Individual risk and time preferences: a joint task approach

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Abstract

This paper analyses the individual attitudes of household members and the portfolio decisions of their households for a large representative sample of the Dutch population. The novelty of our approach is that we use data from an incentivized experiment performed in the LISS Panel which investigates individual attitudes of risk and time preferences jointly. The advantage of this elicitation procedure besides savings in monetary and mental costs, is that we can capture two preferences which have been seen in the literature to be correlated. The rich information available on participants of the panel allows us to study the relationship between our attitude measures and portfolio choices. As opposed to previous findings, our elicitation procedure captures well the relationship between individual attitudes and actual decision making of individuals. More risk averse individuals are less likely to invest and more impatient people have on average less savings in their current accounts. Finally we observe a negative relationship between risk aversion and wealth.

Keywords: risk aversion, individual decision making, time preferences, portfolio choice

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1 Introduction

A central question in the literature on individual decision making asks how much risk are people willing to take in order to attain a higher level of income in the present or to secure higher income in the future (for example, gambling or investing for retirement purposes). Other types of decisions involving risk can vary from the decision to purchase a house and take up a mortgage or the decision to contract a life insurance. All these types of decisions involve different levels of risk and uncertainty about present and possibly future outcomes.

The literature so far has stressed the importance of eliciting and measuring risk aversion in order to have models which better describe individual behavior. Consequently, conclusions derived from these models can better simulate the consequences that changes in policies or decision scenarios would have on choice behavior. It is now common in the literature to include in experiments and surveys elicitation methods for risk aversion (and depending on the context, tasks to elicit time preferences).

Even though a great deal of research has gone into finding the most appropriate way to elicit these preferences, we will not enter into the debate of which one of these is better or worse than others. Depending on what the research question and the context is, some elicitation methods might be more appropriate than others (Charness et al., 2013). If the researcher is looking to fit parameters of a structural model, more complex elicitation methods might be called for. If the interest is instead on having an index of risk aversion, simpler methods might be sufficient (as for example stated preference elicitation).

We show a method to elicit time and risk preferences jointly in one task. This method is based on previous methods which make use of lotteries, specifically in the method used by Holt and Laury (2002). Since our main interest lies on estimating parameters which we can use to model decision making in a structural way, we show with different specifications, how with this task we can identify parameters of risk aversion and discounting. We modified this method in order to make it less time intensive. Since people do not have to go through separate tasks, this reduces also the mental depletion which they can experience during extensive questionnaires.

Separate elicitation has been done already in the past (Andersen et al., 2008). In their research they prove the importance of measuring time preferences and controlling at the same time for risk preferences, since they seem to work through the same mechanisms. The main differences between our method and Andersen et al. are that we elicit preferences in the same task (as opposed to splitting risk elicitation from time preference elicitation), we estimate individual level parameters and we correlate these to actual portfolio decision making. To test our joint elicitation method, we performed an experiment in the field through an internet panel representative of the Dutch population administered by CentER data. We show how this measures can actually help predict preferences outside these lottery tasks, specifically with decisions of investment, saving and wealth accumulation.

In section 2 we position our research in the relevant literature. Section 3 describes in detail the experimental design along with the descriptive data of our sample. Next, we show the structural model and econometric implementation in section 4. In section 5 we show first the results from the experiment and describe the raw data. Second, we present the results from the structural model. Finally, we conclude in 6 and point towards future research applications.

2 Related literature

The existing literature on risk aversion dates back to von Neumann and Morgenstern's Theory of Games and Economic Behavior (1954). Later the seminal work of Arrow (1971) and Pratt (1964) provided the foundations for measuring risk attitudes based on the curvature of the utility function. Expected utility theory assumes linearity in probabilities which would imply linearity of indifference curves. This theory states that the decision maker chooses between risky or uncertain prospects by comparing their expected utility values. One of the first identified challenges to EUT is the well known example of The Allais Paradox (Allais, 1953), where a clear violation on one of the assumptions of EUT is shown to appear. In order to explain anomalies in the expected utility framework, Kahneman and Tversky (1979), introduced Prospect Theory (PT). According to this theory a decision maker's preference is composed of a utility function, a reference point and a pair of probability weighting functions. Several modifications to EUT have been proposed in the literature that would account for observed heterogeneity in the utility curvature.

Concerning the methodologies used for the elicitation of risk attitudes, an important contribution from experimental economics is the risk preference Multiple Price List (MPL) methodology (Binswanger (1980); Holt and Laury (2002)). This method became increasingly popular in laboratory experiments even though it was first introduced in the field. In these types of experiments, subjects make a series of choices involving a safe option and a risky binary gamble with variable outcomes (sometimes it is also presented as two risky lotteries, one with less variance in the payoffs).

A method which is used in numerous studies is the elicitation method of Gneezy and Potters (1997) which provides decision makers with the choice of investing an amount of money in a risky task or in a safe asset. This elicitation method has been used to provide support for myopic loss aversion in financial decisions of students and later on in many other applications.

Another method which is less popular nowadays is the questionnaire to elicit stated preferences. A general risk question is asked to individuals, such as: "Rate your willingness to take risks in ...". The context can be general, or in financial decisions, sports, health, etc. Although it is still debatable, there is evidence that this question can predict behavior fairly well (Dohmen et al., 2011b). On the other hand, other studies claim that in order to ensure that choices reflect true underlying attitudes towards risk, the tasks should be incentivized, and questionnaires are lacking this dimension. For the purposes of this paper, we will briefly compare the stated preferences method to measure risk aversion and an experimental measure(just as an illustration since this is not our main research question). For an informative overview of the elicitation methods, Charness et al. (2013) present a table with a summary of recent studies, their elicitation method, comparisons and results.

Even though there is an extensive literature on laboratory experiments performed at Universities, many researchers are increasingly taking these elicitation methods into the field. Binswanger and Sillers (1983) summarize risk experiments done among peasants in multiple countries (India, El Salvador, Thailand and the Philippines). They find evidence that farmers in developing countries are mainly risk averse but they find no evidence supporting the idea that neither wealth nor income have a significant effect. Binswanger appears to be the first experimental economist to identify risk attitudes using the MPL with real payoffs. The approach by Tanaka et al. (2010) was to gather preference measures experimentally and correlate those measures with demographic and economic variables such as income, ethnicity, literacy rate and education among others. They perform their experiments in Vietnam. They find that people living in poor villages are averse to loss. They also find that household income is correlated with patience (lower interest rate) but not with risk preferences. They also find present bias (preference for immediate reward).

In a more recent study, Von Gaudecker et al. (2011) estimate explicitly parameters for the utility curvature, loss aversion and preferences for different timing of uncertainty resolution. Their study was performed as part of an internet survey representative of the Dutch population using CentER Panel at Tilburg University. Having survey data allowed them to have background socioeconomic information on each household. They find great heterogeneity among participants and find that observed characteristics alone cannot explain this heterogeneity in preferences.

Our study is placed in the literature which looks at risk aversion and time preference jointly. Andersen et al. (2008) elicit jointly risk and time preferences for the Danish population. They find that joint estimation of these two parameters provides estimates of discount rates that are significantly lower than those found in other studies where estimation is done separately. The estimation of the curvature of the utility function and computation of time preference parameters jointly is now an active topic of research (Ventura (2003); Voors et al. (2012)). These studies however elicit preferences in separate tasks. Our method of elicitation aims at capturing both preferences in an integrated experiment. This method can possibly lower the burden on the participant and save survey time by reducing the number of tasks that have to be completed to capture both preferences.

