Leibniz-Institut für
Wirtschaftsforschung
Halle

Censored Fractional Response Model: Estimating Heterogeneous Relative Risk Aversion of European Households

Qizhou Xiong

August 2015 No. 11

IWH-DISKUSSIONSPAPIERE
IWH DISCUSSION PAPERS

Author: *Qizhou Xiong*
Halle Institute for Economic Research (IWH) – Member of the Leibniz Association
Department of Financial Markets
E-mail: Qizhou.Xiong@iwh-halle.de
Phone: +49 345 7753 756

Editor:
Halle Institute for Economic Research (IWH) – Member of the Leibniz Association

Address:	Kleine Maerkerstrasse 8, D-06108 Halle (Saale), Germany
Postal Address:	P.O. Box 11 03 61, D-06017 Halle (Saale), Germany
Phone:	+49 345 7753 60
Fax:	+49 345 7753 820
Internet:	www.iwh-halle.de

ISSN 1860-5303 (Print)
ISSN 2194-2188 (Online)

Censored Fractional Response Model: Estimating Heterogeneous Relative Risk Aversion of European Households*

Abstract

This paper estimates relative risk aversion using the observed shares of risky assets and characteristics of households from the Household Finance and Consumption Survey of the European Central Bank. Given that the risky share is a fractional response variable belonging to [0, 1], this paper proposes a censored fractional response estimation method using extremal quantiles to approximate the censoring thresholds. Considering that participation in risky asset markets is costly, I estimate both the heterogeneous relative risk aversion and participation cost using a working sample that includes both risky asset holders and non-risky asset holders by treating the zero risky share as the result of heterogeneous self-censoring. Estimation results show lower participation costs and higher relative risk aversion than what was previously estimated. The estimated median relative risk aversions of eight European countries range from 4.6 to 13.6. However, the results are sensitive to households' perception of the risky asset market return and volatility.

Keywords: European household finance, relative risk aversion, censored fractional response model, extremal quantile regression

JEL Classification: C21, C24, E44, G11

* I would like to thank Thierry Magnac, Pierre Dubois, Jean-Pierre Florens, Pascal Lavergne, Sylvain Chabe-Ferret, Margaret Leighton, Mattia Giroti, Laura Lasio and all the participants of Applied Microeconometrics Workshop at Toulouse School of Economics for insightful comments and advices. This research has received financial support from the European Research Council under the European Community's Seventh Framework Program FP7/2007-2013 grant agreement No. 295298. The usual disclaimer applies.

1 Introduction

Relative risk aversion is a key component in many expected utility models, such as the ones describing optimal portfolio choice and asset pricing. However the empirical evidence of relative risk aversion is not as precise as we would like. Mehra and Prescott (1985)'s presentation of "risk premium puzzle", which states that no reasonable level of relative risk aversion can justify the high risk premium within the optimal portfolio choice model, has attracted the attention of researchers for decades. The low relative risk aversion estimated in the early literature makes the risk premium irrationally high. Besides studying the financial market with friction, a more precise measurement of relative risk aversion can also help understand the risk premium puzzle. Moreover, the parameter of relative risk aversion is a prerequisite in many empirical studies such as consumption based asset pricing model and most calibration exercises of new classical macroeconomic studies. Such analysis is often sensitive to risk aversion parameter. Using a wrong level of relative risk aversion can undermine many findings of those studies. Therefore, we need empirical studies to reveal the true relative risk aversion.

There are mainly two general approaches in estimating risk aversion parameters: direct elicitation of risk preferences or revealed preferences. The direct elicitation of risk preference developed in experimental economics is often conducted in a controlled laboratory environment or field experiments. Researchers ask survey subjects or experiment participants both qualitative and quantitative questions to learn the risk attitude. For instance, Dohmen, Falk, Huffman, Sunde, Schupp, and Wagner (2011) ask the subjective the willingness of taking risks "in general" to find that gender, age, height, and parental background have a significant impact on risk preference. On the other hand, the revealed preference approach uses the observed financial decisions in survey data to estimate risk aversion. Since those financial decisions are made in daily life instead of a laboratory environment, estimated risk aversions in a revealed preference approach are more likely to capture the risk preferences households have when making similar financial decisions. Often the experimental approach predicts high relative risk aversion compared with the results from the revealed preference approach. The results of this paper bridges the gap between these two approaches.

I adopt the revealed preference approach to estimate households' relative risk aversion using data on observed household portfolios and characteristics. The data is extracted from the first wave of the Household Finance and Consumption Survey of the European Central Bank and covers various Euro zone countries. This follows the early studies by Friend and Blume (1975) and Morin and Suarez (1983), which relies on the fact that households' optimized portfolios directly reflect their risk preference. When the relative risk aversion is high, household is less willing to invest in risky assets. An estimation of the demand for risky asset allows the estimation of relative risk aversion when financial market information is considered as common knowledge. Moreover, the phenomenon of non-participation to stock market characterized in Haliassos and Bertaut (1995) cannot be explained by high relative risk aversion alone. To rationalize non-participation, researchers often assume a participation cost that makes small amount of risky investment unprofitable (Luttmer (1999), Attanasio, Banks, and Tanner (2002), and Vissing-Jørgensen (2002)). It is now typical to consider both participation cost and optimal portfolio choice when estimating the relative risk aversion using household finance survey data.

My main contribution to the literature is that I estimate both the heterogeneous relative risk aversion and heterogeneous participation cost to risky asset market. Since both participation cost and risk aversion can affect the decision of whether to participate in risky asset markets, it is impossible to identify both elements without restrictive assumptions. Most of the researches in the previous literature assume that either relative risk aversion or participation cost is homogeneous. However homogeneity in neither relative risk aversion nor participation cost is plausible based on the empirical findings. The heterogeneity in households' risky asset holdings suggests heterogeneous relative risk aversion, and non-participation by rich households can only be explained by a higher participation cost. In this paper both elements are heterogeneous, however the participation cost is assumed deterministic.

With heterogeneity in both relative risk aversion and participation cost, I consider the choice of holding no risky asset as the result of endogenous self censoring. Non-participation in risky asset markets can be the results of a high risk aversion, a high participation cost or sometimes both. Such reasoning allows us to estimate relative risk aversion using a true representative sample that comprises both risky asset holders and non holders. However, most of the previously literature focus more on the stockholders to estimate the relative risk aversion, for instance Friend and Blume (1975) and Morin and Suarez (1983) have both only used the sub-sample of stockholders for the estimation and as well as the more recent study by Vissing-Jørgensen and Attanasio (2003). The exclusion of non risky asset holders can cause a selection bias considering that non risky asset holders potentially have higher risk aversions. In other words, the previous estimation results are conditional on participation to risky asset markets and therefore are under estimated. The second contribution of this paper is to correct such selection bias.

The third contribution is that risky shares are treated as a fractional response variable belonging in [0,1], and I use a censored fractional response model as a new way of dealing with the boundary observations. The censored fractional response model is a heterogeneous censoring model with unobservable censoring thresholds. With the assumption of deterministic participation costs, this paper identifies the heterogeneous participation costs by approximating the censoring thresholds with extremal quantiles.

Based on the risk premium being 8% and risky asset volatility being 20%, my main result is that the estimated median relative risk aversions is 8.33, which is significantly higher than what was previously estimated. The median of the estimates in different countries range from 4.6 to 13.6, showing strong heterogeneity in households' risk preference across European countries. Chiappori and Paiella (2011) obtain estimates of relative risk aversion using Italian data whose median is 1.7 for stockholders only. Friend and Blume (1975) find that the relative risk aversion should be around 2. I apply these previous methods in the literature to my data and obtain that the estimated relative risk aversion is still significantly higher and exhibits more heterogeneity.

Furthermore, I also find that the median participation cost estimate is around 0.07 % of the total financial wealth. Paiella (2007) find that the average participation cost for one year ranges from 0.7 to 3.3 percent of household non-durable consumption. Attanasio and Paiella (2011) estimate that the lower bound of participation cost at 0.4 percent of non-durable consumption. The participation costs estimated in this paper is consistent with the previous findings in the literature.

This paper also investigates a number of alternative specifications, which could potentially affect the estimation of the relative risk aversion and participation costs. Robustness results show that the estimated relative risk aversion is not qualitatively affected by alternative specifications, but is very sensitive to households' perception of risky asset market return and volatility.

The rest of the paper is organized as follow. Section 2 presents the theoretical framework. Section 3 proposes the censored fractional response regression model. Section 4 describes the data. Section 5 discusses the empirical specification and estimation. Section 6 presents the results and section 7 is the robustness discussion.

2 The Model

In this section, I introduce a simple portfolio choice model within the standard framework of Merton (1969) with the addition of heterogeneous participation costs. Non-participation to the markets of risky assets is a well-known phenomenon that can be explained by the existence of a fixed participation cost as in Haliassos and Bertaut (1995), Vissing-Jørgensen and Attanasio (2003) and Paiella (2007), or be better explained along with other factors, such as Guiso, Sapienza, and Zingales (2008). Based on the previous literature, I take a step further by assuming heterogeneous participation costs, which brings more realism to the model.

2.1 Households

Consider the optimization problem of a risk-averse household, denoted by h, who lives in a two-period economy with no taxes and where all assets are liquid. Each household has an initial endowment W_{h0} at the beginning. Households have the standard borrowing constraint that they cannot invest more than their total financial wealth. At period zero, households invest their wealth and consume nothing. In period one, households gain the return of their investments and consume all wealth.

There are two types of assets in the economy – risky assets and risk-free assets. Thus households face a budget constraint as follows:

$$\mathbf{E}[W_{h1}] = W_{h0}\{1 + r_f + \alpha_h \mathbf{E}[r_m - r_f]\}, \tag{1}$$

where W_{h1} is the uncertain wealth at the end of period one; r_m and r_f are the random rate of return of the risky asset and the risk-free interest rate respectively; α_h is the fraction of wealth invested into the risky asset, which is referred to as risky share in the rest of the paper. In a stochastic financial market identical to Merton (1969), households' expected wealth change can be expressed as follows:

$$\begin{aligned} E_0[W_{h1} - W_{h0}] &= \{r_f + \alpha_h \mathbf{E}[r_m - r_f]\}W_{h0} & (2) \\ E_o[(W_{h1} - W_{h0})^2] &= W_{h0}^2 \alpha_h^2 \sigma_m^2. & (3) \end{aligned}$$

Households derive their utility through a smooth concave utility function $U(W_h)$, and they try to maximize the total expected utility with respect to budget constraint described in (2) and (3).

2.2 Participation Cost

Trading in both markets (risk-free and risky) comes with a fixed per period cost due to information collection and processing, mental costs of portfolio re-balancing, opportunity costs from the time spent in portfolio managing activities and so on. Households must participate in at least one type of financial market to smooth their inter-temporal consumption. There are the three possible choices for each household:

1. "Complete portfolio": households participate to both risky and risk-free markets – $\alpha_h \in (0, 1)$. Most of the previous literature focuses on this type of households.

2. "Risk-free only": households only participate in the risk-free market — $\alpha_h = 0$. This describes the majority of the observed households in many surveys such as "Survey of Consumer Finance" and "Consumer Expenditure Survey".

3. "Risky only": households invest their entire financial wealth into the risky asset – $\alpha_h = 1$. Such behavior can only be explained by very low risk aversion and high participation costs to both markets. This type of household is not often observed in any survey data.

Normalize the participation cost to both risky asset markets and risk-free asset market to zero. Define the participation cost incurred when the household participates in the risk-free market only, rather than both markets, as $-\delta_h^s$, and the participation cost incurred when the household participates in the risky asset market only, rather than both markets, as $-\delta_h^b$. The negative participation costs in such normalization can be understood as the benefit of simplifying the investment tasks. It is also very unlikely that households would choose only between "Risk-free only" and "Risky only". This would imply that households do not have stable risk preference at all. We can consider the three possible investment choices as ordered discrete choices with respect to optimal risky shares.

2.3 Utility Optimization

Households maximize their utility with respect to the risky shares. The decision making process of each household is as follows: first, consider the optimal risk share of the household wealth under all three choices[2]; second, weigh the total expected utility

[2]The optimal risky share is automatically given under the choice "risk-free only" and "risky only".

of the choices; and finally, choose the investment choice that returns the highest total expected utility. As choices are ordered with respect to risky shares, the comparison between choice "risk-free only" and "risky only" is captured by the other two comparisons. For instance, when a household prefers "risk-free" to "complete portfolio", the choice "risky only" is greatly dominated by the other two choices. There is no need to consider the choice switching between "risk-free only" and "risky only".

