefer lottery B rather than lottery A.

The lotteries each subject is presented with are displayed in Table 1.

The experiment was led after face-to-face interviews from February to June 2010. The experiment was the last part of a 2-hour survey aiming at understanding the relation between the adoption of agricultural innovation, production practices and risk management. We also collected farmers' socio-demographic characteristics. The experiment, which lasted around half an hour, was divided into three different tasks: a risk task, an ambiguity task, and a time task. In this paper, we only analyse the results from the risk task. A comprehensive introduction of the methods and goals, as well as examples, were given to respondents prior to the tests to ensure a good comprehension. Subjects were provided with an initial endowment of 15 euros. After the subject had completed all three tasks, one row was randomly selected and the lottery chosen by the subject played for real money. As we were not able to pay the full payoffs (ranging from -600 to 6,000 euros), the respondents were offered only 2% of these payoffs[1]. The average earning from the three tasks was 19 euros.

3.2 Sampling

We organised an *artefactual field experiment* [2], replacing the usual university student population by a farmer population. We constructed a systematic sample of farmers from 62 rural cities of eastern France. The region of Bourgogne is diversified in terms of agricultural production: cereal crops, livestock, as well as market vegetables and wine. We randomly selected 232 farmers from those cities, and contacted them by mail first, and by phone a few days after. Finally, 111 farmers accepted to be surveyed within the alloted time. Among them, 48 had enough time to do the experiment at the end of the survey. In Table 2 are displayed some descriptive statistics of our sample.

4 Estimation methods

4.1 Interval approach

There are several ways of estimating preferences from experimental data. The simplest one consists in calculating bounds for the parameters from the observed choices. Typically, the interval method is not adapted for sophisticated preference functionals, because some statements have to be made about one parameter to calculate the other parameter. However, Tanaka, Camerer, and Nguyen (2010) experimental design partly avoids this problem for a three-parameter CPT model.

Like Tversky and Kahneman (1992), a power utility function defined separately over gains and losses is assumed:

$$U(y) = \begin{cases} y^{\sigma} & if \quad y > 0 \\ 0 & if \quad y = 0 \\ -\lambda \cdot (-y)^{\sigma} & if \quad y > 0 \quad (\lambda > 0) \end{cases} \tag{1}$$

where σ is the parameter controlling the curvature of the utility function [3] and λ is the coefficient of loss aversion of the decision maker. Usually, $\sigma < 1$ and $\lambda > 1$, which stands respectively for risk aversion and a higher sensitivity to loss than to gain.

Following Tversky and Kahneman (1992), decision weights defined over the cumulative probability distributions are introduced. The value of the prospect $(y_1, p; y_2, 1-p)$ writes:

$$U(y_1, p; y_2, 1-p) = \begin{cases} u(y_2) + \omega(p)[u(y_1) - u(y_2)] & if \quad y_1 > y_2 \geq 0 \quad or \quad y_1 < y_2 \leq 0 \\ u(y_1)\omega(p) + u(y_2)\omega(1-p) & if \quad y_1 < 0 < y \quad or \quad y_1 = y_2 \end{cases} \tag{2}$$

[1] This procedure was used by other authors dealing with large payoffs in developed countries (Abdellaoui, Bleichrodt, and L'Haridon 2008) or developing countries (Galarza 2009).

[2] According to the Harrison and List (2004) terminology

[3] In the original specification of CPT by Tversky and Kahneman (1992), two distinct parameters represent the utility function curvature, one for the gain domain and the other for the loss domain. However, in most empirical applications they are merged.

where ω is a probability weighting function. It is strictly increasing from the unit interval into itself and satisfies $\omega(0) = 0$ and $\omega(1) = 1$ [4].

The form of the weighting function has been widely discussed in the literature. Following Tanaka, Camerer, and Nguyen (2010), Prelec (1998) specification is preferred:

$$\omega(p) = \exp -[-\ln p]^{\gamma} \quad (\gamma > 0) \tag{3}$$

where γ is the probability sensitivity. The normal assumption, backed by a substantial amount of empirical evidence is that $\gamma < 1$. This gives the weighting function an "inverse S-shape", characterized by overweighting small probabilities and underweighting high probabilities. If $\gamma > 1$ the function takes the less conventional "S-shape", with convexity for smaller probabilities and concavity for larger probabilities. This CPT model reduces to expected utility if $\lambda = 1$ and $\gamma = 1$.