3 Experimental setup and data description

3.1 The experiment

In order to elicit risk preferences we used a MPL choice list similar to the one used previously by Von Gaudecker et al. (2011) in their CentER panel experiment. The lottery experiment involving gains consisted of four treatments with five choices in each treatment. The first screen included the instructions and an example choice.

In each treatment each individual had to decide between two lotteries which vary in probability throughout the treatment but do not vary in payoffs. Lottery option A had a lower variance than lottery option B and the expected payoff became larger as one proceeds down the list, but the expected value of lottery B increased relative to that of lottery A. Each screen contains five choices and pie charts illustrating the probabilities. Thus each subject had to choose in total 20 times and these choices will be used to estimate their preferences.

The treatments differ in terms of the amounts in euros that can be earned, and in terms of the time periods in which these payments take place. Table A.1 in the appendix shows the experimental design in more detail (the probabilities and quantities used to elicit preferences). This table also shows the expected value of each lottery and which choice a risk neutral individual would take.

Each subject chooses A or B in each row and one of these is at the end selected at random for actual payment. We inform the subjects at the beginning of the experiment that they have a 1/10 probability of actually getting paid and at the end they know whether they were selected or not for payment. This has been seen in the literature as a good strategy to keep the tasks incentive compatible while keeping the costs for the experimenter low (Dohmen et al. (2010)). The average payoffs were 13.4 euros with a standard deviation of approximately 7 euros.

Having an internet implementation allows us to monitor how long they take in completing the tasks, the day and hour in which they completed it. This can be useful for future waves in which we need to control for seasonality or timing.

In Figure 1 we present an example of a screen that subjects faced during one of the treatments. Here, under option A and option B we write down in red the timing of the payment. In this example, they had to choose the lower risk option which would pay out in three months versus the high risk option which would pay out immediately. Since there is no experimenter present in an online experiment we allow participants to switch back, read the instructions if they need to and change their choices.

One type of inconsistency that can arise in these type of elicitation methods is

Figure 1: Screen shot example

multiple switching. This means that if a person switches from a safe lottery to a risky one and then decides to switch back to a safe lottery, that individual is not choosing according to a smooth (concave/convex) utility function. We chose not to enforce a single switching point to later incorporate possible inconsistencies and errors into the decision making models.

Another possible inconsistency are the dominated choices. In every treatment there is a choice which involves a dominated option. For example, in choice 5 of treatment 1, subjects could earn either 20 euros with 100% probability or 25 euros with 100% probability. If subjects choose the sure amount in option A we classify them as picking a dominated choice, since this means they prefer less money with certainty than more money with certainty. In the next section we show the percentage of people falling into our inconsistency categories.

Finally, the key aspect of this design (as opposed to what has already been done in the literature) is that we designed the choice lists with enough variation in its different dimensions such that we would be able to identify individual preferences. The time variations which we implemented were: immediate payments and delayed payments of 3, 6 and 9 months. Before taking the experiment to the field, we ran simulations assuming a structural form of the utility function and parameters to ensure the identifiability of the preference parameters.

At the end of the lottery tasks we included questions to gather self reported measures of risk taking and patience. [1] The risk questions are standard in the literature mentioned in section 2:

- How do you see yourself? Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? Please give a value between 0 and 10, with 0 for "not at all willing to take risks" and 10 for "very willing to take risks".
  - How would you rate your willingness to take risks concerning financial matters?
  - your willingness to take risks... - in your occupation?
  - your willingness to take risks... - during leisure and sport?

To measure stated time preference or discounting, we included the following questions:

- On a scale from 0 to 10, how patient do you consider yourself to be? (10 being the most patient value)
- How much do you agree with the following: If I get money I tend to spend it too quickly (on a scale from 0 strongly disagree to 10 fully agree).

With this information, we compared our structural model results and prediction of

[1] We also gathered information on beliefs of couples attitudes but we will not mention the results in this study.

actual financial decisions.

3.2 The data

The data source for this study comes from the LISS panel which is administered by CentER data at Tilburg University. This panel is representative for the Dutch population and contains approximately 8,000 individuals. Participants are asked to answer different types of surveys every month and receive monetary compensation four times a year. The survey is administered via the Internet and in order to avoid selection problems due to lack of Internet access, respondents without a computer are provided a special computer called "simPC". These computers are also provided with a broadband connection. The panel also contains large information on demographic variables and their self-reported financial situation.

Table 1: Summary statistics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Female	0.501	0.5	0	1	2823
Position in the household	1.597	0.667	1	6	2823
Age	52.043	14.936	18	91	2823
Level of education	3.684	1.464	1	6	2823
High education	0.345	0.475	0	1	2823
Civil status	1.704	1.474	1	5	2823
Number of kids	0.824	1.099	0	6	2823
Financial literacy	2.399	1.028	0	4	1696
Civil servant	0.007	0.082	0	1	2776
Self employed	0.055	0.227	0	1	2823
Monthly gross income	2202.134	1918.852	0	53000	2680
Investments	0.14	0.347	0	1	2532
Savings total	17629.606	46380.989	-90000	700000	2532
Total wealth	19202.391	73004.624	-454250	1300000	2360
Value of loans	0.085	0.279	0	1	2532
Large expenditure 12m	1.784	0.411	1	2	2356
Risk stated	3.223	2.294	0	10	2823
Money patience stated	3.564	2.517	0	10	2823

Table 1 presents the sample descriptive statistics of sociodemographic variables of interest. In our experiment we target those households which consist of two adults who live together (married or unmarried) and in which both household members answer the survey. This is why we probably observe the average age in our sample to be larger than the national Dutch average which is 41 years old.[2].

[2]According to the Dutch Bureau of Statistics (CBS) data for 2014

In total we have a sample of 3,007 individuals who finish the experiment. In order to first inspect the data, Table 3 shows the descriptive statistics for each of the seven treatments where we can see the mean choices for B for each choice and treatment. We observe the predicted pattern that as people move down the choice list, they choose B more often (the expected value is higher). Nevertheless, we note that a percentage of the sample chooses A in the last choice of each treatment and this gives us information on whether subjects are understanding the task properly as is explained next.

As is visible from Table 3, there is a proportion of the population that chooses the dominated option which is presented in each treatment. Option B has probability equal to one of a higher payoff once in each treatment, therefore a rational decision maker who prefers more money to less should opt for this option. Figure 2 shows the frequencies of dominated choices. More than half of the sample never picks the dominated choice and approximately 4% of the sample always picks the dominated choice in each treatment. Dominance errors are not uncommon in the literature of risk elicitation in multiple price lists (Von Gaudecker et al. (2011), Charness et al. (2013)).