Since the choice "risky only" is seldom observed, this paper focuses on the comparison between choice "risk-free only" and "complete portfolio". Households with "complete portfolio" maximize $\mathbf{E}[U(W_{h1})]$ with respect to α_h, and with the budget constraint of

$$\mathbf{E}[W_{h1}] = W_{h0}\{1 + r_f + \alpha_h \mathbf{E}[r_m - r_f]\}. \tag{4}$$

Taking the Taylor series expansion of $U(W_{h1})$ around W_{h0} and keeping the first two terms, the expected utility becomes:

$$\mathbf{E}[U(W_{h1})] = U(W_{h0}) + U^{'}(W_{h0})E_0[W_{h1} - W_{h0}] + \frac{1}{2}U^{''}(W_{h0})E_o[(W_{h1} - W_{h0})^2].$$

Using the results of equation (2) and (3) to replace the expected return and volatility,

$$\mathbf{E}[U(W_{h1})] = U(W_{h0}) + U^{'}(W_{h0})W_{h0}\{r_f + \alpha_h \mathbf{E}[r_m - r_f]\} + \frac{1}{2}U^{''}(W_{h0})W_{h0}^2\alpha_h^2\sigma_m^2. \tag{5}$$

At the optimal choice of the risky share α_h^*, expected utility is maximized and the first order derivative of $\mathbf{E}(U(W_{h1}))$ is equal to zero. Taking the derivative of equation (5) with respect to α_h gives us :

$$\begin{aligned} U^{'}(W_{h0})W_{h0}\mathbf{E}[r_m - r_f] + U^{''}(W_{h0})W_{h0}^2\alpha_h^*\sigma_m^2 &= 0, \\ \alpha_h^* &= -\frac{U^{'}(W_{h0})}{U^{''}(W_{h0})W_{h0}} \cdot \frac{\mathbf{E}[r_m - r_f]}{\sigma_m^2}, \\ \alpha_h^* &= \frac{1}{\gamma_h} \cdot \frac{\mathbf{E}[r_m - r_f]}{\sigma_m^2} \end{aligned} \tag{6}$$

where γ_h is the Arrow-Pratt measure of relative risk aversion, and the borrowing constraint imposes the binding constraint that $\alpha_h^* \in [0,1]$. Equation (6) is as derived by Friend and Blume (1975) and Chiappori and Paiella (2011). The value of choosing "complete portfolio" is

$$\begin{aligned}\mathbf{V}_s(W_{ho}) &= U(W_{h0}) + U^{'}(W_{h0})W_{h0}\{r_f + \alpha_h^*\mathbf{E}[r_m - r_f]\} \\ &+\frac{1}{2}U^{''}(W_{h0})W_{h0}^2\alpha_h^{*2}\sigma_m^2. \end{aligned} \tag{7}$$

If household chooses the portfolio "risk-free only", the total expected utility is:

$$\mathbf{V}_0(W_{h0}) = U(W_{h0}) + U^{'}(W_{h0})W_{h0}[r_f - (-\delta_h^s)] \tag{8}$$

Therefore, the utility difference between "complete portfolio" and "risk-free only" is:

$$V_s - V_0 = U^{'}(W_{h0})W_{h0}\{\alpha_h^*\mathbf{E}[r_m - r_f] - \delta_h^s + \frac{1}{2}\frac{U^{''}(W_{h0})}{U'(W_{h0})}W_{h0}\alpha_h^{*2}\sigma_m^2\}$$

Replacing α_h^{*2} with $-\alpha_h^* \cdot \frac{U^{'}(W_{h0})}{U^{''}(W_{h0})W_{h0}} \cdot \frac{\mathbf{E}[r_m - r_f]}{\sigma_m^2}$ from equation (6) makes

$$\begin{aligned}V_s - V_0 &= U^{'}(W_{h0})W_{h0}\{\alpha_h^*\mathbf{E}[r_m - r_f] - \delta_h^s - \frac{1}{2}\gamma_h\frac{1}{\gamma_h}\frac{\mathbf{E}[r_m - r_f]}{\sigma_m^2}\alpha_h^*\sigma_m^2\} \\ &= U^{'}(W_{h0})W_{h0}\{\alpha_h^*\mathbf{E}[r_m - r_f] - \frac{1}{2}\mathbf{E}[r_m - r_f]\alpha_h^* - \delta_h^s\} \\ &= U^{'}(W_{h0})W_{h0}\{\frac{1}{2}\mathbf{E}[r_m - r_f]\alpha_h^* - \delta_h^s\} \end{aligned} \tag{9}$$

Notice that $U^{'}(W_{h0})$ and W_{h0} are all positive. Therefore households choose the "complete portfolio" when $\frac{1}{2}\mathbf{E}[r_m - r_f]\alpha_h^* - \delta_h^s \geq 0$, and choose "risk-free only" otherwise. Similarly, we can conduct the same analysis with the tradeoff between "complete portfolio" and "risky only", which would lead us to the condition that only when $\mathbf{E}[r_m - r_f](\alpha_h^*/2 + \frac{1}{2\alpha_h^*} - 1) - \delta_h^b \geq 0$, households choose the "complete portfolio" over "risky only". [3]

[3] More details on this result are in the appendix.

3 Censored Fractional Response Model

Households' decisions can be described in model M as follows:

$$\alpha_h = \begin{cases} 0, & if \quad \alpha_h^* \in (0, L(X)) \\ \alpha_h^*, & if \quad \alpha_h^* \in [L(X), H(X)] \\ 1, & if \quad \alpha_h^* \in (H(X), 1). \end{cases} \tag{M}$$

where $L(X) \equiv 2\delta_h^s/\mathbf{E}[r_m - r_f]$ and $H(X) \equiv (\frac{\delta_h^b}{\mathbf{E}[r_m-r_f]} + 1) - \sqrt{(\frac{\delta_h^b}{\mathbf{E}[r_m-r_f]})^2 + \frac{2\delta_h^b}{\mathbf{E}[r_m-r_f]}}$.

Assume all public information is homogeneously received by all households. Thus $\mathbf{E}[r_m - r_f]$ and σ_m^2 should be the same for all households. The only source of heterogeneity in risk shares comes from relative risk aversion γ_h. I parametrize the optimal risky share defined in equation (6) as:

$$\alpha_h^* = G(X_h\theta_M + u_h) \tag{10}$$

Where X_h are co-variates that can affect the relative risk aversion and u_h is a random component. Assume that u_h is normally distributed for the simplicity, which will be later relaxed in the robustness discussion. For further extension of such work, we can drop the distributional assumption on the error terms and fully adopt a non-parametric approach since the extremal quantile regression do now require any function form of unobservable heterogeneity. $G()$ is logistic transformation function which ensures that $\alpha_h^* \in (0, 1)$. Once we estimate θ, we will be able to recover the deterministic part of risk aversion using:

$$\hat{\gamma}_h = \frac{\mathbf{E}(r_m - r_f)}{\sigma_m^2} \frac{1}{\mathbf{E}[G(X\hat{\theta_M} + u_h)]}. \tag{11}$$

Moreover, I also parametrize the censoring thresholds as:

$$L(X) = G(X_h\theta_L) \quad \& \quad H(X) = G(X_h\theta_H), \tag{12}$$

so that $L(X)$ and $H(X)$ satisfy $0 < L(z) < 1$ and $0 < H(z) < 1$ for all $z \in \mathbf{R}$. Notice that I assume there is no unobserved heterogeneity in censoring thresholds, which is the key of identifying both heterogeneous relative risk aversion and participation costs. Once the censoring threshold functions are estimated, we can estimate the participation costs based on the participation conditions in the previous section.

3.1 The Advantage of Model M

Consider the model M and assume that we observe a random independent sample $\{(X_i, \alpha_i) : i = 1, 2, ..., N\}$, in which α is the fractional response variable of interest, $\alpha \in [0, 1]$, and X are independent co-variates with dimension of k. Let θ be the vector of parameters to be estimated. Let α^* be a latent variable as described in model (M). Given such a construction, the model M can be described as a Censored Fractional Response Model with the special feature of a fractional dependent variable variable and heterogeneous censoring.

In the fractional variables literature, there are two key features which require special treatment: the boundedness of the variable and the observations on the boundaries. To deal with the boundedness of fractional response variables, this paper adopts the additive log-ratio transformation to ensure that the response variable is bounded in $(0, 1)$. Such an approach overcomes the mismatch between the support of the dependent variable and the support of the error term, an obvious drawback in a simple OLS regression. Moreover, this also ensures that the conditional expectation function is nonlinear since it maps onto a bounded interval; and its variance will approach zero as the mean approaches either boundary. The parametric specification of α^* allows for the precise definition of censoring probability.[4]

For some data where the number of boundary observations is too sizable to be

[4] Papke and Wooldridge (1996) propose a quasi parametric approach in which$\mathbf{E}[\alpha|X] = G(X\theta)$, where $G(\cdot)$ is a know function satisfying $0 < G(z) < 1$ for all $z \in \mathbf{R}$. $G(\cdot)$ have two popular choices – the logistic function and the standard normal cumulative distribution function. There is no assumption on the distribution of error term. On the other hand, Paolino (2001) and Ferrari and Cribari-Neto (2004) propose beta regression models for fractional response variables, which is fully parametric and easy to estimate with maximum likelihood. This paper uses the log-ratio transformation for its baseline analysis, which already offers good estimation results accordingKieschnick and McCullough (2003).

ignored, Hoff (2007), Cook, Kieschnick, and McCullough (2008) and Ospina and Ferrari (2012) introduce two-part models that treat boundary observations as discrete choices resulting from positive probability masses at boundaries. Two-part models require the very strong underlying economic assumption that the decision is made in two separate steps. In the context of risky asset invest, it is less convincing that household blindly decide whether to invest in stocks and then decide how much to invest. The decision of participating risky asset markets depends on the benefit one can gain from investing in risky assets, which is determined by the optimal risky share of the household. Therefore one cannot decide whether it is worth to invest in risky asset market without knowing his optimal risky share. The assumption of a two-part model reverses the decision making process, while the censored fractional response model is consistent with the economic reasoning of the investment decision.

Fagereng, Gottlieb, and Guiso (2013) uses another type of two-step model, which incorporates a simple Heckman selection bias correction to model the participation decision. However Heckman selection requires an exclusion restriction to generate credible estimates: there must exist at least one variable which appears with a non-zero coefficient in the selection equation but does not appear in the equation of interest. It is difficult to find such a variable that only affects the participation cost but has no effect on risk aversion.

The censored fractional response model is the natural result of a structural model without any exogenous assumption on individual behaviors except for the existence of a participation cost, in which all unobserved heterogeneity is excluded. This assumption is necessary for the identification of the model, and also assigns all the heterogeneity in risky shares to the relative risk aversion. The censored fractional response model allows the decision to be governed by only one random shocks, which is the random risk preference shock that affects their optimal fractional response. While the usual two-step models assume that risky share is governed by two separated random shocks.

3.2 Identification and Parametric Estimation

There are two parameters to identify in (M) — θ_L and θ_H affect the censoring functions and θ_M affects the risky share. All three are parameters of interest in this paper. For notational convenience, I introduce three indicator random variables $I_M = \mathbf{1}\{\alpha^* \in [L(X), H(X)]\}$, $I_L = \mathbf{1}\{\alpha^* \in (1, L(X))\}$, and $I_H = \mathbf{1}\{\alpha^* \in [H(X), 1)\}$. Using the independence assumption between covariates and errors and the assumption of continuously differentiable $G(\cdot)$, Altonji, Ichimura, and Otsu (2012) prove that θ_M and θ_L and θ_H in censoring functions are identified. This paper imposes a restriction on the choice of function $G(\cdot)$, which states that it should be confined within (0,1). The key assumption for identification is that $G(\cdot)$ is continuously differentiable almost surely. The logistic function $G(\cdot)$ fits this assumption and thus the identification holds.

Denote censoring probabilities $P_M(x) = \mathbf{Pr}\{I_M(X) = 1|X = x\}$,$P_L(x) = \mathbf{Pr}\{I_L(X) = 1|X = x\}$ and $P_H(x) = \mathbf{Pr}\{I_H(X) = 1|X = x\}$. $P_L(x) + P_M(x) + P_H(x) = 1$. The functional forms of censoring probabilities are derived from the distribution of risk preference shocks and expected risky shares. The censoring probability is well defined under the baseline specification with the normal assumption on the random shocks. However, it is also possible to use the empirical distribution of random shocks to derive the censoring probability as well. Then the estimation of the model becomes semi-parametric.

As suggested by Altonji et al. (2012), we can first estimate θ_L and θ_H by extreme quantile regressions:[5]

$$\hat{\theta}_L = arg \min_{\theta_L \in \Theta_L} \sum_{i=1}^{n} \rho_{\tau_n}(\alpha_i - L(X_i;\theta_L)) I_M(X_i, X_i) \quad for \quad \tau_n \to 0, \tag{13}$$

$$\hat{\theta}_H = arg \min_{\theta_H \in \Theta_H} \sum_{i=1}^{n} \rho_{\tau_n}(\alpha_i - H(X_i;\theta_H)) I_M(X_i, X_i) \quad for \quad \tau_n \to 1, \tag{14}$$

where function $\rho_\tau(v) = (\tau - \mathbf{1}(v \leq 0))v$. The properties of extreme quantile estimates are based on the asymptotic theory of extremal quantiles developed by Chernozhukov (2005).