4.2 Structural estimation

A more flexible way of eliciting preference parameters is the direct estimation of some structural decision model, as exposed by Harless and Camerer (1994). In particular, this approach is suitable for specifications with several preference parameters, as in decision weighting models. Applied to data from Tanaka, Camerer, and Nguyen (2010) experimental design, it enables us to estimate jointly all three parameters of CPT. Moreover, in structural estimation, subjects can be easily allowed to make some errors.

We follow such a strategy to identify several random preference models under EUT and CPT.

In the experiment, we have asked the participants to choose between lotteries A and B. We compute now the likelihood function derived from individual choices associated to the EUT model and the CPT model.

Let us first assume that the utility of income is defined by $u(y) = y^r$ which corresponds to the usual constant relative risk aversion (CRRA) specification.

Assuming that the subjects choose the lottery A if $\Delta^{EUT} + \epsilon \geq 0$ where $\Delta^{EUT} = EU_A - EU_B$ and ϵ is a normally distributed error term with mean zero and variance v^2 , then the likelihood of the observed responses, conditional on the EUT and CRRA specifications being true, writes:

$$\ln L^{EUT}(r; \delta, X) = \sum_i l_i^{EUT} = \sum_i \Big[\Big(\ln \Phi(\Delta^{EUT}) \times \mathbb{I}(\delta_i = A) \Big) + \Big(\ln(1 - \Phi(\Delta^{EUT})) \times \mathbb{I}(\delta_i = B) \Big) \tag{4}$$

where i indexes the different lotteries in tasks, $\Phi(.)$ denotes the cumulative normal distribution function, $\mathbb{I}$ is the indicator function, $\delta_i = A[B]$ denotes the choice of the lottery A [B] and X is a vector of observable characteristics of the individual. The maximum-likelihood estimation for the CRRA r is therefore $\hat{r} = \arg\max \ln L^{EUT}(r; \delta, X)$.

Since the CRRA might appear very restrictive, one may consider other functional forms of utility which allow, for instance, for varying degrees of relative risk aversion (RRA). Here we consider, the Expo-Power (EP) utility function proposed by Saha (1993):

$$u(y) = [1 - \exp(-\beta y^r)]/\beta \tag{5}$$

where β and α are two parameters controlling the shape of the absolute and the relative risk aversion functions. The EP utility function collapses with the CRRA specification when $\beta \to 0$ and

[4]Tversky and Kahneman's (1992) CPT allows different probability weighting functions, one for the gain domain and the other for the loss domain. However, in most empirical applications they are the same.

with a CARA utility if $r \to 1$. An alternative paradigm for subject behavior could be cumulative prospect theory (CPT). We use the same specification as in Section 4.1.

The implementation of the maximum likelihood for the three models of behaviour has been done in STATA. We take into account the possibility of correlation between responses by the same subject. The standard errors on estimates are corrected for the possibility that the 33 responses are clustered for the same subject. The STATA program uses the STATA maximum likelihood routines on our structural choice models (EUT and CPT).

5 Results

5.1 Risk Task Results

The distribution of switching points over respondents is shown in Table 3. Extreme switches, namely at the first row or never, represent more than half of the responses in Series 1 and Series 2, and one third of the responses in Series 3. In Series 2 and Series 3 "never switch" responses are twice as much numerous than "switch at the first row" responses. Thus, these particular response patterns are expected to affect the estimation of parameters. Such responses could partly proceed from a a low commitment to the experiment, a bad comprehension of instructions, or a cognitive burden that some individuals are not able to handle, and, as such, deserve some extra consideration. We build two sub-samples S_1 and S_2. In S_1 individuals who chose either "switch at the first row" or "never switch" for all three series (11 individuals) are excluded [5], and in S_2 the ones who chose "switch at the first row" or "never switch" in each of the three series (11 individuals). Thus, S_2 is included into S_1.

5.2 Estimation of risk preferences with the interval method

In this section we discuss σ, λ and γ estimations provided by the interval method described in Section 4.1. Table 4 reports the results for the full sample of farmers, and the two sub-samples.