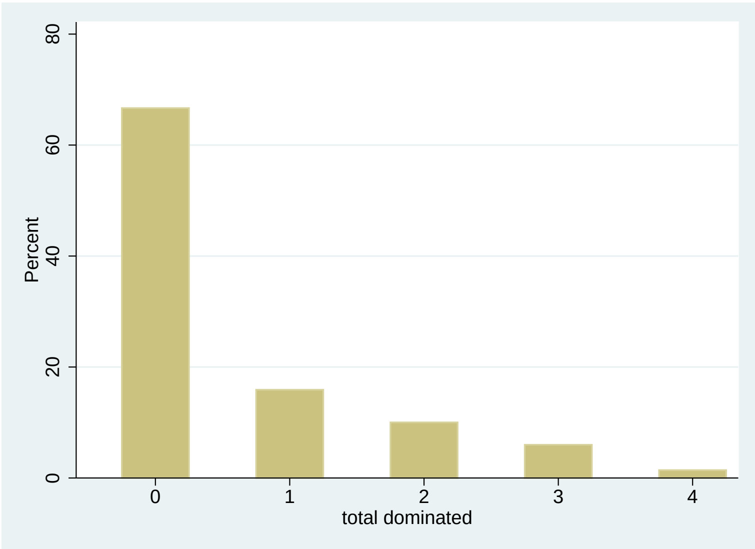


Figure 2: Dominated choices

For the rest of the analysis we do not include the 133 people which pick four times the dominated option since they are people who did not understand the task or did not put any mental effort into it. In table 2 we took a closer look at the characteristics that these 133 subjects have. We found that on average this subsample is significantly older and less educated. Since this is only 4.42% of the sample we decided to exclude them from the sample along with individuals for which we do not have data for age or education. Our final sample consists of 2825 individuals.

Table 2: Dominated options and demographics

Variable	Mean dom	std.	Mean rest	std	Difference
Female	0.57	0.50	0.50	0.50	Pr(T > t) = 0.0495
Position	1.65	0.62	1.59	0.67	Pr(T > t) = 0.1540
Age	58.26	12.87	52.01	14.91	Pr(T > t) = 0.0000
Civil status	1.40	1.13	1.70	1.47	Pr(T < t) = 0.0092
Income	1737.80	1394.92	2195.76	1913.89	Pr(T < t) = 0.0045
Family income	4101.86	1859.92	4594.95	2876.05	Pr(T < t) = 0.0326
Education cat	3.02	1.49	3.68	1.46	Pr(T < t) = 0.0000
Num kids	0.56	0.87	0.83	1.11	Pr(T < t) = 0.0024
Risk stated	2.95	2.41	3.25	2.31	Pr(T < t) = 0.0765
Money pat	6.34	2.32	6.45	2.02	Pr($\|T\| > \|t\|$) = 0.5358
Obs	133		2874		

Note: the last column presents the p-values of a two sample t-test. Income is stated as the gross income per month in euros. *Mean dom* shows the means for the subsample of people who choose always dominated options. *Mean rest* shows the means for the rest of the sample.

4 The Model

4.1 Utility specification

According to behavioral theories of utility in economics, we should take into account possible deviations from expected utility in terms of risk and discounting preferences. To do this we estimated a *discounted expected utility* model where we incorporate curvature of the utility function and quasi-hyperbolic discounting functions.

We show the results for the CARA utility (exponential) function which does not encounter problems around 0 as do typically CRRA functions Köbberling and Wakker (2005). This is useful given that our monetary incentives are not high. Von Gaudecker et al. (2011) also found this parametric form to best describe the choices made by the participants of their CentERpanel experiment. Later we performed sensitivity checks by changing the functional assumption of utility and time preference.

The utility function in the gains domain:

$$U(\gamma, \lambda) = \frac{1}{\gamma}(1 - e^{-\gamma z}) \tag{1}$$

where $\gamma \in \mathbb{R}$ is the coefficient of absolute risk aversion. The monetary payoff of the lotteries is denoted by $z \in \mathbb{R}$.

We model time preferences with the following quasi-hyperbolic discounting model:

$$D(\beta, r) = \beta e^{-rt} \tag{2}$$

where β is a present bias parameter and r is the discount rate (note that when $t = 0$

this term becomes 1). Therefore, the discounted expected utility (DEU) function would be the product of (1) and (2):

$$DEU = D(\beta, r) * U(\gamma, \lambda) \tag{3}$$

In addition to people choosing the lottery which maximizes their discounted expected utility (DEU), we introduce Fechner errors to model the choices. Therefore a subject will choose lottery B if:

$$DEU^B + \tau\varepsilon_B > DEU^A + \tau\varepsilon_A \tag{4}$$

where the ε's follow a type I extreme value distribution and are independent of each other and the difference of the errors $\varepsilon = \varepsilon_A - \varepsilon_B$ follow a logistic distribution. The parameter τ can be interpreted as determining the size of the probability of making a mistake when choosing between A and B (for example, choosing A when the DEU^B is higher.

Lets denote the difference between the DEU of option A and the DEU of option B as:

$$\Delta DEU_{ij} = DEU_{ij}^B - DEU_{ij}^A \tag{5}$$

If an individual chooses option B, $Y_{ij} = 1$ and zero otherwise. We will observe in choice j for person i choice B if:

$$Y_{ij} = \mathbb{I}\{\Delta DEU_{ij} > \tau\varepsilon\} \tag{6}$$

4.2 Empirical specification

In order to estimate individual level preference parameters we first estimate them with simulated maximum likelihood. In a second step, and using the information provided by their choices individually, we approximate the posterior distribution of their individual parameters through Bayes rule. Previous studies have shown that in a representative sample such as this one, it is likely that we will observe a great deal of heterogeneity. Because of this we estimated a parameter which is specific to each person according to their characteristics(observed and unobserved) and their actual choices made in the experiment.

The individual likelihood to observe choice Y_{ij} is given by

$$l_{ij} = \Lambda\big((2Y_{ij} - 1)\frac{\Delta DEU_{ij}}{\tau}\big) \tag{7}$$

where $\Lambda(\,\cdot\,)$ is the cumulative standard logistic distribution (since we assumed ε follows a logistic distribution).

For the individual specific preference parameters we formulate a random coefficients model which we estimate by simulated maximum likelihood. We allow for each parameter to depend on some observed and unobserved characteristics. Previous studies have found that observed characteristics are rather poor predictors of risk attitudes, therefore we also introduce unobserved heterogeneity parameters. The observed heterogeneity can be included by adding characteristics such as age, gender, level of education, income, etc.

$$\eta_i = g_\eta(X_i^\eta \mu^\eta + \xi_i^\eta), \qquad \eta_i \in \{\gamma_i, \tau_i, r_i, \beta_i\} \tag{8}$$

where η_i denotes the individual specific preference parameters, X_i^η is the vector of observed characteristics (with an intercept), μ^η are the parameter vectors, and ξ_i^η are the unobserved heterogeneity components. The functions $g_\eta(\cdot)$ specify the theoretical restrictions on the parameters, for example, for γ_i it is the identity function, for the discount rate r_i and τ_i this is an exponential function to ensure positive values of these parameters.

We assume that the vector ξ^η follows a joint normal distribution independent of all regressors. The variance covariance matrix of ξ^η is $\Sigma'\Sigma$ and we define $\xi^* = (\Sigma')^{-1}\xi$. Therefore we can express the likelihood contribution of subject i as:

$$l_i = \int_{\mathbb{R}^3} [\prod_{j \in J_i} l_{ij}(DEU^A, DEU^B, g(X^\eta \mu^\eta + \xi^\eta))]\phi(\xi^*)d\xi^* \tag{9}$$

where l_{ij} is the individual likelihood given in (7) and $\phi(\cdot)$ denotes the joint standard normal probability density function. The loglikelihood is given by the sum of the individual contributions of l_i over all subjects and we maximize it with simulated maximum likelihood methods (to solve the integral above we use Halton draws of length R=200). The variance covariance matrix of the parameter estimates is based on the outer product of the gradients of the logarithm in (7).