The intuition of using extremal quantiles to approximate the censoring thresholds is as follows. According to the participation condition $\frac{1}{2}\mathbf{E}[r_m - r_f]\alpha_h^* - \delta_h^s \geq 0$, when participation cost is the same for every household, there exists a cut off threshold of risky shares below which should have no observation. Then the lowest positive observation is the estimate of such a cut off thresholds. However this is not exactly the true cut off threshold. It is only certain that the true cut off threshold is below the estimate. Consider the sparse observations at the tail, it is not likely that we can have a very precise approximation of the threshold with the limited sample size. Thus, I use the extremal quantile estimation to have a more precise approximation that is sufficiently close to the cut off threshold. Since the extremal quantile regression uses a simulation base estimation using the sub-sample re-sampling technique to have unbiased estimation of the extreme quantiles. Moreover, when the sample size is sufficiently large, we can push the extreme quantile to zero, which is exactly the minimum. Figure 1 demonstrates the intuition of approximation of extreme quantile. Adding heterogeneity to the participation cost, the extremal quantile estimation becomes the extremal quantile

[5] This method circumvents the difficulty of directly estimating the observable censoring thresholds. Instead, it approximates the thresholds with the extreme quantiles at both ends. However, with the normality assumption for the baseline specification, extremal quantile regression is not the only approach that we can obtain estimation of the model. As long as we have non-linear functional form of cumulative distribution function, we can estimate all the parameters of the model using maximum likelihood. Then this approach is close to a control function approach in a simple sample selection problem. This paper insists on using extremal quantile regression for its flexibility and applicability in different empirical specifications.

regression with a set of controls. I assume that with enough controls in the extremal quantile regression, the unobserved heterogeneity can be ignored. [6]

After this stage, we can estimate θ_M by maximizing the following criterion function:

$$\begin{aligned}\ell(\theta_M; X_i, \alpha_i) &= \sum_{i=1}^{N}\{I_L(X_i) logP_L(X_i; \hat{\theta}_L, \hat{\theta}_H, \theta_M) \\ &\quad + I_M(X_i) logP_M(X_i; \hat{\theta}_L, \hat{\theta}_H, \theta_M) \\ &\quad + I_H(X_i) logP_H(X_i; \hat{\theta}_L, \hat{\theta}_H, \theta_M)\} \\ &\quad - \sum_{i=1}^{N}(\alpha_i - G(X_i\theta_M))^2 I_M(X_i). \end{aligned} \tag{15}$$

Estimating using such criterion function require one important assumption, which is that the distribution of the error terms beyond the censoring points follows the same pattern of the observed part. Then the standard asymptotic theory on extremum estimators apply in this case (Newey and McFadden (1994)). The asymptotic distribution of θ_M is equivalent to a standard extremum estimator with θ_L and θ_H known. Combining with the asymptotics of extremal quantile regression, we have asymptotic normality for all the parameters: $\hat{\theta} = (\hat{\theta}_L, \hat{\theta}_H, \hat{\theta}_M)$.

4 Data

The main empirical source of this paper is the European Central Bank's Household Finance and Consumption Survey (HFCS). HFCS is a decentralized cross sectional survey of the Eurosystem whereby participating nations conduct parallel micro-level data on households' finances and consumptions. For the purpose of this paper, I mostly focus on the financial portion of the survey. The first wave of HFCS was pushed

[6]Another issue that justifies the approximation of extreme quantile. Even Household Finance and Consumption Survey is carefully executed, there are still a significant amount of confusing observations, such as the ones holding 20 euros in all types of risky financial assets when one's total financial wealth is well above 5000 euros. Those observations cannot be deem rational simply consider the existence of transaction fee. Thus some necessary data cleaning is need to such observations. In this paper, households who have less than 100 euros in risky assets are considered to be measurement errors. Therefore the minimum of risky shares is partly arbitrary.

forward in 2013, collected between the years 2008 and 2010. During this time, the global financial crisis was in effect and Europe was experiencing the euro zone crisis. These crises may have induced a higher level of risk aversion due to the bad experience and negative information surrounding the financial markets.

I use data from the following 8 European countries: Austria, Belgium, Finland, France, Germany, Italy, Netherlands, Spain. These are countries with relatively large sample sizes, especially France, Finland and Italy.[7] Most of these countries are also the major economies in euro zone, which have similar per capita GDP and similar financial development. The original survey data contains 15 countries in the first wave of HFCS. This paper does not consider the rest of the countries for the following reasons. First, the sample sizes vary throughout the different countries, for instance in Malta, they only collect 843 observations. I exclude the countries with too small a sample size. Second, the development of financial institutions differs greatly across countries. For example, the eastern European countries, Slovakia and Slovenia have a relatively low financial development index according to the financial development reports of the World Economic Forum. [8] Third, a few countries were experiencing severe financial turmoil during the sampling period, such as Greece and Portugal. This may have caused irregular financial behaviors by household, which prevents recovering households' true risk attitude.

The HFCS consists of three main parts: household level information, household member information and personal information. The household level part is composed of questions referring to the household as a whole. There is a main respondent for every household answering all the survey questions. The household-level questions cover households' real assets and their financing, liabilities and credit constraints, private businesses and financial assets, inter-generational transfers and gifts and consumption/savings. The other two parts are targeted to individual household members. [9].

[7]A quick look at the survey sample size overview can be found in this link: http://qizhouxiong.weebly.com/hfcs-data-presentation.html

[8]see their website: http://www.weforum.org/world-economic-forum

[9]Basic demographic information is collected for all household members, and personal questionnaire

Questions to individuals cover the following areas: employment, future pension entitlements and labor-related income (other income sources being covered at the household level).

The demographics and personal information of household members, especially the main respondent, can also be influential in the financial decisions of a household. This paper uses the key personal information of the main respondent, such as marital status, employment status and working hours. Moreover, the survey also provides personal information on other households members, such as age, gender, working status and education. These types of covariates may also have an impact on the household level investment decision. To account for these effects of these variables, however, we must model the family decision making dynamics. To focus on the assumption that households are the economic decision making units, this paper does not include these variables for the moment .

In addition to the original data from the questionnaire, HFCS also provides some of the derived key variables, such as total net wealth, total assets, total financial wealth, value of household's main residence and etc. Sophisticated imputation techniques have been applied to the survey so that incomplete observations do not have to be discarded. This paper takes as granted the imputation and derivation of the survey, and builds on the analysis based on the data provided by HFCS.

4.1 Summary Statistics

This section presents the summary statistics of the key variables that the estimation uses. Descriptive statistics are provided at both pooled and country levels. In the censored fractional response model developed above, households are able to adjust their portfolios freely and quickly. Thus, in investment decision making only the non-tangible financial assets is considered as households' wealth, which is a similar concept to the "cash on hand" in Cocco et al. (2005). Housing generally a large portion of households' wealth, but often lacks liquidity. Households cannot easily adjust the amount of real

is answered by every household member over 16 estate assets they want to hold, and they only liquidate their real estate when very big negative income shocks occur. Moreover, it is unlikely that households borrow against their real estate to invest in financial markets so that they can gain additional return for the total wealth they own.

The HFCS categorize the financial assets into seven types: deposits, mutual funds, bonds, stocks, money owed to household, private pension and life insurance, and other assets. This paper uses the definition of risky assets from Brunnermeier and Nagel (2008) to categorize the following assets as risky: mutual funds, publicly traded stock, private business investment, managed accounts, money owed to households and others. Other financial assets such as bonds, deposits, pension and insurance investment are considered to be risk-free assets. For the baseline specification, I consider the bond as a risk-free asset for the majority of bond investment is in state or government bonds. The sum of those types of assets divided by total financial assets gives us the risky shares.

4.1.1 Explanatory Variables

Table (1) reports the descriptive statistics about the dependent variable — risky share and the explanatory variables. The summary statistics are from the pooled data of eight euro zone countries. 66.1% of the households do not hold any risky assets, and 0.2% households only invest in risky assets. Among those who have complete portfolios, the average risky share is 0.364 and the median is 0.286.

European households do not invest much into financial market compared with their total wealth and total income. For instance, the median financial wealth of households is lower than the median total income. For richer households, investments in financial markets become relatively larger. Education is categorized into four educational levels: primary, secondary, post secondary and tertiary. The majority of respondents have post secondary education or more. The ownership of the main residence is quite high in the HFCS: 72% of the households own or partly own the residence (households purchasing their residence using mortgage are also considered to be house owners); and 34% of the main respondents of households are retired. This pooled statistics have a surprising low level of public pensioners for European standard. This is probably mostly due to the fact that all pension variables are missing for the data from Finland, that comprises a big percentage of the total observations. Finally, the ownership of other property is 36%, which is higher than the ownership of risky assets.

4.1.2 Financial Variables

Households with different demographic or personal status make different financial decisions as seen in Table (3) and Table (4). First of all, the total net wealth is one of the most important and interesting elements in the discussion about risky attitudes, starting from the early works of Morin and Suarez (1983) and Cohn, Lewellen, Lease, and Schlarbaum (1975) to the more recent works by Brunnermeier and Nagel (2008) and Chiappori and Paiella (2011). The relationship between wealth and risk aversion offers insights into the true risk preference with respect to wealth. More recently, studies using panel data note that a constant relative risk aversion maybe the right description as they find that the change of wealth does not seem to affect the risk attitude. However, cross sectional study often finds the opposite effect. From the first part of Table (3) and (4), it is obvious that rich households are more active in financial market, with higher participation rates and higher shares in risky assets such as mutual funds and stocks, especially in the top 20% income households. Moreover, rich households also have higher shares of their total financial wealth into risky assets such as mutual funds, bonds and stocks. This may imply decreasing relative risk aversion as well as more guided and/or sophisticated investing. Such a pattern is consistent with most of the empirical findings in the literature of household finance.

The life-cycle of portfolio choices is another important issue in household finance. People have a finite horizon in working and biological lives and adjust their portfolios as they age. Empirical evidence on the life-cycle of portfolio choice can be found in applied micro-econometric studies and macroeconomic calibration works such as Cocco et al. (2005), Fagereng et al. (2013) and Gomes and Michaelides (2005). In the second part of the tables, we can see that participation to all types of financial markets steadily increases until retirement and starts to fall afterward. Such a finding consistent with both previous findings and the theoretical explanation that households start to deplete their financial wealth when they no longer have labor income. As people age, they tend to invest relatively more shares of their financial wealth in risky assets and much less in pension and life insurance. The composition of financial assets tilts towards mutual funds, bonds and stocks. It is easy to understand that after retirement, the sources of income are mainly in financial assets and pensions. This may be why retired individuals have higher shares of investment in risky assets than working individuals.

Housing is a major background risks, as discussed in Heaton and Lucas (2000); this has a significant impact on household portfolio choices. Homeowners, with or without mortgage, are more confident and more willing to invest in financial assets. Among homeowners, households with a housing mortgage tend to hold fewer shares in risky assets but more in pensions, and behave more like renters. But this may also be attributed to the fact that outright homeowners are usually much wealthier than those with standing mortgages. Employment status makes a difference in the participation rate of financial assets in that both employees and self employed individuals have significantly higher participation rates compared to retirees and unemployed individuals. However employment does not make a significant difference in portfolio choices. A temporary employment status shock should not affect a person's general risk preference. Finally, education plays an important role in financial behavior, especially regarding the investment in mutual funds and stocks. Participation rate doubles at each level of education. People with college education are four times more likely to participate the mutual funds and stocks. Higher education also leads households to invest more shares of their total financial wealth to risky assets.

Apart from the demographic differences, the first wave of HFCS also shows significant country differences. Table (2) presents the country profiles on the seven financial categorizes, which consists the median real values[10], the shares of financial assets and

[10]Note that the median value for all the categorizes do not add up to total. That is due to the fact

participation rate to financial assets. For the total financial portfolio sizes, those selected countries differ greatly. The Netherlands and Belgium invest more in financial market, while households in Spain, Finland and France do not invest as much. The difference in income cannot account for all the difference in the amount of investment across countries as most of the selected countries have similar GDP per capita. Households in different countries have different preferences across financial assets as well. Bonds are considered to be unattractive in most countries, and this is reflected in both participation rates and investment shares. Yet interestingly, bonds are quite popular in Belgium and Italy. As for private pension and whole life insurance, households in France, Germany and Netherlands are much more enthusiastic than in other countries. Finland's stock market participation stands out from the rest with a participation rate as high as 22.2%. Different investment behaviors at the country level implies that there might be country specific features affecting households' investment decisions, such as the cultural difference, the financial institution or legal system difference. For instance, countries with a better protection of renters usually have lower ownership of residence. I conduct both the pooled estimation with country fixed effects and a country level estimation in attempt to capture different household finance behaviors. However, this paper will not focus on understanding the country difference.

5 Empirical Specification

This section discusses the empirical details of the two step estimation of censored fractional response model.