In the full sample, the mean values of σ and λ are 0.54 and 2.78, which means that, on average, respondents are risk averse and loss averse. Regarding probability sensitivity, we find an average γ of 0.67, indicating that respondents overweight low probabilities according to an inverse S-shaped weighting function. These estimates are in line with those calculated by Tanaka, Camerer, and Nguyen (2010) and Liu (2010) for rural people from developing countries with the same kind of experimental design [6]. The λ parameter is the only one to be impacted by extreme response patterns. It is estimated to be 2.60 for sub-sample S_1 and 2.32 for sub-sample S_1.

As previously informed, the CRRA expected utility model is nested into our PT model. The mean values of λ and γ are significantly different from 1 at the 1% level by t-test, meaning that, overall, CPT describes our data better than EUT.

In order to identify the determinants of the risk preference parameters, we lead OLS regressions against socio-demographic variables. Results are displayed in Table 5. We find that more educated subjects tend to be less loss averse. Income security also lowers loss aversion significantly.

[5] Liu (2010) find that 7.6% of individuals in her sample of farmers follow this kind of response patterns. In our case, it is 10.3%.

[6] Tanaka, Camerer, and Nguyen (2010) and Liu (2010) report respectively mean values of about 0.60 and 0.52 for utility curvature and 2.63 and 3.47 for loss aversion. They find 0.74 and 0.69 for probability sensitivity.

5.3 Estimation of a structural model of risk preferences

In Table 6, we report the estimations of risk preferences for the various decision models considered (EUT with CRRA utility function, EUT with EP utility function, CPT with power utility function). We report in parts A, C and E of this Table the direct estimation of the parameter of interest. In part B, D and F we introduce individual covariates.

Part A reports the maximum likelihood estimates obtained with the EUT-CRRA specification. The coefficient r is estimated to be 0.27, with a 95% confidence interval between 0.24 and 0.30. This indicates very risk averse behaviors. Introducing covariates (part B) results in a very similar point estimate of r, the average distribution of r being still 0.27. Highly educated farmers and those who have adopted innovations appear to be less risk averse.

Relaxing the CRRA assumption, we consider now the EP utility function in part C and D of Table 6. In part C, both r and β are significant at 1%. Since $\hat{\beta}$ is strictly positive and since $\hat{r}$ belongs to $]0, 1[$, risk preferences appear to be characterized by DARA (decreasing absolute risk aversion) and IRRA (increasing relative risk aversion). None of the covariates we have considered appears to be significant to explain the variability of r and β across individuals.

Part E and F of Table 6 report maximum likelihood estimates of the CPT specification without and with covariates. All the three parameters of the homogenous CPT model are significant at 1%. The estimated loss aversion parameter λ is 2.49 and is significantly different from 1 at the 1% significance level. Our estimate of the loss aversion is highly consistent with the value (2.25) reported by Tversky and Kahneman (1992). The estimated probability sensitivity parameter γ is equal to 0.78 and is significantly different from 1 as well. This provides some evidence of probability weighting in the expected direction: the weighting function has an 'inverse S-shape" characterized by overweighting of small probabilities and underweighting of high probabilities.

As in the EU-CRRA specification, in the CPT specification highly educated farmers and those who have adopted innovations appear to be less risk averse. On the contrary, the older the farmer is then the higher will be the risk aversion. Age, education level and household size decrease farmers' loss aversion. Finally, older farmers or farmers with a large farm size have more linear probability weighting functions. On the contrary, farmers with a high level of secured income are more likely to overweight small probabilities and to underweight high probabilities.

6 Conclusion

In this paper, we have contributed to the literature on risk behaviour by eliciting preferences under EUT and CPT on a sample of non-standard subjects. Our sample is made of 107 French farmers who have made choices between gain-lotteries and mixed lotteries. We used real monetary incentives. Two different estimation methods, namely the interval approach and the estimation of a random preference model lead to close results. The latter has the advantage of allowing individuals to make some errors when making choices. On average, farmers are risk averse and loss averse. They also exhibit an inverse S-shape probability function, meaning that they tend to overweight small probabilities and underweight high probabilities. We infer from our results that CPT explains farmers' behaviour better than EUT in the context of our experiment. The values elicited for risk aversion, loss aversion and probability sensitivity are close to those in Tanaka, Camerer, and Nguyen (2010) and Liu (2010) which us the same experimental design in developing countries.

We also investigated how preferences correlate with individual socio-demographic characteristics. We find that education and agricultural innovation are negatively linked with risk aversion. Our results also show that age, education, household size and the level of secured income tend to lower farmers' loss aversion. Finally, older farmers or farmers with large farms do not distort probabilities as much as the others.