Once we have estimated our parameters with simulated maximum likelihood, we construct for each individual a posterior distribution of parameters conditional on their observed choices in the experiment ($P(\eta_i|y_i, X_i)$). By estimating their posterior distributions we take into account information gathered in their decision making. The equation for estimating the posterior distribution of individual parameters is:

$$P(\eta_i|y_i, X_i) = \frac{P(y_i|\eta, X_i)k(\eta, X_i)}{l(y_i, X_i)} \tag{10}$$

where $l(y_i, X_i)$ is the likelihood contribution of individual i as defined in equation 9 where we partial out the individual heterogeneity parameters. $k(\eta, X_i)$ is our prior assumption on the probability distribution function of parameters which we assume to be a multivariate normal distribution. $P(y_i|\eta, X_i)$ is the probability of observing choice y by individual i given a certain parameter from the distribution $k(\eta, X_i)$.

Finally, we use the posterior distribution 10 to compute the posterior average parameter for each individual in our sample. Since our $\eta's$ are a function of X_i, μ_i, ξ_i we can compute the posterior mean as:

$$\hat{\eta}_i = \int\limits_{\eta \in \mathbb{R}^3} g_\eta(X_i^\eta \hat{\mu}^\eta + \hat{\xi}_i^\eta) P(\eta_i | y_i, X_i) d\eta \tag{11}$$

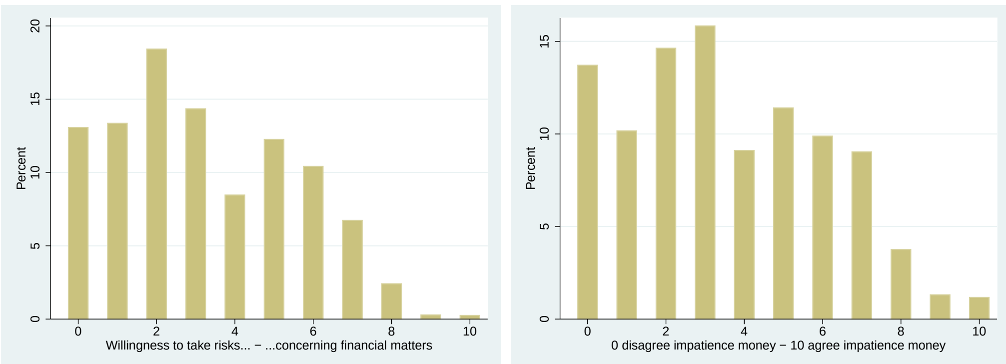
To approximate this integral we used a grid in $\mathbb{R}^3$ and the following equation:

$$\hat{\eta}_i = \sum_{r=1}^{R^3} g_\eta(X_i^\eta \hat{\mu}^\eta + \hat{\xi_i^\eta}) P(\eta_i | y_i, X_i) d\eta \tag{12}$$

In the next section we show the results for this estimation. As will be shown, we can use these parameters to predict savings and investments in real portfolios of households.

5 Results

From the lottery tasks we first looked at how many risky choices they made (when they picked the lottery with the higher variance) and we also looked at how many choices they pick which involve a payoff closer to the current time period. In table 3 we show the average choices per round. Choosing "B" is labeled "1" and choosing "A" is labeled "0". From this table we see, as expected, that when people go down the list, they switch from A to B. These are average choices and as we will show, there is a lot of heterogeneity among people in them (we can already see it by looking at the high standard deviation from the table in the third column). There is also variation per person between tasks, we see for example that in treatment 2 people choose more often the risky choice than in other treatments since choice one. This is because treatment 2 by design has an earlier switchpoint (according to differences in EV). These variation in the payoffs between lotteries allow us to identify our model parameters.



(a) Willingness to take risk

(b) Patience spending money

Figure 3: Stated preferences

Table 3: Summary Statistics of Choices

Choice	Mean	Std. Dev.	Choice	Mean	Std. Dev.
ch1t1	0.2161	0.4116	ch1t3	0.1912	0.3933
ch2t1	0.2429	0.4289	ch2t3	0.1985	0.3989
ch3t1	0.4362	0.4960	ch3t3	0.2795	0.4488
ch4t1	0.6881	0.4633	ch4t3	0.5045	0.5001
ch5t1	0.8691	0.3374	ch5t3	0.8167	0.3870
ch1t2	0.3401	0.4738	ch1t4	0.1985	0.3989
ch2t2	0.4242	0.4943	ch2t4	0.2302	0.4210
ch3t2	0.6609	0.4735	ch3t4	0.4142	0.4927
ch4t2	0.8146	0.3887	ch4t4	0.6602	0.4737
ch5t2	0.9001	0.2999	ch5t4	0.8342	0.3719

As mentioned in the section 3 if people were fully rational and made no mistakes, we should observe for each treatment in choice five only ones (choice B). These summary statistics already excluded people who always picked A in choice five. Next, we show the results from our structural model estimates and their relationship to real portfolio choices.

To compare our experimental measures, we show in Figure 3 the distribution of responses to the stated subjective preference measures. We can see that we have a relatively risk averse sample with its distribution skewed right. They also claim to be patient in terms of how they spend their money.

5.1 Estimation results

The results of the estimation done by SMLE of the structural utility model CARA with quasi-hyperbolic discounting function are depicted in Table 4. These parameters give us the mean and variance of η over all decision makers. The parameters shown are the untransformed parameters. In the appendix we show the relevant results of estimating a CRRA utility function with quasi-hyperbolic and hyperbolic discounting.

Model I shows the estimates of our parameters of interest without any covariates (risk aversion, error, time preference and present bias) and the second column presents the standard errors of the estimates. Model II shows the estimates of our preference parameters as a function of observed heterogeneity covariates, specifically, age, gender and level of education. Finally, Model III shows the full model with observed and unobserved heterogeneity.

At first glance, we can see a negative relationship between risk aversion and education, a positive relationship with gender (as has been seen repeatedly in the literature: Croson and Gneezy (2009), Eckel and Grossman (2008)) and older people seem to exhibit more risk aversion which has also been recorded in the literature before (Donkers and van Soest (1999) find a positive relation, Hartog et al. (2002) find a positive relation except of accountants in their sample). According to Models II and III, older people, low educated people and males have a higher propensity to make mistakes in the utility calculation. Von Gaudecker et al. (2011) also find the same direction of effects for the error propensity and Bellemare et al. (2015) find an effect for males having a higher propensity to make mistakes (only at the 10% level).

Table 4 also shows the variance and covariance of our preference parameters corresponding to the vector ξ^{η} of unobserved heterogeneity. We find heterogeneity around the averages. The variances of the unobserved heterogeneity terms are significantly different from zero (p¡0.001). We find a lot of heterogeneity of the discount rate parameter. Moreover, we calculated the correlation coefficients ρ_{η} between these preferences at the individual level. The correlation between the risk aversion coefficient and the time discount rate is significant but very close to zero ($\rho_{\gamma,r}$ = -0.0289). The correlation of the posterior coefficients is also close to zero and only significant at the 10% level.

Our time preference parameters from Model II and III show that women are more impatient than men and higher educated and older people are more patient. In general, for most parameters, when we controlled for unobserved heterogeneity, we obtained more precise estimates.

As mentioned in the previous section, these estimated parameters from the simulated maximum likelihood estimation are used to construct a distribution of parameters for each individual conditional on their observed choices in the experiment $P(\eta|y, X_i)$. The following figures show how these posterior distributions look like for four participants in our sample. Table 5 shows the average parameters γ, τ, r, the number of risky choices that they took and whether they switched more than once during a treatment. We can observe that someone who took more risky choices, for example subject S4 who took 16 risky out of 20, has a negative coefficient of risk aversion (implying risk seeking behavior). This is opposed to what we observe from participant S2500, who only took 2 risky choices and has a higher coefficient. The higher the coefficient the more curved her utility function is.