5.1 Extremal Quantile Regression

The estimation of the model starts with the extreme quantiles of the observed risky shares in the open interval $(0, 1)$. As only the observations with risky shares belonging to (0,1) enter this stage of estimation, applying the log-ratio transformation to the

that the conditional median value is computed separately in each category. In other words, conditional on participation means participation to that very financial asset, not all the financial assets.

observed real risky share α_h^* simplifies the conditional extremal quantile regression to:

$$Q_{G^{-1}(\alpha^*)}(\tau|Z) = Z'\theta_L(\tau) \quad \& \quad Q_{G^{-1}(\alpha^*)}(1-\tau|Z) = Z'\theta_H(1-\tau). \tag{16}$$

The conditional extremal quantile estimators are:

$$\hat{\theta}_L = arg \min_{\theta_L \in \Theta_L} \sum_{i=1}^{n} \rho_\tau(G^{-1}(\alpha_i) - Z_i\theta_L))I_M(X_i, Z_i) \tag{17}$$

$$\hat{\theta}_H = arg \min_{\theta_H \in \Theta_H} \sum_{i=1}^{n} \rho_{(1-\tau)}(G^{-1}(\alpha_i) - Z_i\theta_H)I_M(X_i, Z_i). \tag{18}$$

This estimation follows closely the method proposed by Chernozhukov and Fernández-Val (2011). Set the extreme quantile at $\tau = 0.05$. The rules of thumb in deciding whether to use extreme quantile regression is that $\tau N/50 \leq 15 - 20$. The sample size for the pooled extremal quantile regression is 16415, which still fits the rules of thumbs with a $\tau = 0.05$. Therefore this also fits the rule of thumb for all the country level extremal quantile regression. However, the rule of thumb only specifies the upper bound for using extremal quantile regression. If τ is too large, it defeats its purpose of approximating the censoring thresholds. If τ is too small, the observations below the quantile would be very limited, which biases the estimation. Moreover, given the average financial wealth in the data is around fifteen thousand euros, if one invests less than 5% of the financial wealth in risky assets, he will have nearly 750 euros. If such households invest in a asset with risk premium rate of return and 100 % certainty of return, he would only earn around 50 euros, which is barely enough to cover the basic transaction costs and account management costs. Applying similar logic, Chiappori and Paiella (2011) delete all the observation with less than 3.5 % of financial wealth in risky assets.

The conditional extremal quantile regression uses the subsampling method to obtain the unbiased asymptotic statistics. The estimation sets the sub-sample size to be 30% of the total sample for each resampling. The asymptotic distribution of the parameters are derived from resampling 199 times. [11]

Given the definition of participation cost in the model, the baseline specification incorporates five variables to explain the participation costs of the households: Age, gender and education, labor status, and total household income. The participation cost to financial markets mainly comes from two channels: the learning cost and the opportunity cost.

Age, gender and education may be able to capture the learning cost for households. Age is an important indication of how strong the learning ability of an investor. On one hand, the younger investors are more used to modern technology, which allows them to learn the rules and process the information more quickly; on the other hand, the older investors have more experience and connection, that potentially allows them to get the information and deal with the investment tasks more efficiently. Education is another obvious variable that can affect the participation cost. Education indicates people's cognitive ability and learning ability, for instance, people with higher education should have relatively lower learning cost to understand financial markets.

The labor status and total income of the households are indicative of the opportunity cost the households face. The labor status in this study is a dummy variable indicating whether he/she is a wage earner. The employed may be too busy for the trouble of trading in financial market which leads to a higher opportunity cost for participating the risky asset markets. Meanwhile, employed people may have more exposure to financial market information that encourages them to invest. For instance, many employees hold stocks of their own companies. This implies that people obtain inside information of their own companies or closely related companies.

5.2 Censored Fractional Response Regression

Once θ_L and θ_H are estimated by extremal quantile regressions, it only requires specification of the censoring probabilities to run the maximization of the criterion function

[11] I chose this low number for the sake of reducing computation burden. Higher number of simulation will be carried out in the robustness check.

in equation (15). The censoring probabilities P_M, P_L and P_H take the functional form as follows:

$$\begin{aligned} P_L(X,Z) &= Pr\{G(X_h\theta_M + u_h) \leq G(Z_h\hat{\theta}_L)|\hat{\theta}\} = \Phi_{(o,\sigma^2)}(Z_h\hat{\theta}_L - X_h\theta_M) \\ P_H(X,Z) &= Pr\{G(X_h\theta_M + u_h) \geq G(Z_h\hat{\theta}_H)|\hat{\theta}\} = \Phi_{(0,\sigma^2)}(Z_h\hat{\theta}_H - X_h\theta_M) \quad (19) \\ P_M(X,Z) &= 1 - P_L(X,Z) - P_H(X,Z) \end{aligned}$$

where $\Phi_{(0,\sigma^2)}(\cdot)$ is the normal cumulative distribution function centers at zero with a standard deviation of σ. σ will be simultaneously estimated with the rest of parameters.

The selection of explanatory variables is based on the previous findings in the literature. The financial wealth or the total wealth of the households is always the key determinant of risk preference. A positive correlation between risky shares and wealth implies increasing relative risk aversion, and a negative correlation suggests decreasing relative risk aversion. If the correlation is not significant, constant relative risk aversion is the more likely implication. The early work of Morin and Suarez (1983) includes age and wealth as the two main determinants of demand for risky assets. In a more recent work, Brunnermeier and Nagel (2008) investigates whether liquid wealth changes would induce a change of the demand for risky assets.

It is well documented in the literature that demographic characteristics of households have a systematic impact on risk preference. Barsky, Juster, Kimball, and Shapiro (1997) show that age and gender partially explain the heterogeneity in risk attitude. Education is also one of the potential determinants of risk aversion. However, the previous literature does not reach a consensus about the impact of education on risk preference. Chiappori and Paiella (2011) shows that education have positive impact on risk taking behavior and Christiansen, Joensen, and Rangvid (2008) find out that economists are more likely to own stocks indicating that better educated people may have lower risk aversion. But Calvet and Sodini (2013) find that general level of education does not influence risk preferences in a study of the twins' financial behavior using the Swedish tax registry data. Moreover, Love (2010) studies the effect of marital status and children and finds that a larger family with children might take less financial risks.

Background risk is a well known economic environmental factor that may affect risk preference. It is the risk that cannot be avoided by trade nor insurance, such as human capital, housing wealth, and private business. For instance Cocco, Gomes, and Maenhout (2005) investigate the effect of human capital on risk aversion, and Campbell (2006) mentions that housing might be the largest background risk. Moreover, Heaton and Lucas (2000) discusses private business investment as the background risk to explain the reluctance of investing in risky financial assets. Another interesting question that can be answered by this analysis is whether pension is a complement or a substitute to financial assets. The estimation therefore includes personal pension status.

6 Results

The baseline specification assumes that all the explanatory variables affect households the same way in all eight different countries, and the country difference is captured only by the country dummies. I also suppress the constant in $X_h\theta_M$. It is worth stressing that some extreme sample observations are screened out in the data. There are observations which record extreme low level of risky asset holding that cannot be justified under the rationality assumption. For instance, some household hold less than 100 euros in total as their risky shares. Even their risky asset portfolio has the rate of return of 15% with 100% certainty, it is still not enough to cover the base transaction costs in trading the assets. Therefore, I consider those risky shares as measurement errors, and consider them to have zero risky shares as well.

6.1 The Unbiased Relative Risk Aversion

The censored fractional response model estimates the expected demand for risky shares, which leads us to the estimation of relative risk aversion using the equivalence in equation (11). The last part of Table (5) presents the estimates of relative risk aversion in the Euro zone. The average relative risk aversion is 8.82 and the median is 8.33. Estimates are significantly higher than the previous results in the literature. For example, Chiappori and Paiella (2011) state that the average relative risk aversion for Italian population should be 4.2 (2.5 if you do not account for the households who hold less than 6% of risky share). Attanasio and Paiella (2011) estimate relative risk aversion using US Consumption Expenditure Survey and find that the average relative risk aversion is 1.7. Finally, Friend and Blume (1975), the first paper that estimates relative risk aversion, find that the relative risk aversion should be around 2. Most importantly, large amount of Macroeconomic studies consider the relative risk aversion to be between 2 and 4. Given that most of the calibration results are sensitive to risk aversion parameters, such a large dispersion between my results and convention level could undermine many macroeconomic calibration results.

To make sure that the difference in the estimated relative risk aversion is not just because of the different data, I apply the methods used in the previous literature to the HFCS data. The three studies are included: Friend and Blume (1975), Morin and Suarez (1983) and Chiappori and Paiella (2011). The lower parts of table (6) reports the results estimated by those methods. Figure (2), (3) and (4) compare the four estimates in three different ways. We can see that the estimates of this paper is higher on average than the other three, which implies that by ignoring the households who do not invest in risky assets, the relative risk aversion might have been under estimated. This also implies that the risky asset holders have lower relative risk aversion on average. The t-test of two subgroups – the households with and without risky asset, proves that these two subgroups have different means. The inclusion of the households who do not hold risky assets also allows the estimation to capture more heterogeneity in relative risk aversion.

6.2 Determinants of Relative Risk Aversion

The dependent variable in the censored fractional response model is risky share, thus the regression is an estimation of demand for risky assets. The second part of table (5) reports the regression results. With the assumption that asset market information is common knowledge, the heterogeneity in demand for risky assets can only be explained by heterogeneity in relative risk aversion. Therefore, with equation 11, explanatory variables' impact on the relative risk aversion is the opposite as on the demand for risky assets.

Among the factors that influence the relative risk aversion, country difference is the most pronounced in my results. Figure 5 shows the great difference among different countries in Europe, who are already economically similar within the euro zone. The Dutch are the most risk averse and the Spanish seem to be the most courageous in investing in risky assets. The exact reason behind the difference is beyond this paper. But most evidently the different political institution and taxation policies may have a big impact, and possible the cultural difference as well. However, there is another clear difference that may explain the low relative risk aversion of Spain is that the data is collected in Spain before the European Sovereign debt crisis. This brings another question that whether the macroeconomic shocks can affect the risk attitude of individuals, which is another direction that this paper can take for its extension.

The results suggest that age has positive impact on the demand for risky assets. It is constant with the empirical findings that people accumulate their investment in risky asset markets in preparation for the retirement. Moreover, the investment in risky assets still increases after a short period after retirement age as seen in the data. Such positive impact implies that older people are less risk averse. One way to understand the decreasing risk aversion is that when people age, they do not only deplete their labor capital, they also eliminate the background risk from labor income. Thus they can afford to be less risk averse.

Marital status and family size both have significant negative impact on risky shares. It is consistent with the findings of Love (2010) that the responsibility of marriage and family members will discourage risky investment. Labor income risk is one of the important background risks for the households. When people retire they no longer have labor income, thus no longer have any such background risk. The result shows that such status switch does not change households' risk attitudes.

The coefficient of wealth suggests whether rich households invest more to risky assets. The relative risk aversion is likely to be decreasing in these countries as the wealthier households hold higher risky shares. Although panel data studies find that wealth change does not affect risk attitude as found byBrunnermeier and Nagel (2008), the absolute amount of wealth however do matter in risk preferences in cross sectional analysis.

Education shows that better educated people tend to have higher risky shares and thus are less risk averse. This is probably due to the correlation of education and wealth or the fact that better educated people are better informed of the financial markets.

Housing is usually a large part of household wealth, which imposes some background risk to the households. The results imply that net housing value has positive impact on risky shares, which means that more housing asset the household has the less risk averse she is. The tenure status of the main residence however has negative impact on risky shares. One possible explanation maybe that households view the housing investment as risky, so that they do not take on more risks on the financial market. The variable other property indicates whether the household owns other property except for the main residence. This is an indication that whether the household is using the real estate market as an investment vehicle for his portfolio. If the coefficient is positive, it means that households are more likely to consider the real estate as risk free assets; if the coefficient is negative, households intend to treat the real estate as risky assets. The positive sign of the coefficient shows that households are less risk averse when they hold other properties and they are more likely to view real estate to be less risky than the financial risky assets.

6.3 The Participation Costs

The first part of table (5) describes the estimation results of the extremal quantile regression, the censoring thresholds in terms of risky shares and the corresponding participation costs using three indices: the censoring percentage of the risky shares, the percentage cost with respect to the financial wealth, and the participation cost in euro. Both lower censoring and upper censoring predictions are presented in the tables.

The lower censoring thresholds show the approximated lower bound for holding positive risky shares. The corresponding average participation costs in percentage with respect to total financial wealth is 0.07 %. However, most estimation of the participation costs are either in percentage of consumption. Luttmer (1999) is one of the first who tries to quantify the participation cost, and he found the cost to be at least 3 percent of monthly per capital consumption. Paiella (2007) find that the lower bound for participation ranges from 0.7 to 3.3 percent. Attanasio and Paiella (2011) estimate the participation cost to be 0.4 percent of non-durable consumption. Consider that the total financial wealth is only 3 times the food consumption in the data, my results are lower than the previous findings. A very small amount of fixed per period cost is already capable of deterring risky assets market participation by many less wealthy households.