Further research would consist in estimating a mixture model, assuming explicitly that the observed behaviour can proceed from different theoretical frameworks, according to choices and subjects.

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Table 1: Experimental design, adapted from Tanaka et al. (2010).

	Option A		Option B		Expected payoff difference (A-B)
Series1					
Row	Prob 30%	Prob 70%	Prob 10%	Prob 90%	
1	400	100	680	50	77
2	400	100	750	50	70
3	400	100	830	50	60
4	400	100	930	50	52
5	400	100	1060	50	39
6	400	100	1250	50	20
7	400	100	1500	50	-5
8	400	100	1850	50	-40
9	400	100	2200	50	-75
10	400	100	3000	50	-155
11	400	100	4000	50	-255
12	400	100	6000	50	-455
Series2					
Row	Prob 90%	Prob 10%	Prob 70%	Prob 30%	
1	400	300	540	50	-3
2	400	300	560	50	-17
3	400	300	580	50	-31
4	400	300	600	50	-45
5	400	300	620	50	-59
6	400	300	650	50	-80
7	400	300	680	50	-101
8	400	300	720	50	-129
9	400	300	770	50	-164
10	400	300	830	50	-206
11	400	300	900	50	-255
12	400	300	1000	50	-325
13	400	300	1100	50	-395
14	400	300	1300	50	-535
Series3					
Row	Prob 50%	Prob 50%	Prob 50%	Prob 50%	
1	250	-40	300	-210	60
2	40	-40	300	-210	-45
3	10	-40	300	-210	-60
4	10	-40	300	-160	-85
5	10	-80	300	-160	-105
6	10	-80	300	-140	-115
7	10	-80	300	-110	-130

Table 2: Sample descriptive statistics.

	Mean	Standard Deviation
Total number of individuals	107	
Age	45.8	9.34
Adopt	0.55	0.50
Educ+	0.34	0.47
HHsize	2.97	1.40
Fsize	194	103
SecureInc	0.27	0.24

Age: age of the subject (years)
Adopt: dummy if the subject grows miscanthus, an innovative crop that appeared in the region around 2005
Educ+: dummy if education level beyond secondary school
HHsize: household size (number of individuals)
FSize: farm size (ha)
SecureInc: proportion of the household income coming for another professional activity than farming (%)

Table 3: Distribution of switching points.

	Proportion of respondents		
Switching point	Series 1	Series 2	Series 3
1	15	26	10
2	3	2	7
3	1	1	14
4	0	0	13
5	3	3	24
6	7	2	5
7	14	3	4
8	2	8	22
9	5	5	
10	8	4	
11	2	3	
12	2	7	
13		0	
14		5	
never	38	33	22
Total	100	100	100

Table 4: Parameter estimates with the interval method.

Parameter	Mean	Standard Deviation
Full sample (107 individuals)		
σ	0.54	0.41
λ	2.78	2.35
γ	0.67	0.33
Sample S_1 (96 individuals)		
σ	0.55	0.37
λ	2.60	2.29
γ	0.68	0.35
Sample S_2 (85 individuals)		
σ	0.55	0.37
λ	2.32	1.84
γ	0.67	0.32

Table 5: OLS regressions of risk parameters on socio-demographic characteristics.

Variable	Utility curvature (σ)		Loss aversion (λ)		Probability sensitivity (γ)	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Age	-0.001	0.005	-0.028	0.027	0.001	0.004
Adopt	0.044	0.088	0.012	0.480	0.111	0.071
Educ+	0.083	0.097	-1.106**	0.532	0.048	0.079
HHsize	-0.034	0.030	-0.244	0.164	-0.014	0.024
Fsize	0.000	0.000	0.001	0.002	-0.000	0.000
SecureInc	0.192	0.176	-1.930**	0.963	-0.138	0.143
Constant	0.544**	0.276	5.430***	1.509	0.701***	0.223
Number of observations	107		107		107	
R^2	0.05		0.14		0.04	

***,**,* for significant at 1,5,10% respectively.

Table 6: Maximum likelihood estimates of preferences using various structural models.