Figure 4 shows the posterior distributions along with their prior distributions. Subject '100' has a mean closer to the average risk aversion as can be seen in the lower left quadrant of the figure. This is opposite to subject '4' who has a coefficient much lower than the average.

The advantage of having computed individual level parameters is that we have incorporated heterogeneity in two ways. The first is to include observed characteristics that we know from the panel and second, a random coefficients model to control for unobserved heterogeneity. Having individual measurements for preferences can allow us to relate these to actual real life decisions more precisely as opposed to an average.

In Table 6 we show more detailed information on the relationship between pref-

Table 4: Estimates of Risk and Time Preferences with Exponential Utility

	Model I	ses	Model II	ses	Model III	ses
γ_{cons}	0.0481	0.0006	0.0496	0.0007	0.0584	0.0020
γ_{edu}			-0.0026	0.0005	-0.0043	0.0014
γ_{fem}			0.0197	0.0012	0.0291	0.0039
γ_{age}			0.0003	0.0000	0.0001	0.0001
τ_{cons}	1.0330	0.0113	1.0180	0.0115	0.4079	0.0326
τ_{edu}			-0.1117	0.0074	-0.1203	0.0232
τ_{fem}			-0.0890	0.0190	-0.2280	0.0654
τ_{age}			0.0050	0.0007	0.0100	0.0023
r_cons	-4.1052	0.0765	-4.1338	0.0840	-8.2237	0.2686
r_edu			-0.2498	0.0435	-0.5318	0.0302
r_fem			-0.0383	0.1111	-0.2897	0.0678
r_age			-0.0017	0.0039	0.0158	0.0026
β	0.9642	0.0058	0.9624	0.0058	0.9849	0.0026
n=2825	No		No		Yes	
		Correlations		*Unobserved heterogeneity*		
		$\rho(\gamma,\tau)$	-0.75337138	$V(\xi^{\gamma})$	0.0105	0.0003
		$\rho(\gamma,r)$	-0.02886324	$V(\xi^{\tau})$	2.7254	0.1014
		$\rho(\tau,r)$	-0.22998561	$V(\xi^{r})$	15.6874	1.1861
				$Cov(\xi^{\gamma},\xi^{\tau})$	-0.1275	0.0047
				$Cov(\xi^{\gamma},\xi^{r})$	-0.0117	0.0032
				$Cov(\xi^{r},\xi^{\tau})$	-1.5038	0.0933

Table 5: Example Subjects: 4, 5, 100, 2500

Participant	Experimental			Raw choices		
	γ	τ	r	Tot risky	Tot present	Switching
S4	-0.0880	22.8596	0.0113	16	15	yes
S5	0.0119	1.6838	0.0042	11	10	no
S100	0.1277	3.1998	0.0050	9	12	no
S2500	0.1928	2.2376	0.0035	2	7	yes

erences and different levels of education, their gross income, age and gender. We computed clustered standard errors at the household level. We also allowed for the errors of these regressions to be correlated. We see that higher wealth is correlated with less propensity to make mistakes, this effect disappears if we control for numerical abilities (see Appendix table A.3).

The mean risk aversion parameter for the whole sample is 0.0609, the mean error parameter is 5.574306 and the discount rate is 0.0736. This is not directly comparable to other studies since our statistical method and/or functional forms differ. Neverthe-

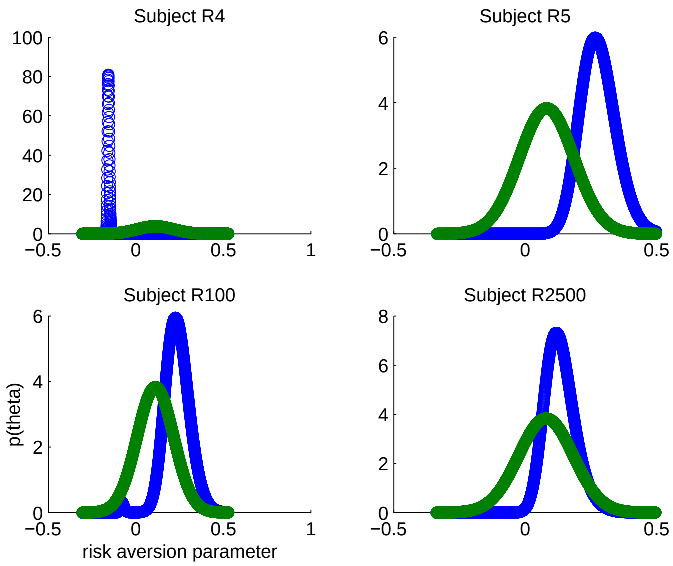


Figure 4: Parameters of risk aversion

less, if we look at Von Gaudecker et al. (2011), using an expo-power utility function, we obtain slightly larger estimates for γ. For time preferences we obtain a lower estimate for the discounting rate than Andersen et al. (2008) who find it around 10% for the case of quasi-hyperbolic discounting. For completeness, in the following sections, we include in the appendix estimations of other utility functions and discounting functions (hyperbolic discounting and CRRA utility). These results do not vary significantly.

5.2 Financial outcomes

5.2.1 Investment and savings

In the remaining of this section we will look at the effect of our measurements for risk and time preferences on decisions such as savings and investments in risky assets. We will also explore the relationship between preferences and wealth. The LISS panel contains this information for most of our participants, whether they have savings accounts or investments and the amount assigned to each of them. We are interested in knowing whether from such experimental measures we can actually say something about financial risk taking outside these tasks. Previous experiments have shown failures of rationality or EUT but still fail to find a relationship of risk with real life investment decisions.

To model the relationship between investment decisions and our experimental variables we perform a latent variable analysis using a probit model. With this model we have as our observed outcome the decision whether to invest or not. We take information from the LISS panel on the ownership of risky assets, specifically from a question

Table 6: Parameters with observed characteristics

	(1) riskpost	(2) tp3	(3) rp3
Female	0.025***	-0.848***	0.013
	(0.004)	(0.314)	(0.009)
Intermed voc. Educ.	-0.011**	-0.718*	-0.047***
	(0.005)	(0.376)	(0.011)
Higher voc. Educ	-0.016***	-1.726***	-0.074***
	(0.005)	(0.383)	(0.011)
University	-0.017**	-2.649***	-0.068***
	(0.007)	(0.545)	(0.016)
Age category	0.002	0.683***	0.010***
	(0.001)	(0.108)	(0.003)
loginc	-0.001	-0.049	-0.003
	(0.001)	(0.072)	(0.002)
logwealth2	-0.000	-0.065***	-0.001*
	(0.000)	(0.023)	(0.001)
Constant	0.050***	3.791***	0.072***
	(0.011)	(0.873)	(0.026)
Observations	2,402	2,402	2,402
BP test of indep	1016.32		
R-squared	0.034	0.048	0.039

Robust standard errors in parentheses
$***p < 0.01, **p < 0.05, *p < 0.1$

in the survey which asks:

Did you own one of the following assets in the previous year? Investments (growth funds, share funds, bonds, debentures, stocks, options, warrants).
Yes / No

Unfortunately we do not have more detailed information on the exact type of investment which they posses, therefore we treat everything as a "risky investment" even though the risk between these can be quite different. Subjects are asked to respond yes or no to this question. We tested the predictive power of our measures on this binary outcome by means of the following models.