Measuring the participation costs in euros, the participation cost is 66 euros on average, and the median cost is only 9.9 euros. These results are in line with the previous literature. For instance, Vissing-Jorgensen (2004) does a simple estimation finding that a per period stock market participation cost around 55 dollars in year 2003 prices is enough to explain the non-participation of half the nonparticipants. Mulligan and Sala-i Martin (2000) finds that the participation cost is 111 dollars per year. The results of Attanasio and Paiella (2011) show that the participation cost is 72 euros per year on average.

6.4 Extremal Quantile Regression Results

Both lower extreme quantile regression and upper extreme quantile regression results are reported in the table. In general, the variables explain the lower censoring thresholds much better than they do for the upper censoring. This is probably due to the fact that we have very limited amount of upper censored observation in our sample even when the total sample size is over 40,000. Therefore the analysis of the results will be more focused on the lower censoring thresholds, which corresponds to the participation cost of to participating both risky and risk free markets instead of only participating risk free market. This is also the participation cost that is most widely discussed in the literature.

Age has a positive effect on the participation costs, which means that the older the households the higher the participation costs. This signals that the declining learning ability caused by aging is dominant in determining the participation cost. The negative coefficient of gender suggests that the participation costs are significantly lower for women than men.

Education is a good indication of learning ability, and is expected to have negative effect on participation costs. Intuitively better educated people learn faster the rules of risky asset markets and process faster the information. However education actually has positive effects as seen in the table. This suggests that the learning cost might not the main driving force of participation cost. Note that the participation costs in this paper is the subjectively perceived participation cost. Such positive impact of the education indicates that better educated people understand better the difficult of the task required by participating risky asset markets, and they are able to evaluate the participation costs more precisely. While the less educated people might just formulate a rough lower bound of participation costs or under estimate the participation costs[12] when they make the investment decision.

Employment and income are the measures of opportunity cost of participating risky financial markets. We can see from the table that they both have negative impact on the participation cost except for a few exceptions such as Netherlands, which implies that opportunity cost does not play an important role when households evaluate their participation costs.

[12] In the literature of financial literacy, understanding the risk of financial market is certainly not an easy task for people with insufficient level of education. It is possible that less educated people will under estimate the participation cost due to the lack of knowledge about risk.

7 Robustness of the results

There are a few assumptions and empirical setting in the baseline specification can be relaxed to test the robustness of the results found in the previous section. This section discusses a few factors that may affect the estimates of relative risk aversion to see whether the estimated results of the censored fractional response model is sensitive to changes of those factors. Table (7) and (8) show the estimation results of different specifications. Due the very limited amount of observation at the upper censoring, I only consider the censoring near zero for all the robustness specifications.

7.1 Definition of Risky Assets

The definition of risky assets plays an obvious role in the estimation results of demand for risky assets. If one categorizes too many types of assets as risk-free assets, the risky shares are systematically lower and the estimated risk aversion will be higher. In the baseline specification, the bond is categorized as safe asset since the majority of the bonds are state or national government bonds. In a survey data with more details on bonds, the government bonds are normally considered as risk-free assets and corporate bonds are considered as risky assets. Moreover, some researches adopt a narrower deifnition of risky assets that only includes stocks and mutual funds.

This paper considers two alternative definitions of risky assets to study whether the high risk aversion is affected by the definition. The first alternative definition treats the bonds as risky assets instead of risk-free asset, which systematically increases the risky shares for the households who hold bonds in their portfolio. The second alternative definition only considers the stocks and mutual funds as risky assets, which systematically lowers the risky shares for the households who hold other types of risky assets in the baseline specification, such as money owed to the household and private business investment.

In the second and third column of table (7), different definition of risky assets do not affect much the coefficients of extremal quantile regresssion and censored fractional response regression. Compare with the baseline results, all the coefficients stay consistent in two alternative definitions. The second and third column of table (8) shows the summary statistics of the censoring thresholds, participation costs and estimated relative risk aversion. In these tables only the lower censoring thresholds and participation costs are reported since the upper censoring thresholds estimation is insignificant due the lack of observations. The censoring thresholds and participation costs remain consistent with the baseline results despite the different definition of risky assets. Especially the results in the second column are very close to the baseline results. The estimated relative risk aversion shows the expected deviation from the baseline results. Adding bonds to the risky assets category has made the estimated relative risk aversion lower, but the difference is not very drastic given that only 5.3 % of the households hold bonds and only 6.6 % of the financial wealth is invested in bonds on average. However, the narrow definition has a bigger impact on the estimated risk aversion, implying that if one only considers the stocks as the risky assets, it is more likely to find a higher risk aversion.

In summary, the definition of risky assets does not affect the coefficients of the estimation, but it has a systematic impact on the estimate relative risk aversion. Treating the bonds as risk-free asset in the baseline specification does not matter as much as only considering stocks and mutual funds as risky assets.

7.2 Extremal Quantiles

A high participation cost can increase the probability of being censored, and leads to the conclusion of high risk aversion. In the baseline specification, the extremal quantile that approximate the censoring thresholds for each households is 5%, which corresponds to the minimal risky share of the average financial wealth that covers the transaction cost once a year. The fourth and fifth column of table (7) and (8) show the results of estimation when the extremal quantiles are set to be 2% and 10%. The signs of the coefficients in extremal quantile regressions remain consistent with the baseline results, but the significance changes especially in the case of extremal quantile being 2%. It is expected that the level of extremal quantiles changes the censoring thresholds and participation costs. However, the censored fractional response model estimation results are not largely influenced by the extremal quantile setting.

The estimated risk aversion under the extremal quantile of 2% and 10% differ from the baseline results mildly. In the estimation, using a higher extremal quantile to approximate the censoring threshold will force the distribution of risky share lean towards the censoring threshold, and therefore estimates higher relative risk aversion. In general, the level of extremal quantiles is not the dominant factor that determines the high relative risk aversion found in the baseline results.

7.3 Estimation with Beta Distribution

Recall that in the baseline specification, the random shock to relative risk aversion is assume to be additive to the linear index within the log ratio function, and is assumed to be normally distributed (equation (19)). Another common choice of distribution in the context of fractional variables is beta distribution. The last column of table (7) and (8) shows the result of using beta distribution to model the censoring probabilities instead of normal distribution. [13] Using beta distribution gives us a significantly higher estimate of risk aversion. It is probably due to the asymmetric and flexible structure of beta distribution, which allows the beta distribution to better describe the observed empirical distribution. With large amount of zero observations in the original data, the flexibility of beta distribution makes the distribution tilt more towards zero compare with the normal distribution.

Another reason that one may want to use Beta distribution is that it performs significantly better in predicting the censoring in simulated results. In the baseline specification, the symmetry of normal distribution over smooth the skewness towards zero, which is only able to predict 33 % of censoring as oppose to 66% in the data. However, when we use Beta distribution, there will be 55% of the households being censored in the simulation.

[13]The detailed specification can be found in the appendices.

7.4 Perception of Market Return and Volatility

The estimated relative risk aversion has a linear relation with the market price of risk at risky asset markets as in equation (11). Households' expectation of risky asset return and volatility affects the estimated relative risk aversion directly and linearly. Since the definition of risky asset is not limited in stock markets only, the baseline specification of market return and volatility is not the observed long term stock market return and volatility. The market expectation with 0.08 risk premium and 20% market volatility is an optimistic opinion of the risky asset market. In Chiappori and Paiella (2011), they use a more pessimistic calibration of the risky asset market with risk premium being 0.04 and market volatility being 20%. If we consider other types of risky assets have similar market return and volatility as the stock market, the market price of risk is with risk premium being 0.07 and market volatility being 23.4%, which is the post second world war long term stock market performance in the developed countries. Fernandez et al. (2013) provide the evaluation of subjective expectation of market risk premium in many countries around the world. The European countries on average have market risk premium around 6%. Meanwhile, the European region is known for relatively low market volatility, which means that a 20% market volatility is likely to be an reasonable expectation.

Table (9) shows the estimated relative risk aversion with different expectation of risky asset markets. It is evident that the perception of market return and volatility has a big impact on the results. With the pessimistic expectation of risky asset market, the mean risk aversion becomes close to the results of Chiappori and Paiella (2011), but the median is still much higher. If one tends to believe that households have perfect information about the risky assets market, the results with the post second world war developed country average is more convincing. In all the cases, the estimated relative risk aversion in this paper is still significantly higher than what was estimated in the previous literature.

7.5 Country by Country Estimation

Although the selected eight countries have similar economic development levels, there are also many institutional and cultural differences that cannot be controlled for by the observed household characteristics. The country dummy approach in the baseline specification is a very simplistic way of capturing such difference. However, it is still a very strong assumption that all the explanatory variables affect households the same way in different countries. Moreover, the heterogeneity in investment behaviors across different countries is well known in the literature, which implies that the country characteristics may interact with individual characteristics. Therefore, I run country by country estimations to see whether the findings in the pooled eurozone estimation are consistent.

Table (10), table (11) and table (12) present the coefficients of extremal quantile regression and censored fractional response model estimation. Due to the limited sample size for the country level estimation, the extremal quantile regression loses significance in countries with small sample size. For the coefficients that are still significant at country level, they remain consistent with the pooled eurozone results. The estimation results in Netherlands are significant in extremal quantile regression, but it has only 1288 households, among which only less 400 households hold risky assets. Thus it is not likely that it provides credible extremal quantile regression results. As to the censored fractional response model coefficients, most of them are consistent with the pooled eurozone results. The coefficients of log wealth and retiree are two interesting exceptions. In Austria, Belgium and Germany, the rich households have less risky shares which implies increasing relative risk aversion as oppose to the other countries' decreasing relative risk aversion. However, the different investment behavior in those countries may be due to different economic and legislate institutions. For instance, in Germany, there is favorable taxation policy for investing in real estate as a risky asset. It is likely that the rich households in Germany hold less risky asset because they invest more in real estate. To fully understand the heterogeneous households finance behavior in different countries, we would need more country specific characteristics.

8 Concluding Remarks

This paper estimates the heterogeneous relative risk aversion of households using data about their observed household portfolios and characteristics. Under the assumption of a participation cost to risky asset markets, the estimation includes both risky asset holders and non risky asset holders by treating the zero share of risky assets as the results of heterogeneous self censoring. The estimated results show that the relative risk aversion of households are higher than what was previously estimated using the stock holders only. Therefore, the macroeconomic calibration works should consider using a higher relative risk aversion parameter for the representative agent in the models. The average participation cost in this paper falls in the range of the previous findings, only slightly lower. This ensures that the estimated high relative risk aversion is not just the direct effect of setting the participation costs high. The robustness checks also make sure that the results are not very sensitive to certain empirical specifications.

To give an example of how a higher relative risk aversion can change some of the well known macroeconomic calibration studies. I use the results of this paper to calibrate the model of Barro (2006). He proposes a model with the probability of rare disasters that destroy the economies in large scales to try to understand the observed high risk premium. I take the estimated relative risk aversion using the post second world war developed country average performance for the risky asset markets. When the relative risk aversion is 5.6, and rare disaster probability is 0.82%, Barro's model predicts the risk premium to be 6.5% and risk-free rate to be 1.6%. This is very close to the observed results from the data, and with a much more reasonable probability of rare disaster, which is 1.7% in Barro's calibration.

However there are much more works to do. This paper only uses cross sectional data to study the determinants of the risk preference. It would be very interesting to apply this model in a dynamic setting with a panel data. The estimation results show strong country specific heterogeneity in investment behavior and risk attitude. If we can have more information on the country level characteristics of the economic and legislative institution, we would be able to understand such heterogeneity better. Last but not least, the heterogeneity in both risk aversion and participation cost opens the possibility of modeling the economy with multiple types of representative households. The heterogeneity can be extended to the households' utility parameters from only the heterogeneity in random shocks.