Parameter	Variable	Coef	Std. Err.	z	P>|z|	95% Conf. Interval	
A/ EUT CRRA utility and homogenous preferences (Log pseudolikelihood = -2404.0794)							
	Constant	0.266	0.015	18.23	0.000	0.237	0.294
B/ EUT CRRA utility and heterogenous preferences (Log pseudolikelihood = -2366.5955)							
r	Age	0.001	0.002	0.33	0.745	-0.003	0.004
	Adopt	0.052	0.030	1.76	0.078	-0.006	0.110
	Educ+	0.053	0.029	1.81	0.071	-0.004	0.110
	HHsize	0.012	0.010	1.13	0.257	-0.009	0.032
	Fsize	0.000	0.000	-1.23	0.220	-0.001	0.000
	SecureInc	0.003	0.060	0.05	0.963	-0.116	0.121
	Constant	0.201	0.084	2.4	0.017	0.037	0.366
C/ EUT Exo-Power utility and homogenous preferences (Log pseudolikelihood = -2310.8171)							
r	Constant	0.357	0.015	23.34	0.000	0.327	0.387
β	Constant	0.091	0.011	8.32	0.000	0.070	0.113
D/ EUT Exo-Power utility and heterogenous preferences (Log pseudolikelihood = -2245.661)							
r	Age	0.000	0.003	-0.13	0.895	-0.006	0.005
	Adopt	-0.007	0.033	-0.21	0.837	-0.072	0.058
	Educ+	-0.024	0.042	-0.57	0.572	-0.105	0.058
	HHsize	0.011	0.011	0.97	0.333	-0.011	0.033
	Fsize	0.000	0.000	-1.36	0.174	-0.001	0.000
	SecureInc	-0.096	0.066	-1.46	0.146	-0.226	0.033
	Constant	0.442	0.147	3.02	0.003	0.155	0.729
β	Age	-0.002	0.002	-1.01	0.311	-0.005	0.002
	Adopt	-0.027	0.021	-1.3	0.193	-0.067	0.014
	Educ+	-0.055	0.037	-1.49	0.136	-0.127	0.017
	HHsize	-0.010	0.008	-1.26	0.206	-0.026	0.006
	Fsize	0.000	0.000	1.17	0.243	0.000	0.001
	SecureInc	-0.002	0.053	-0.03	0.973	-0.106	0.103
	Constant	0.197	0.088	2.23	0.026	0.024	0.369
E/ CPT and homogenous preferences (Log pseudolikelihood = -2246.4701)							
σ	Constant	0.344	0.006	57.03	0.000	0.333	0.356
λ	Constant	2.488	0.096	25.87	0.000	2.300	2.677
γ	Constant	0.779	0.017	46.26	0.000	0.746	0.812
F/ CPT and heterogeneous preferences (Log pseudolikelihood = -2159.3605)							
σ	Age	-0.002	0.001	-2.2	0.028	-0.003	0.000
	Adopt	0.046	0.014	3.34	0.001	0.019	0.073
	Educ+	0.043	0.014	3.06	0.002	0.016	0.071
	HHsize	0.003	0.005	0.64	0.520	-0.006	0.012
	Fsize	0.000	0.000	-1.51	0.132	0.000	0.000
	SecureInc	0.037	0.028	1.330	0.183	-0.018	0.092
	Constant	0.393	0.041	9.6	0.000	0.313	0.474
λ	Age	-0.025	0.012	-2.13	0.033	-0.049	-0.002
	Adopt	0.143	0.209	0.68	0.494	-0.267	0.552
	Educ+	-0.808	0.226	-3.57	0.000	-1.251	-0.365
	HHsize	-0.124	0.067	-1.86	0.062	-0.255	0.006
	Fsize	-0.001	0.001	-1.35	0.177	-0.003	0.001
	SecureInc	-1.753	0.431	-4.070	0	-2.599	-0.908
	Constant	5.040	0.667	7.56	0.000	3.733	6.347
γ	Age	0.004	0.002	1.77	0.077	0.000	0.007
	Adopt	0.042	0.037	1.14	0.255	-0.030	0.114
	Educ+	0.012	0.037	0.32	0.753	-0.060	0.083
	HHsize	-0.016	0.012	-1.33	0.184	-0.038	0.007
	Fsize	0.000	0.000	-1.99	0.047	-0.001	0.000
	SecureInc	-0.232	0.073	-3.180	0.001	-0.376	-0.089
	Constant	0.772	0.106	7.28	0.000	0.565	0.980