In the first specification of Table 7 we show the experimental measures of risk aversion and error parameter as explanatory variables of the probability to have risky assets (investments). We estimate the parameters using a probit Model.

We find that they are significant at the 1% level. People who have a higher risk aversion parameter are less likely to have any sort of investment as described above. Those people who are more prone to mistakes in our tasks are also less likely to invest.

Table 7: Portfolio decisions

	(1)	(2)	(3)
	inv.	log val. Inv.	log val sav.
Female	-0.219***	-2.652**	-1.068***
	(0.066)	(1.111)	(0.226)
Age category	0.135***	2.051***	-0.133
	(0.028)	(0.440)	(0.087)
Intermed voc. Educ.	0.045	-0.852	-0.238
	(0.100)	(1.630)	(0.292)
Higher voc. Educ	0.395***	3.834***	0.317
	(0.093)	(1.447)	(0.286)
University	0.655***	6.970***	0.866**
	(0.127)	(1.867)	(0.418)
riskpost	-1.813***	-28.033***	-3.211*
	(0.540)	(8.688)	(1.734)
Tau	-0.019***	-0.231**	-0.052**
	(0.007)	(0.111)	(0.022)
Time pref.	0.022	-2.850	-1.474***
	(0.190)	(2.938)	(0.526)
Log(income)	0.088***	1.163**	0.140***
	(0.029)	(0.487)	(0.052)
Log(wealth)	0.042***	1.337***	0.796***
	(0.007)	(0.203)	(0.033)
Constant	-2.575***	-43.623***	0.976
	(0.276)	(4.479)	(0.714)
sigma		13.828***	4.714***
		(0.495)	(0.168)
Observations	2,402	2,402	2,406

Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

We also controlled for variables which are observed to be important according to our economic intuition and the literature on savings and investments of households. Higher education, age and income result in a higher likelihood of investment. Women have a lower likelihood of owning risky assets compared to men. Specification two shows the results if we use the amount invested as the outcome variable. To control for left censoring at zero, we estimate this using a tobit regression.

Next, we look at their decision to save. We define this outcome variable as the amount of money people have in their savings accounts at the bank. We present the results for this model in Table 7. This is the amount of savings stated by individuals. As opposed to the case of investments, time preference is very significant in predicting the amount saved. The negative coefficient in *Time preference* means that more impatient people save less on average. It is interesting to note that with an experimental measure for discounting in a lottery task, we find a significant correlation with the level of savings of individuals.

5.2.2 Wealth

Further, we look at the effect that different levels of risk and time preferences on the wealth of individuals. In Table 8 we find that for two different types of wealth specifications, the parameters for risk and time preference are significant in explaining the level of individual wealth. People who are more risk averse and more impatient, have on average less wealth. We controlled for whether the individual has investments or not by introducing a dummy variable. We also control for the subject being self employed but found this not to have an effect.

We see the expected effects for the other controls. For example, higher education results in higher wealth at both the higher vocational level and university level. Women have on average less wealth, this effect is less if we do not take into account wealth relating to real estate property (specifications (2) and (4)).

In the Appendix we show that these results hold when we use different utility functions and different discounting specifications. For example, Table A.5 shows the same results for the regressions on individual preferences with CRRA utility and QH discounting for two definitions of wealth. In this same analysis, we summarized results on investments, savings and wealth on Table A.7 and find that our results are not sensitive to utility specifications.

5.2.3 Stated preferences

Finally, we look at the results when using stated preferences in our regressions of portfolio decisions. This type of preference elicitation is not incentivized and therefore might or might not capture true financial attitudes (Charness et al., 2013). However, some studies with elicitation performed in large scale panels (Dohmen et al. (2011a), Dohmen et al. (2005)) show that this method provides a good measure of risk attitudes. Based on the literature so far, we consider that these type of elicitation procedures can be of use and it depends on the research question and context at hand which method is more appropriate. We extend these studies by also measuring time preferences with a question on impatience to spend money.

Table 9 shows the results for the same regressions as in previous sections but with stated preferences included. Risk taking is positively correlated to the investment decision and the amount invested given that they invest. This means that people who claim to be more willing to take risks in their financial matters are more likely to have investments in risky assets and given that they invest, a larger quantity of money.

Table 8: Wealth and individual preferences for risk and discounting

	(1)	(2)	(3)	(4)
	logwealth	logwealth2	logwealth	logwealth2
Female	-1.051***	-0.923***	-1.166***	-1.021***
	(0.331)	(0.329)	(0.330)	(0.328)
Age	0.694***	0.661***	0.493***	0.454***
	(0.164)	(0.165)	(0.165)	(0.165)
Intermed voc. Educ.	0.475	0.295	0.750*	0.562
	(0.452)	(0.449)	(0.451)	(0.449)
Higher voc. Educ	1.414***	1.274***	1.894***	1.735***
	(0.448)	(0.448)	(0.442)	(0.441)
University	2.559***	2.192***	3.063***	2.640***
	(0.599)	(0.605)	(0.591)	(0.595)
Married	-1.297**	-1.453***	-1.328***	-1.484***
	(0.509)	(0.508)	(0.512)	(0.511)
Household size	-0.222	-0.203	-0.182	-0.159
	(0.181)	(0.182)	(0.182)	(0.182)
Log(income)	0.178**	0.194**	0.202**	0.219**
	(0.086)	(0.086)	(0.087)	(0.087)
Invest	3.563***	3.677***	3.689***	3.772***
	(0.461)	(0.462)	(0.464)	(0.464)
Self employed	0.150	0.187	0.203	0.239
	(0.828)	(0.815)	(0.839)	(0.825)
Risk aversion	-8.770***	-8.262***		
	(2.463)	(2.462)		
Tau	-0.145***	-0.139***		
	(0.032)	(0.032)		
Time pref.	-1.616*	-1.638*		
	(0.861)	(0.861)		
Riskstated			0.002	0.014
			(0.078)	(0.078)
Moneypat			-0.225***	-0.256***
			(0.070)	(0.070)
Constant	0.788	0.731	0.741	0.838
	(1.325)	(1.325)	(1.371)	(1.368)
Sigma	6.960***	6.956***	6.988***	6.973***
	(0.137)	(0.137)	(0.139)	(0.138)
R^2	0.0231	0.0223	0.0212	0.0209
Observations	2,248	2,248	2,248	2,248

Note: logwealth includes savings, investments life insurances, real estate investments minus mortgages on real estate and loans. Logwealth2 specification is computed only with savings and investments minus loans. Robust standard errors in parentheses, *** p< 0.01, ** p< 0.05, * p< 0.1.

These effects are significant at the 1% level. Impatience with money is negatively correlated with all of our dependent outcome variables. More impatient people are less likely to invest in risky assets and to have also less savings in their bank accounts.

Hence, both variables are highly correlated with actual observed behavior, they are easier to implement in large scale panels and do not have to be incentivized. It is important to note that the risk and time preference questions are both specifically for financial matters and expenditures, we also analyzed the questions in terms of the general domains and we found no relationships. Researchers in the future should keep this in mind if they are interested in this type of elicitation.