Appendices

A Choice between "complete portfolio" and "risky only"

Households with choice"risky only" invest all their financial wealth to risky assets. Their budget constraints are:

$$\mathbf{E}[W_{h1}] = W_{h0}\{1 + \mathbf{E}[r_m]\}.$$

By taking Taylor series expansion of $U(W_{h1})$ around W_{h0} and keeping the first two terms, the expected utility becomes:

$$\mathbf{E}[U(W_{h1})] = U(W_{h0}) + U^{'}(W_{h0})W_{h0}[\mathbf{E}[r_m] - (-\delta_h^b)] + \frac{1}{2}U^{''}(W_{h0})W_{h0}^2\sigma_m^2.$$

Compare with the optimal expected utility of "complete portfolio" in equation (7):

$$V_b - V_0 = U^{'}(W_{h0})W_{h0}\{r_f + \alpha_h^{*}\mathbf{E}[r_m - r_f] - \mathbf{E}[r_m] - \delta_h^b\} + \frac{1}{2}U^{''}(W_{h0})^2(\alpha_h^{*2} - 1)\sigma_m^2.$$

Replacing α_h^{*2} with $-\alpha_h^* \cdot \frac{U'(W_{h0})}{U''(W_{h0})W_{h0}} \cdot \frac{\mathbf{E}[r_m - r_f]}{\sigma_m^2}$ from equation (6) makes

$$\begin{aligned} V_b - V_0 &= U'(W_{h0})W_{h0}\{r_f + \alpha_h^*\mathbf{E}[r_m - r_f] - \mathbf{E}[r_m] - \delta_h^b - \frac{1}{2}\mathbf{E}[r_m - r_f]\frac{\alpha_h^{*2} - 1}{\alpha_h^*}\} \\ &= U'(W_{h0})W_{h0}\{\mathbf{E}[r_m - r_f](\alpha_h^* - 1)(1 - \frac{1}{2}\frac{\alpha_h^* + 1}{\alpha_h^*}) - \delta_h^b\} \\ &= U'(W_{h0})W_{h0}\{\frac{1}{2}\mathbf{E}[r_m - r_f](\frac{\alpha_h^*}{2} + \frac{1}{2\alpha_h^*} - 1) - \delta_h^b\} \end{aligned} \tag{20}$$

Solve the equation $V_b - V_0 = 0$ and discard the solution outside of the interval $[0, 1]$, we would have the upper censoring function $H(X) \equiv (\frac{\delta_h^b}{\mathbf{E}[r_m - r_f]} + 1) - \sqrt{(\frac{\delta_h^b}{\mathbf{E}[r_m - r_f]})^2 + \frac{2\delta_h^b}{\mathbf{E}[r_m - r_f]}}$.

B Data: variable definitions and treatment

Some of the variables in the original HFCS data are coded differently as the variables used in this paper. Some necessary treatment is applied to the original data to fit the purpose of the study. Here are the details of the variable definition and treatment.

- Gender is coded as male =1 and female = 2, this paper has recoded the variable as male =0 and female =1.

- In this paper, education of the head of household in the survey is defined as the highest level of education obtained by the respondents of households, which have 4 levels. level 1 is the primary education; level 2 is secondary education; level 3 is post secondary education but lower than university level; level 4 is 4 year university education or higher. However in the original data, education is the answer to the question "What is the highest level of education (you/he/she) (has/have) completed?", and coded as follow (Categories based on ISCED-97 classification): 1 Primary or below (No formal education or below ISCED 1 + ISCED 1: Primary education); 2 Lower secondary (ISCED 2: Lower secondary or second stage of basic education); 3 Upper secondary (ISCED 3: Upper secondary + ISCED 4: Post-secondary); 5 Tertiary (ISCED 5: First stage tertiary + ISCED 6: Second stage tertiary). It is coded in four categories but skips the level 4. To make it a more regular categorical variable, this paper recodes the level 5 to level 4, while everything else remains the same.

- The employment status in the original data is the answer to the question "What is (your/Xs) current employment status. Which categories best describe (your/his/her) situation? Please start with the most important employment status", and is coded as follow:

    1. Doing regular work for pay / self-employed/working in family business
    2. On sick/maternity/other leave (except holidays), planning to return to work
    3. Unemployed
    4. Student/pupil/unpaid intern
    5. Retiree or early retiree
    6. Permanently disabled
    7. Compulsory military service or equivalent social service
    8. Fulfilling domestic tasks
    9. Other not working for pay (specify)

    However, this paper is only concerned with the households' broad employment status, which leads to a much simple coding: 1 – wage earner (including 1, 2, 4,7 in the original coding); 0 – not working.

- This paper only consider the general marital status, thus married and consensual union on a legal basis are considered to be married (coded as 1), and single, divorced and widowed are consider to be unmarried (coded as 0).

- Whether the households owns certain types of pension plans is coded similarly as the gender. 1 means that the household has it, 0 otherwise.

C Estimation with Beta Distribution

The alternative method of parametrize the censoring probability is to assume that the distribution of the unobserved heterogeneity in risky shares is a Beta distribution. Therefore the censoring probabilities P_M, P_L and P_H take the functional form as follows:

$$\begin{aligned}
P_L(X,Z) &= Pr\{G(X_h\theta_M) + u_h \leq G(Z_h\hat{\theta}_L)|\hat{\theta}\} = I_{G(Z_h\hat{\theta}_L)}(\alpha,\beta) = \frac{\mathbf{B}(G(Z_h\hat{\theta}_L),\alpha,\beta)}{\mathbf{B}(\alpha,\beta)} \\
P_H(X,Z) &= Pr\{G(X_h\theta_M + u_h) \geq G(Z_h\hat{\theta}_H)|\hat{\theta}\} = I_{G(Z_h\hat{\theta}_H)}(\alpha,\beta) = \frac{\mathbf{B}(G(Z_H\hat{\theta}_L),\alpha,\beta)}{\mathbf{B}(\alpha,\beta)} \\
P_M(X,Z) &= 1 - P_L(X,Z) - P_H(X,Z)
\end{aligned}$$

where $I_x(\alpha,\beta)$ is the regularized incomplete beta function, which is the cumulative distribution function of beta distribution, $\mathbf{B}(x,\alpha,\beta)$ is the incomplete beta function, and $\mathbf{B}(\alpha,\beta)$ is the beta function.

Following the suggestion of Ospina and Ferrari (2012), I re-parametrize the beta distribution with μ and ϕ ($\mu \in (0,1)$ and $\phi > 0$). The relation with the original parameters α and β are as follow:

$$\begin{aligned}
\mu &= \tfrac{\alpha}{\alpha+\beta} \\
\frac{\mu(1-\mu)}{(\phi+1)} &= \tfrac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)}.
\end{aligned}$$

Then for the beta distribution, μ is the distribution mean and $\frac{\mu(1-\mu)}{(\phi+1)}$ is the variance, in which ϕ plays the role of a precision parameter. With such parametrization, by making $\mu = G(X_h\theta_M)$, we can compute the censoring probability easily. ϕ will be estimated along with the rest of the parameters in the censored fractional response model.

9 Tables and Figures

Table 1: Summary Statistics

Risky shares:

	$\alpha = 0$		$\alpha = 1$		$\alpha \in (0, 1)$	
Number of Ob.	32174		86		16415	
Percentage	66.1%		0.2%		33.7%	
	Mean	Min	25%	Median	75%	Max
	0.364	0.000	0.104	0.286	0.588	1.000

Other explanatory variables:

	Mean	Min	25%	Median	75%	Max
Financial wealth (1000 €)	103.28	0	3.42	15.30	56.10	54444.61
Age	54.6	16.0	42.0	55.0	67.0	85.0
Female	0.44	0.00	0.00	0.00	1.00	1.00
Education	2.75	1.0	2.0	3.0	4.0	4.0
Marital status	0.58	0.0	0.0	1.0	1.0	1.0
Family size	2.41	1.0	1.0	2.0	3.0	15.0
Retirement status	0.34	0.0	0.0	0.0	1.0	1.0
Employement	0.52	0.0	0.0	1.0	1.0	1.0
Total wealth (1000 €)	467.32	-1143.30	41.36	192.63	411.01	401119.66
Total income (1000 €)	51.20	-449.25	20.62	35.80	60.15	8760.32
Residence tenure status	0.72	0.0	0.0	1.0	1.0	1.0
Net housing value (1000 €)	162.80	-611.48	0	120	230	8000
Other property ownership	0.36	0.0	0.0	0.0	1.0	1.0
Public pension	0.64	0.0	0.0	1.0	1.0	1.0
Occupational pension	0.06	0.0	0.0	0.0	0.0	1.0
Voluntary pension	0.29	0.0	0.0	0.0	1.0	1.0

Table 2: Household Finance Summary by Country

	Total	Deposits	Mutual Funds	Bond	Stocks	Money Owed	Pension & Life	Other
Austria(2010)								
Real value	13.5	10.6	11.2	13.8	7.1	2.6	8.1	7.7
Shares	100.0	63.5	11.8	6.9	3.1	3.5	8.9	2.2
Participation	99.5	99.4	10.0	3.5	5.3	10.3	17.7	1.6
Belgium(2010)								
Real value[1]	26.5	10.0	20.4	30.8	5.1	2.3	19.9	21.0
Shares[2]	100.0	39.1	13.0	14.8	10.4	1.5	16.7	4.5
Participation[3]	98.0	97.7	17.6	7.5	14.7	7.7	43.3	3.5
Germany(2010)								
Real value	17.1	7.9	10.0	16.0	8.6	2.7	11.4	2.1
Shares	100.0	44.4	10.4	5.6	6.5	2.7	26.8	3.6
Participation	99.3	99.0	16.9	5.2	10.6	13.7	46.5	11.3
Spain(2008)								
Real value	6.0	3.5	13.9	19.2	6.1	6.0	7.4	12.0
Shares	100.0	51.4	7.7	1.9	9.1	6.4	15.1	8.4
Participation	98.3	98.1	5.6	1.4	10.4	6.3	23.6	1.9
France(2010)								
Real value	10.7	6.5	6.9	12.0	6.9	3.0	10.6	5.0
Shares	100.0	33.8	5.8	1.4	11.6	1.0	39.0	7.4
Participation	99.6	99.6	10.7	1.7	14.7	5.0	37.5	7.8
Finland(2009)								
Real value	7.4	4.5	2.6	10.0	3.8	NA	4.3	NA
Shares	100.0	51.9	11.5	1.0	26.1	NA	9.5	NA
Participation	100.0	100.0	27.4	0.8	22.2	NA	23.7	NA
Italy(2010)								
Real value	10.0	5.9	20.0	20.0	10.9	4.0	10.1	10.4
Shares	100.0	46.9	9.6	20.4	4.5	0.5	8.8	9.3
Participation	92.0	91.8	6.3	14.6	4.6	1.3	18.0	3.7
Netherlands(2009)								
Real value	34.7	10.1	7.1	15.5	5.6	2.0	53.2	5.5
Shares	100.0	33.9	6.4	4.3	3.5	1.7	49.3	0.9
Participation	97.8	94.2	17.7	6.0	10.4	8.5	49.8	2.7

[1] Median value in thousand EUR conditional on participation.
[2] Average shares of all type financial asset conditional on participation.
[3] Percentage of households participating specific type of financial assets.

Table 3: Participation in Financial Assets by Household Demographics

	Total	Deposits	Mutual Funds	Bond	Stocks	Money Owed	Pension &Life	Other
Euro Zone	96.8	96.4	11.4	5.3	10.1	7.6	33.0	6.0
Percentile of Net Wealth								
less than 20	93.2	92.5	2.0	0.2	1.2	7.8	15.9	1.7
20-39	96.7	96.3	8.1	1.7	5.0	10.2	32.7	4.6
40-59	96.4	96.1	10.4	3.9	8.0	5.9	31.5	4.7
60-79	98.4	98.1	12.4	6.6	11.0	5.7	35.8	5.4
80-100	99.5	99.1	23.8	14.0	25.2	8.6	49.1	13.8
Age of Reference Respondent								
16-34	97.4	97.1	9.7	1.7	6.7	10.3	33.7	4.8
35-44	97.5	97.0	12.9	3.4	10.1	9.0	41.1	6.3
45-54	97.0	96.7	13.0	5.0	11.2	8.0	43.7	5.4
55-64	97.2	96.4	13.1	7.6	13.3	7.5	37.7	7.4
65-75	96.4	96.1	10.9	8.1	10.4	5.8	19.4	7.3
75+	95.0	94.7	6.9	6.6	7.6	4.2	12.8	4.9
Work Status of Reference Respondent								
Employee	97.9	97.6	13.3	4.2	11.4	7.9	42.3	5.7
Self-Employed	96.9	96.6	12.7	7.9	12.5	12.6	44.7	10.4
Retired	95.9	95.6	9.4	7.5	9.3	5.5	19.0	6.4
Other No Work	94.9	94.1	6.8	1.5	3.8	8.6	21.9	3.0
Housing Status								
Owner-Outright	96.6	96.3	11.9	8.9	12.4	5.1	28.9	6.3
Owner-Mortgage	98.7	98.1	16.2	3.7	13.6	7.8	47.8	7.4
Renter or Other	96.2	95.7	8.5	2.4	6.0	10.1	30.1	5.2
Education of Reference Respondent								
Primary or Non	93.6	93.1	4.0	4.0	4.2	4.5	19.0	2.4
Secondary	98.2	97.9	10.8	5.2	9.2	8.9	36.4	6.1
Tertiary	99.0	98.7	22.6	7.2	19.6	9.9	46.8	11.1