Table 9: Stated preferences

	(1)	(2)	(4)
	inv	log(inv)	log(savings)
Female	-0.185***	-3.567***	-1.757***
	(0.065)	(1.187)	(0.324)
Age category	0.130***	2.474***	0.234*
	(0.028)	(0.466)	(0.133)
Intermed voc. Educ.	0.088	0.323	0.246
	(0.101)	(1.756)	(0.450)
Higher voc. Educ	0.485***	6.680***	1.950***
	(0.093)	(1.517)	(0.432)
University	0.760***	10.846***	3.340***
	(0.123)	(1.857)	(0.584)
Risk stated	0.106***	1.476***	0.063
	(0.016)	(0.254)	(0.076)
Patience	-0.056***	-0.834***	-0.224***
	(0.016)	(0.267)	(0.070)
log(income)	0.099***	1.540***	0.289***
	(0.031)	(0.588)	(0.090)
Constant	-2.853***	-48.703***	0.538
	(0.300)	(5.613)	(1.160)
Sigma		15.503***	7.293***
		(0.407)	(0.141)
Observations	2,402	2,402	2,406

Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

6 Discussion

In this paper we analyzed the risk and time preferences of a representative sample of the Dutch population. To measure individual attitudes we proposed a joint task that can identify both preference parameters along with other behavioral measures (fechner errors and present bias). We also present results for alternative risk measures such as stated preference measure.

In terms of preferences, we find that women and older people are more risk averse and discount the future more. Higher educated and higher income individuals in turn are less risk averse and discount the future less. We observe that controlling for education, wealthier people have a lower propensity to make mistakes. We find heterogeneity in parameters specially for time preferences.

Using information on their personal finances we looked at whether our measures correlate with three outcomes: investments, savings and wealth accumulation. We find that risk aversion is negatively correlated with the probability of owning investments, and the amount invested in them.

In the case of savings, we observe that the discounting factor from our quasi-hyperbolic specification is significant in predicting the amount of money that an individual holds in their savings account. The negative coefficient implies that people who value consumption in the future less have on average also less savings. This is interesting from a policy perspective since identifying the "high discounters" can help better target savings products or investments in a more attractive way.

Next, we looked at the relationship between individual preferences and wealth. We find a negative relationship between risk aversion and wealth. Individuals with a high level of risk aversion accumulate less wealth on average. We studied this causality by exploring the effects of wealth on risk aversion and find no effect. This can be due to the fact that our structural model helps us identify preferences already taking into account their wealth.

Nevertheless, in future research we would like to study the dynamics on risk and their effect on wealth with a panel structure (we only had one observation of risk from one year in our experiment).

Finally, we compared our stated preference measures to financial decision making and found strong correlations between these them with the expected signs. People who state to be willing to take more risk are more likely to have investments in risky assets in their actual portfolio. Those who claim to be impatient spending their money are less likely to have investments and have on average less money in their savings account (controlling for their individual income).

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A Appendix

Table A.1: Details of the experimental design

Treatment	prob1a	ah	prob2a	al	EVA	prob1b	bh	prob2b	bl	EVB	EVA-EVB	Risk neutral	Mean
Treatment1	0.15	11	0.85	9	9.3	0.15	23	0.85	0	3.45	5.85	A	0.216058
	0.3	11	0.7	9	9.6	0.3	23	0.7	0	6.9	2.7	A	0.242936
	0.5	11	0.5	9	10	0.5	23	0.5	0	11.5	-1.5	B	0.436251
	0.85	11	0.15	9	10.7	0.85	23	0.15	0	19.55	-8.85	B	0.688146
	1	11	0	9	11	1	23	0	0	23	-12	B	0.869056
Treatment2	0.15	15	0.85	10	10.75	0.15	29	0.85	4	7.75	3	A	0.34011
	0.3	15	0.7	10	11.5	0.3	29	0.7	4	11.5	0	A or B	0.42419
	0.5	15	0.5	10	12.5	0.5	29	0.5	4	16.5	-4	B	0.660924
	0.85	15	0.15	10	14.25	0.85	29	0.15	4	25.25	-11	B	0.814611
	1	15	0	10	15	1	29	0	4	29	-14	B	0.900069
Treatment3	0.15	20	0.85	15	15.75	0.15	25	0.85	2	5.45	10.3	A	0.191247
	0.3	20	0.7	15	16.5	0.3	25	0.7	2	8.9	7.6	A	0.198484
	0.5	20	0.5	15	17.5	0.5	25	0.5	2	13.5	4	A	0.279462
	0.85	20	0.15	15	19.25	0.85	25	0.15	2	21.55	-2.3	B	0.50448
	1	20	0	15	20	1	25	0	2	25	-5	B	0.816678
Treatment4	0.15	12	0.85	7	7.75	0.15	22	0.85	0	3.3	4.45	A	0.198484
	0.3	12	0.7	7	8.5	0.3	22	0.7	0	6.6	1.9	A	0.230186
	0.5	12	0.5	7	9.5	0.5	22	0.5	0	11	-1.5	B	0.414197
	0.85	12	0.15	7	11.25	0.85	22	0.15	0	18.7	-7.45	B	0.660234
	1	12	0	7	12	1	22	0	0	22	-10	B	0.834252

Table A.2: Individual preferences

Covariates	(1) risk aversion	(2) tau	(3) time pref
Female	0.025***	-0.912***	0.015*
	(0.004)	(0.291)	(0.009)
Intermed Voc Ed	-0.010**	-0.697*	-0.049***
	(0.004)	(0.376)	(0.011)
Higher Voc Ed	-0.015***	-1.699***	-0.073***
	(0.005)	(0.371)	(0.010)
University	-0.010*	-2.912***	-0.071***
	(0.006)	(0.459)	(0.012)
Age	0.000**	0.062***	0.001***
	(0.000)	(0.010)	(0.000)
Income	-0.000**	-0.000	-0.000**
	(0.000)	(0.000)	(0.000)
Constant	0.047***	3.823***	0.073***
	(0.008)	(0.647)	(0.017)
N	2,682	2,682	2,682
R-squared	0.039	0.047	0.038

Robust standard errors in parentheses

$***p < 0.01, **p < 0.05, *p < 0.1$

Table A.3: Preferences

	(7)	(8)	(9)
CARA + QH	riskpost	tp3	rp3
Female	0.020***	-0.907**	0.010
	(0.006)	(0.438)	(0.013)
Intermed voc. Educ.	-0.012*	-0.968*	-0.044***
	(0.006)	(0.513)	(0.015)
Higher voc. Educ	-0.014**	-1.283**	-0.060***
	(0.007)	(0.535)	(0.016)
University	-0.013	-2.200**	-0.046*
	(0.011)	(0.857)	(0.025)
Age category	0.001	0.633***	0.012**
	(0.002)	(0.163)	(0.005)
loginc	-0.001	0.077	-0.000
	(0.001)	(0.099)	(0.003)
logwealth2	-0.000	-0.050	-0.001
	(0.000)	(0.034)	(0.001)
Numeracy	-0.002*	-0.470***	-0.007***
	(0.001)	(0.087)	(0.003)
Constant	0.078***	7.121***	0.095**
	(0.018)	(1.466)	(0.043)
Observations	1,320	1,320	1,320
R-squared	0.033	0.067	0.042

Standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.4: CARA preferences and Hyperbolic discounting