Table 4: Shares in Financial Assets by Household Demographics

	Total	Deposits	Mutual Funds	Bond	Stocks	Money Owed	Pension &Life	Other
Euro Zone	100.0	42.9	8.7	6.6	7.9	2.2	26.3	5.3
Percentile of Net Wealth								
less than 20	100.0	65.7	1.8	NA	1.2	4.4	26.1	0.6
20-39	100.0	62.3	5.4	1.4	1.7	3.9	23.9	1.3
40-59	100.0	55.4	5.5	2.5	2.9	1.9	30.1	1.7
60-79	100.0	53.5	6.7	4.0	4.1	1.8	28.2	1.7
80-100	100.0	35.4	10.4	8.6	10.6	2.2	25.4	7.4
Age of Reference Respondent								
16-34	100.0	56.6	5.1	1.1	4.6	1.7	26.3	4.3
35-44	100.0	43.3	6.8	3.5	7.0	2.9	30.0	6.4
45-54	100.0	40.4	8.8	3.9	6.7	2.8	32.7	4.7
55-64	100.0	39.0	9.9	7.1	7.7	2.0	27.9	6.3
65-75	100.0	44.0	10.7	10.0	10.4	2.2	18.3	4.4
75+	100.0	46.0	7.6	10.6	9.4	1.3	20.2	4.8
Work Status of Reference Respondent								
Employee	100.0	44.4	8.2	3.8	7.1	1.7	30.3	4.4
Self-Employed	100.0	34.0	8.3	6.6	8.8	3.8	27.4	11.2
Retired	100.0	45.2	9.4	9.8	9.0	2.0	20.5	4.2
Other No Work	100.0	46.4	11.0	4.3	4.9	3.5	27.6	2.4
Housing Status								
Owner-Outright	100.0	43.5	8.7	8.6	9.1	1.7	22.4	6.0
Owner-Mortgage	100.0	40.3	7.8	2.7	6.4	2.9	35.9	4.0
Renter or Other	100.0	43.8	9.7	4.6	6.3	3.1	27.8	4.7
Education of Reference Respondent								
Primary or Non	100.0	51.3	5.1	7.1	4.7	2.5	26.1	3.1
Secondary	100.0	45.6	7.1	6.3	6.6	2.0	27.9	4.5
Tertiary	100.0	37.7	11.4	6.5	10.1	2.3	25.2	6.7

Table 5: Pooled Euro Zone Estimation Results

Extremal Quantile Regression:

	(Intercept)	Age	Gender	Education	Employ	Income
$\hat{\theta_L}$	-2.922	0.004	-0.112	0.104	-0.167	-0.138
s.e.	(0.430)***	(0.002)***	(0.060)*	(0.029)***	(0.084)**	(0.035)***
$\hat{\theta_H}$	3.872	0.002	0.015	0.016	-0.496	-0.106
s.e.	(1.026)***	(0.005)	(0.112)	(0.063)	(0.145)***	(0.094)

Participation Costs Predictions:

	Mean	Min	25%	Median	75%	Max
$L(\hat{X})$	0.01674	0.00684	0.01442	0.01616	0.01860	0.09165
$\hat{\delta^s}$	0.00067	0.00027	0.00058	0.00065	0.00074	0.00367
Cost in €	66.1	0.0	2.3	9.9	36.7	27003.6
$H(\hat{X})$	0.9258	0.8522	0.9065	0.9184	0.9465	0.9842
$\hat{\delta^b}$	0.00013	0.00001	0.00006	0.00014	0.00019	0.00051
Cost in €	15.9	0.0	0.34	1.7	7.1	11818.1

Censored Fractional Response Model:

Country dummies:		Austria	Belgium	Germany	Spain	
		-2.045	-1.821	-2.035	-0.971	
		(0.087)***	(0.085)***	(0.084)***	(0.082)***	
Country dummies:		Finland	France	Italy	Netherlands	
		-1.821	-2.219	-1.749	-2.599	
		(0.083)***	(0.083)***	(0.084)***	(0.088)***	
Coefficients:	Age	Female	Educ	Marital	Family	Retiree
	0.002	-0.172	0.197	-0.217	-0.085	0.011
	(0.001)**	(0.012)***	(0.006)***	(0.014)***	(0.006)***	(0.024)
Coefficients:	Employ	Wealth	Income	Residence	Housing	Othprop
	-0.260	0.016	0.073	-0.383	0.015	0.136
	(0.021)***	(0.002)***	(0.008)***	(0.028)***	(0.002)***	(0.012)***
s.d. of Error:		6.86	Pseudo R^2:		0.44	

Relative Risk Aversion Estimates:

	Mean	Min	25%	Median	75%	Max
	8.82	2.86	6.72	8.33	10.45	55.23

[1] In the first panel, s.e. is the simulated pseudo standard errors by the extremal quantile estimation.
[2] The extreme quantile is set to be $\tau = 0.05$.
[3] In the second panel, $L(\hat{X})$ and $H(\hat{X})$ are the censoring thresholds near zero and near one; $\hat{\delta^s}$ and $\hat{\delta^b}$ are the participation cost in percentage of total financial wealth. Cost in € are the participation costs in euro computed using $\hat{\delta^s}$ and $\hat{\delta^b}$ and household total financial wealth.

Table 6: Relative Risk Aversion Prediction

Country Level Results:

	Mean	Min	25%	Median	75%	Max
Austria	9.32	4.75	7.66	8.80	9.32	37.63
Belgium	7.75	3.97	6.34	7.45	8.79	20.15
Germany	8.70	4.29	7.10	8.30	9.81	27.22
Spain	4.73	2.85	3.97	4.60	5.27	15.78
Finland	8.15	3.97	6.78	7.77	9.05	28.86
France	10.84	4.69	8.74	10.53	12.39	30.21
Italy	8.16	3.74	6.93	8.01	9.09	24.76
Netherlands	14.7	7.09	11.01	13.57	17.06	54.84

Pooled Euro Zone Results:

	Mean	Min	25%	Median	75%	Max
	8.82	2.86	6.72	8.33	10.45	55.23
Risky Asset Participants Only:						
	8.15	2.86	6.34	7.84	9.59	36.34

Friend and Blume 1975 method:

	Mean	Min	25%	Median	75%	Max
	5.53	4.64	5.06	5.61	5.88	7.35

Morin and Suarez 1983 method:

	Mean	Min	25%	Median	75%	Max
	4.98	3.40	4.73	4.96	5.20	83.48

Chiappori and Paiella 2011 method:

	Mean	Min	25%	Median	75%	Max
	6.90	5.11	6.47	6.89	7.33	10.04

[1] The relative risk aversion is computed from equation $r_h = \frac{\mathbf{E}(r_m - r_f)}{\sigma_m^2} \frac{1}{G(X\hat{\theta})}$.

[2] The market risk premium is set to be 8%, and market volatility is set to be $(0.20)^2$.

Table 7: Results of Different Specifications – Part 1

	Baseline	Risky 1	Risky 2	$\tau = 0.02$	$\tau = 0.10$	Beta
Extremal Quantile Regression Coefficients:						
(Intercept)	-2.975	-3.026	-3.270	-3.288	-3.178	-2.975
Age	0.004	0.008	0.005	0.001**	0.006	0.004
Female	-0.110	-0.107	-0.111**	0.086**	-0.071**	-0.110
Education	0.103	0.091	0.171	0.102	0.149	0.103
Employement	-0.176	-0.183	-0.146	-0.074**	-0.168	-0.176
Income (log)	-0.137	-0.129	-0.144	-0.185	-0.072	-0.137
Censored Fractional Response Model Coefficients:						
Australia	-2.249	-2.043	-3.157	-1.866	-2.597	-3.732
Belgium	-2.024	-1.831	-2.875	-1.661	-2.348	-3.449
Germany	-2.237	-2.171	-2.961	-1.884	-2.546	-3.556
Spain	-1.175	-1.265	-2.207	-0.790	-1.533	-2.938
Finland	-2.023	-2.164	-2.487	-1.666	-2.338	-3.414
France	-2.422	-2.549	-3.268	-2.050	-2.756	-3.775
Italy	-1.957	-0.999	-2.637	-1.529	-2.369	-3.677
Netherlands	-2.800	-2.776	-3.511	-2.445	-3.110	-4.004
Age	0.002	0.005	0.003	0.002	0.001	0.000
Female	-0.173	-0.147	-0.187	-0.162	-0.183	-0.173
Education	0.199	0.196	0.269	0.182	0.223	0.234
Marital	-0.217	-0.252	-0.246	-0.219	-0.213	-0.150
Family	-0.085	-0.079	-0.096	-0.080	-0.091	-0.085
Retiree	0.013**	0.044**	0.179**	-0.010**	0.045**	0.099
Employment	-0.258	-0.301	-0.168	-0.275	-0.235	-0.134
Wealth(log)	0.017	0.025	0.026	0.012	0.023	0.032
Income(log)	0.074	0.078	0.089	0.055	0.101	0.165
Residence	-0.380	-0.270	-0.201	-0.413	-0.336	-0.187
Housing Value	0.015	0.011	0.011	0.016	0.013	0.008
Other Prop	0.138	0.126	0.075	0.115	0.168	0.240

[1] This table shows the estimation results of different empirical specifications.

[2] ** means the coefficient is not significant at 5% level; all the other coefficients are significant.

[3] The column of "Risky 1" shows the result of treating bond as risky asset; the column of "Risky 2" shows the result of only considering stocks and mutual funds as risky assets; the column of "Beta" reports the result of using beta distribution for the errors.

Table 8: Results of Different Specifications – Part 2

	Baseline	Risky 1	Risky 2	$\tau = 0.02$	$\tau = 0.10$	Beta
Lower Censoring Thresholds – $L(\hat{X})$						
Min.	0.007	0.007	0.005	0.003	0.016	0.007
1st Quartile	0.015	0.016	0.013	0.007	0.029	0.015
Median	0.017	0.018	0.014	0.007	0.033	0.017
Mean	0.018	0.019	0.015	0.008	0.034	0.018
3rd Quartile	0.020	0.022	0.016	0.008	0.037	0.020
Max.	0.094	0.099	0.097	0.061	0.100	0.094
Participation Costs – δ_h^s						
Min.	0.0003	0.0003	0.0002	0.0001	0.0007	0.0003
1st Quartile	0.0006	0.0006	0.0005	0.0003	0.0012	0.0006
Median	0.0007	0.0007	0.0006	0.0003	0.0013	0.0006
Mean	0.0007	0.0008	0.0006	0.0003	0.0013	0.0007
3rd Quartile	0.0008	0.0009	0.0007	0.0003	0.0015	0.0007
Max.	0.0038	0.0040	0.0039	0.0024	0.0040	0.0033
Participation Costs in €						
Min.	0.0	0.0	0.0	0.0	0.0	0.0
1st Quartile	2.4	2.5	2.0	1.1	4.4	2.4
Median	10.5	11.1	8.7	4.5	19.9	10.5
Mean	69.7	76.8	60.7	26.4	148.0	69.7
3rd Quartile	38.7	41.5	33.0	16.1	76.0	38.7
Max.	28650	32530	25150	8430	76660	28650
Estimated Relative Risk Aversion:						
Min.	2.86	2.53	3.25	2.85	2.87	2.95
1st Quartile	6.74	4.89	7.74	6.46	7.12	7.77
Median	8.37	7.18	10.30	7.94	9.01	9.97
Mean	8.87	7.76	11.75	8.36	9.68	11.04
3rd Quartile	10.51	9.77	14.37	9.86	11.51	13.18
Max.	55.98	53.27	87.17	47.54	69.63	149.30

[1] The column of "Risky 1" shows the result of treating bond as risky asset; the column of "Risky 2" shows the result of only considering stocks and mutual funds as risky assets; the column of "Beta" reports the result of using beta distribution for the errors.

Table 9: RRA with Different Perception of Risky Asset Markets

Optimistic Expectation of Risky Asset Markets

$\mathbf{E}[r_m - r_f] = 0.08$ and $\sigma_m = 0.20$

Mean	Min	25%	Median	75%	Max
8.82	2.86	6.72	8.33	10.45	55.23

Pessimistic Expectation of Risky Asset Markets

$\mathbf{E}[r_m - r_f] = 0.04$ and $\sigma_m = 0.20$

Mean	Min	25%	Median	75%	Max
4.41	1.43	3.36	4.16	5.22	27.6

Post Second World War Developed Country Average

$\mathbf{E}[r_m - r_f] = 0.07$ and $\sigma_m = 0.234$

Mean	Min	25%	Median	75%	Max
5.62	1.83	4.29	5.31	6.66	34.99

Subjective Risky Asset Markets Expectation

$\mathbf{E}[r_m - r_f] = 0.06$ and $\sigma_m = 0.20$

Mean	Min	25%	Median	75%	Max
6.59	2.14	5.03	6.23	7.81	41.06

[1] The relative risk aversion is computed from equation $r_h = \frac{\mathbf{E}(r_m - r_f)}{\sigma_m^2} \frac{1}{G(X\hat{\theta})}$.

[2] The market risk premium is set to be 8%, and market volatility is set to be $(0.20)^2$.