	(1)	(2)	(3)	(4)	(5)	(6)
CARA + H	riskcarah	taocarah3	rcarah3	riskcarah	taocarah3	rcarah3
Female	0.022***	-0.653***	0.008	0.023***	-0.649**	0.001
	(0.004)	(0.247)	(0.013)	(0.004)	(0.255)	(0.013)
Intermed voc. Educ.	-0.005	-1.005***	-0.025*	-0.005	-0.892***	-0.021
	(0.004)	(0.296)	(0.015)	(0.005)	(0.303)	(0.016)
Higher voc. Educ	-0.008*	-1.905***	-0.046***	-0.008	-1.697***	-0.038**
	(0.005)	(0.301)	(0.016)	(0.005)	(0.314)	(0.016)
University	-0.010	-2.632***	-0.056**	-0.011	-2.675***	-0.047**
	(0.006)	(0.428)	(0.022)	(0.007)	(0.447)	(0.023)
Age category	0.000	0.658***	0.009**	0.001	0.661***	0.011**
	(0.001)	(0.085)	(0.004)	(0.001)	(0.087)	(0.004)
loginc	-0.000	-0.021	-0.002	-0.000	-0.007	-0.004
	(0.001)	(0.057)	(0.003)	(0.001)	(0.058)	(0.003)
logwealth2	0.000	-0.059***	-0.001			
	(0.000)	(0.018)	(0.001)			
logwealth				-0.000	-0.065***	-0.001
				(0.000)	(0.019)	(0.001)
Constant	0.049***	2.804***	0.094***	0.048***	2.613***	0.097***
	(0.010)	(0.686)	(0.035)	(0.011)	(0.700)	(0.036)
Observations	2,402	2,402	2,402	2,248	2,248	2,248
R-squared	0.021	0.073	0.012	0.022	0.073	0.012

Standard errors in parentheses

$***p < 0.01, **p < 0.05, *p < 0.1$

Table A.5: CRRA preferences and Quasi-hyperbolic discounting

	(1)	(2)	(3)	(4)	(5)	(6)
CRRA + QH	riskcrraqh	taocrraqh3	rcrraqh3	riskcrraqh	taocrraqh3	rcrraqh3
Female	0.095***	-0.504	0.009	0.098***	-0.493	0.005
	(0.023)	(0.317)	(0.011)	(0.024)	(0.327)	(0.012)
Intermed voc. Educ.	-0.111***	0.321	-0.076***	-0.104***	0.435	-0.068***
	(0.028)	(0.380)	(0.014)	(0.029)	(0.389)	(0.014)
Higher voc. Educ	-0.156***	-0.422	-0.122***	-0.154***	-0.218	-0.112***
	(0.028)	(0.386)	(0.014)	(0.030)	(0.403)	(0.015)
University	-0.136***	-1.499***	-0.124***	-0.140***	-1.553***	-0.115***
	(0.040)	(0.549)	(0.020)	(0.042)	(0.574)	(0.021)
Age category	0.022***	0.549***	0.014***	0.022***	0.561***	0.015***
	(0.008)	(0.109)	(0.004)	(0.008)	(0.112)	(0.004)
loginc	-0.003	-0.029	-0.004	-0.003	-0.030	-0.004
	(0.005)	(0.073)	(0.003)	(0.005)	(0.074)	(0.003)
logwealth2	0.002	-0.067***	-0.002***			
	(0.002)	(0.024)	(0.001)			
logwealth				0.001	-0.065***	-0.002**
				(0.002)	(0.025)	(0.001)
Constant	0.283***	3.740***	0.130***	0.284***	3.550***	0.126***
	(0.064)	(0.880)	(0.032)	(0.066)	(0.899)	(0.033)
Observations	2,402	2,402	2,402	2,248	2,248	2,248
R-squared	0.036	0.023	0.064	0.036	0.024	0.059

Standard errors in parentheses

$***p < 0.01, **p < 0.05, *p < 0.1$

Table A.6: CARA preferences and Hyperbolic discounting

	(1)	(2)	(3)
CARA + H	investments1	log(savings)	log(wealth)
Female	-0.255***	-0.965***	-1.074***
	(0.074)	(0.234)	(0.330)
Age category	0.123***	-0.209**	0.701***
	(0.029)	(0.090)	(0.164)
Intermed voc. Educ.	0.043	-0.408	0.465
	(0.107)	(0.298)	(0.452)
Higher voc. Educ	0.377***	0.069	1.422***
	(0.100)	(0.289)	(0.449)
University	0.617***	0.663	2.514***
	(0.135)	(0.444)	(0.599)
Married			-1.275**
			(0.506)
Household size			-0.228
			(0.181)
loginc	0.069**	0.159***	0.185**
	(0.029)	(0.053)	(0.086)
Investments			3.541***
			(0.460)
Self employed			0.149
			(0.825)
riskcarah	-2.090***	-2.907	-9.201***
	(0.607)	(1.861)	(2.562)
taocarah3	-0.021**	-0.068***	-0.190***
	(0.009)	(0.026)	(0.037)
rcarah3	-0.333**	-1.186***	-1.658**
	(0.154)	(0.428)	(0.679)
logwealth	0.047***	0.800***	
	(0.008)	(0.035)	
Constant	-2.434***	1.165	0.816
	(0.279)	(0.735)	(1.315)
Sigma		4.717***	6.956***
		(0.173)	(0.137)
Observations	2,248	2,248	2,248

Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.7: CRRA preferences and Quasi-hyperbolic discounting

	(1)	(2)	(3)
CRRA + QH	investments1	log(savings)	log(wealth)
Female	-0.275***	-0.966***	-1.098***
	(0.073)	(0.233)	(0.327)
Age category	0.115***	-0.219**	0.684***
	(0.029)	(0.091)	(0.165)
Intermed voc. Educ.	0.045	-0.442	0.527
	(0.106)	(0.297)	(0.453)
Higher voc. Educ	0.379***	0.005	1.461***
	(0.099)	(0.289)	(0.450)
University	0.645***	0.661	2.646***
	(0.134)	(0.442)	(0.600)
Married			-1.353***
			(0.507)
Household size			-0.228
			(0.182)
loginc	0.068**	0.156***	0.177**
	(0.029)	(0.053)	(0.086)
Investments			3.646***
			(0.461)
Self employed			0.150
			(0.833)
riskcrraqh	-0.180	-0.272	-1.102**
	(0.112)	(0.330)	(0.481)
taocrraqh3	-0.005	-0.022	-0.112***
	(0.009)	(0.028)	(0.040)
rcrraqh3	-0.290	-1.954***	-2.140***
	(0.200)	(0.507)	(0.773)
logwealth	0.049***	0.800***	
	(0.008)	(0.035)	
Constant	-2.502***	1.117	0.703
	(0.281)	(0.733)	(1.338)
		4.707***	6.965***
		(0.173)	(0.138)
Observations	2,248	2,248	2,248

Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.8: Financial literacy and numeracy

	(1)	(2)
	inv	log(wealth)
Female	-0.212*	-0.858*
	(0.119)	(0.464)
Age category	0.151***	0.772***
	(0.050)	(0.232)
Intermed voc. Educ.	0.102	-0.106
	(0.155)	(0.608)
Higher voc. Educ	0.185	0.986
	(0.143)	(0.616)
University	0.599***	1.745**
	(0.206)	(0.815)
log(income)	0.027	0.126
	(0.036)	(0.117)
Risk aversion	-2.002***	-5.705*
	(0.773)	(3.157)
tau	-0.004	-0.078**
	(0.007)	(0.033)
Time pref	0.004	-0.136
	(0.031)	(0.213)
Financial literacy	0.088	0.894***
	(0.071)	(0.260)
Numeracy	0.086***	0.287**
	(0.029)	(0.111)
log(wealth)	0.077***	
	(0.016)	
Married		-1.816**
		(0.720)
Household size		0.078
		(0.238)
Investments		4.427***
		(0.550)
Self employed		0.462
		(1.103)
Constant	-3.712***	-4.518**
	(0.520)	(2.102)
Sigma		6.733***
		(0.181)
Observations	1,171	1,171

Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$