Table 10: Extremal Quantile Regression Results

Country	Obv.	Coefficients					
		Constant	Age	Female	Education	Employ	Income
Austria	2327						
Coefficients		-2.765	0.014	0.397	-0.409	0.368	-0.121
s.e.		(2.061)	(0.012)	(0.261)	(0.289)	(0.327)	(0.175)
Belgium	2316						
Coefficients		-0.759	-0.000	-0.720	-0.072	-0.990	-0.187
s.e.		(2.338)**	(0.019)	(0.369)**	(0.216)	(0.538)*	(0.158)
Germany	3490						
Coefficients		-2.507	-0.015	-0.284	0.548	-0.301	-0.190
s.e.		(1.908)	(0.013)	(0.279)	(0.286)**	(0.412)	(0.177)
Spain	6023						
Coefficients		-4.258	0.010	0.376	0.171	0.009	-0.085
s.e.		(2.209)**	(0.014)	(0.343)	(0.149)	(0.391)	(0.166)
Finland	10989						
Coefficients		-2.110	0.001	-0.159	0.227	-0.202	-0.229
s.e.		(0.777)**	(0.002)	(0.078)**	(0.043)**	(0.086)**	(0.070)**
France	14916						
Coefficients		-3.096	0.005	-0.124	0.068	-0.119	-0.129
s.e.		(0.626)**	(0.004)	(0.075)*	(0.037)*	(0.106)	(0.049)**
Italy	7326						
Coefficients		-1.633	-0.008	0.044	0.042	-0.192	-0.071
s.e.		(1.705)	(0.011)	(0.205)	(0.121)	(0.254)	(0.153)
Netherlands	1288						
Coefficients		-14.46	0.045	1.189	-0.043	0.693	0.539
s.e.		(2.163)**	(0.014)**	(0.262)**	(0.149)	(0.355)**	(0.206)**

[1] This table reports the extreme quantile regression of $G^{-1}(\alpha^*) = constant + age + gender + education + employ + income$, where α^* is the risky shares, G() is the logistic function, "labor in" is the labor income, and "work hour" is working hours per week.
[2] This table reports only lower censoring estimates and s.e. means the simulated pseudo standard errors by the extremal quantile estimation.
[3] The extreme quantile is set to be $\tau = 0.05$.

Table 11: Results of the Censored Fractional Response Model 1

Country:	Austria	Belgium	Germany	Spain
(Intercept)	-0.146	-1.427	-1.583	-2.937
	(0.482)	(0.306)***	(0.275)***	(0.234)***
Age	-0.001	0.025	0.0057	0.007
	(0.004)	(0.003)***	(0.002)**	(0.002)***
Gender	0.093	-0.201	-0.130	-0.018
	(0.067)	(0.053)***	(0.039)***	(0.038)
Education	-0.202	0.158	0.469	0.217
	(0.063)***	(0.032)***	(0.034)***	(0.015)***
Marital status	-0.198	-0.399	-0.320	0.022
	(0.079)**	(0.060)***	(0.048)***	(0.042)
Family size	-0.050	0.038	-0.044	-0.072
	(0.033)*	(0.025)*	(0.021)**	(0.017)***
Retiree	0.112	-0.282	-0.370	0.104
	(0.163)	(0.113)**	(0.085)***	(0.061)*
Employment	-0.556	-0.203	-0.229	-0.312
	(0.126)***	(0.094)**	(0.069)***	(0.056)***
Wealth (log)	-0.024	-0.007	-0.021	0.172
	(0.009)**	(0.013)	(0.006)***	(0.011)*
Income (log)	0.039	-0.015	0.010	0.056
	(0.047)	(0.024)	(0.025)	(0.017)***
Residence	-0.426	-1.585	-0.426	-0.256
	(0.145)**	(0.249)***	(0.105)***	(0.191)
Net housing (log)	0.013	0.107	0.022	-0.012
	(0.012)	(0.019)***	(0.008)**	(0.015)
Other property	-0.174	0.293	0.060	-0.129
	(0.079)**	(0.055)***	(0.041)*	(0.040)***
$\hat{s.d.}$	10.9585	7.1573	5.0259	7.0152

[1] This tables reports the regression results of $\alpha^* = G(X\theta)$, where α^* are the risky shares, X are all the co-variates, θ are the parameters, and G() is the logistic function.

[2] $\hat{s.d.}$ is the estimated standard error of the distribution of $G^{-1}(\alpha^*)$.

[3] 'residence' indicates whether households own the residence they live in, 'other property' indicates whether households own additional property other than residence.

Table 12: Results of the Censored Fractional Response Model 2

Country:	Finland	France	Italy	Netherlands
(Intercept)	-2.282	-2.937	-7.427	-7.404
	(0.189)***	(0.176)***	(0.447)***	(0.617)***
Age	-0.007	0.012	-0.008	0.026
	(0.001)***	(0.001)***	(0.003)**	(0.005)***
Gender	-0.142	-0.219	0.008	0.217
	(0.020)***	(0.023)***	(0.049)	(0.097)**
Education	0.201	0.171	0.176	0.104
	(0.014)***	(0.011)***	(0.011)***	(0.043)**
Marital status	-0.287	-0.112	-0.139	-0.427
	(0.025)***	(0.026)***	(0.061)**	(0.099)***
Family size	-0.126	-0.110	-0.168	-0.115
	(0.010)***	(0.010)***	(0.026)***	(0.041)**
Retiree	0.410	-0.396	-0.082	0.260
	(0.043)***	(0.057)***	(0.115)	(0.149)*
Employment	-0.095	-0.352	-0.188	0.271
	(0.034)**	(0.055)***	(0.107)***	(0.121)**
Wealth (log)	0.040	0.020	0.289	0.028
	(0.003)***	(0.005)***	(0.023)***	(0.009)***
Income (log)	0.145	0.121	0.292	0.307
	(0.019)***	(0.015)***	(0.041)***	(0.046)***
Residence	-0.492	-1.672	-0.032	0.422
	(0.042)***	(0.154)***	(0.205)	(0.142)***
Net housing (log)	-0.003	0.133	-0.034	-0.001
	(0.003)	(0.013)***	(0.016)**	(0.009)
Other property	0.079	0.249	0.127	0.522
	(0.022)***	(0.023)***	(0.047)**	(0.093)***
$\hat{s.d.}$	5.528	6.180	7.913	6.427

[1] This tables reports the regression results of $\alpha^* = G(X\theta)$, where α^* are the risky shares, X are all the co-variates, θ are the parameters, and G() is the logistic function.

[2] $\hat{s.d.}$ is the estimated standard error of the distribution of $G^{-1}(\alpha^*)$.

[3] 'residence' indicates whether households own the residence they live in, 'other property' indicates whether households own additional property other than residence.

Table 13: Prediction of Censoring Thresholds and Participation Costs – part 1

Country	Descriptive statistics					
	mean	min	25%	50%	75%	max
Austria						
$L(\hat{X})$	0.02375	0.00851	0.01717	0.02222	0.02813	0.08782
$\hat{\delta}^s$	0.00095	0.00034	0.00069	0.00089	0.00113	0.00351
Cost in €	44.0	0.0	3.8	12.2	34.8	1793.6
RRA	7.71	2.76	5.69	7.09	8.77	30.40
Belgium						
$L(\hat{X})$	0.01387	0.00233	0.00698	0.01038	0.02148	0.13911
$\hat{\delta}^s$	0.00055	0.00009	0.00028	0.00042	0.00086	0.00556
Cost in €	80.4	0.0	2.6	12.4	49.4	6571.3
RRA	8.54	2.67	4.56	6.25	11.19	196.46
Germany						
$L(\hat{X})$	0.01761	0.00346	0.01226	0.01633	0.02144	0.17178
$\hat{\delta}^s$	0.00070	0.00014	0.00049	0.00065	0.00086	0.00687
Cost in €	62.2	0.0	4.7	19.8	57.1	4645.1
RRA	9.63	2.89	5.68	7.79	12.12	48.25
Spain						
$L(\hat{X})$	0.02940	0.01171	0.02327	0.02838	0.03428	0.11847
$\hat{\delta}^s$	0.00118	0.00047	0.00093	0.00114	0.00137	0.00474
Cost in €	242.1	0.0	3.3	18.1	95.3	46386.5
RRA	6.30	2.18	3.74	4.54	5.56	319.61

[1] In each country subsection of the table, the first line reports the censoring thresholds, the second line reports the participation cost in percentage with respect to total financial wealth, and the third line reports the participation cost in euro.

[2] Censoring thresholds are computed directly from $Q_{\hat{\alpha}^*}(\tau)|_{\tau=0.05}$.

[3] Participation costs in percentage with respect to total financial wealth are computed via the equations: $\delta_L = 2\delta_h^s/\mathbf{E}[r_m - r_f]$.

[4] Participation costs in euro are computed by participation costs in percentage times the total financial assets.

Table 14: Prediction of Censoring Thresholds and Participation Costs – part 2

Country	Descriptive statistics					
	mean	min	25%	50%	75%	max
Finland						
$\hat{L(X)}$	0.01533	0.00486	0.01285	0.01488	0.01722	0.14575
$\hat{\delta^s}$	0.00061	0.00019	0.00051	0.00060	0.00069	0.00583
Cost in €	23.2	0.0	1.8	6.6	21.2	6056.0
RRA	8.57	3.45	6.68	8.07	9.66	42.44
France						
$\hat{L(X)}$	0.01495	0.00699	0.01317	0.01463	0.01664	0.04708
$\hat{\delta^s}$	0.00060	0.00028	0.00053	0.00059	0.00067	0.00188
Cost in €	80.5	0.0	1.8	10.0	40.5	24013.1
RRA	11.54	3.21	7.92	10.06	13.49	506.33
Italy						
$\hat{L(X)}$	0.05972	0.04071	0.05431	0.05799	0.06272	0.16832
$\hat{\delta^s}$	0.00239	0.00163	0.00217	0.00232	0.00251	0.00673
Cost in €	74.4	0.0	7.1	23.7	73.0	8318.0
RRA	111.31	2.50	7.32	10.46	17.43	44891.90
Netherlands						
$\hat{L(X)}$	0.01445	0.00002	0.00772	0.01155	0.01712	0.08635
$\hat{\delta^s}$	0.00058	0.00000	0.00031	0.00046	0.00068	0.00345
Cost in €	61.3	0.0	5.9	21.9	58.7	6415.6
RRA	19.29	3.29	9.57	14.70	23.02	461.55

[1] In each country subsection of the table, the first line reports the censoring thresholds, the second line reports the participation cost in percentage with respect to total financial wealth, and the third line reports the participation cost in euro.
[2] Censoring thresholds are computed directly from $Q_{\hat{\alpha}^*}(\tau)|_{\tau=0.05}$.
[3] Participation costs in percentage with respect to total financial wealth are computed via the equations: $\delta_L = 2\delta_h^s/\mathbf{E}[r_m - r_f]$.
[4] Participation costs in euro are computed by participation costs in percentage times the total financial assets.

Figure 1: Intuition of Extremal Quantile Approximation

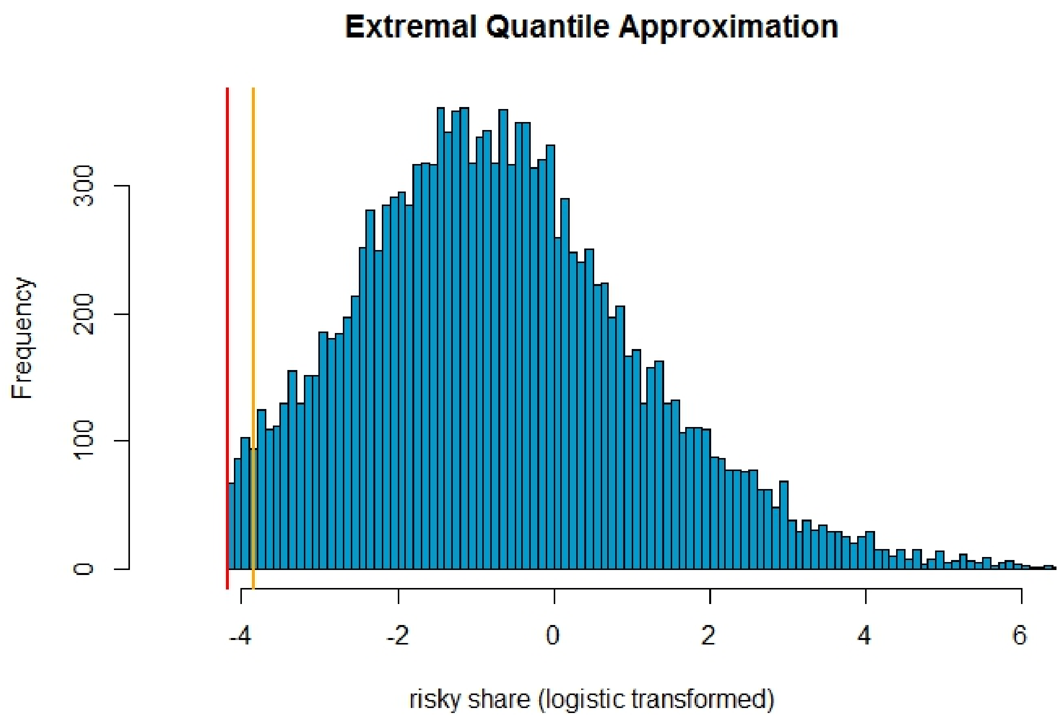
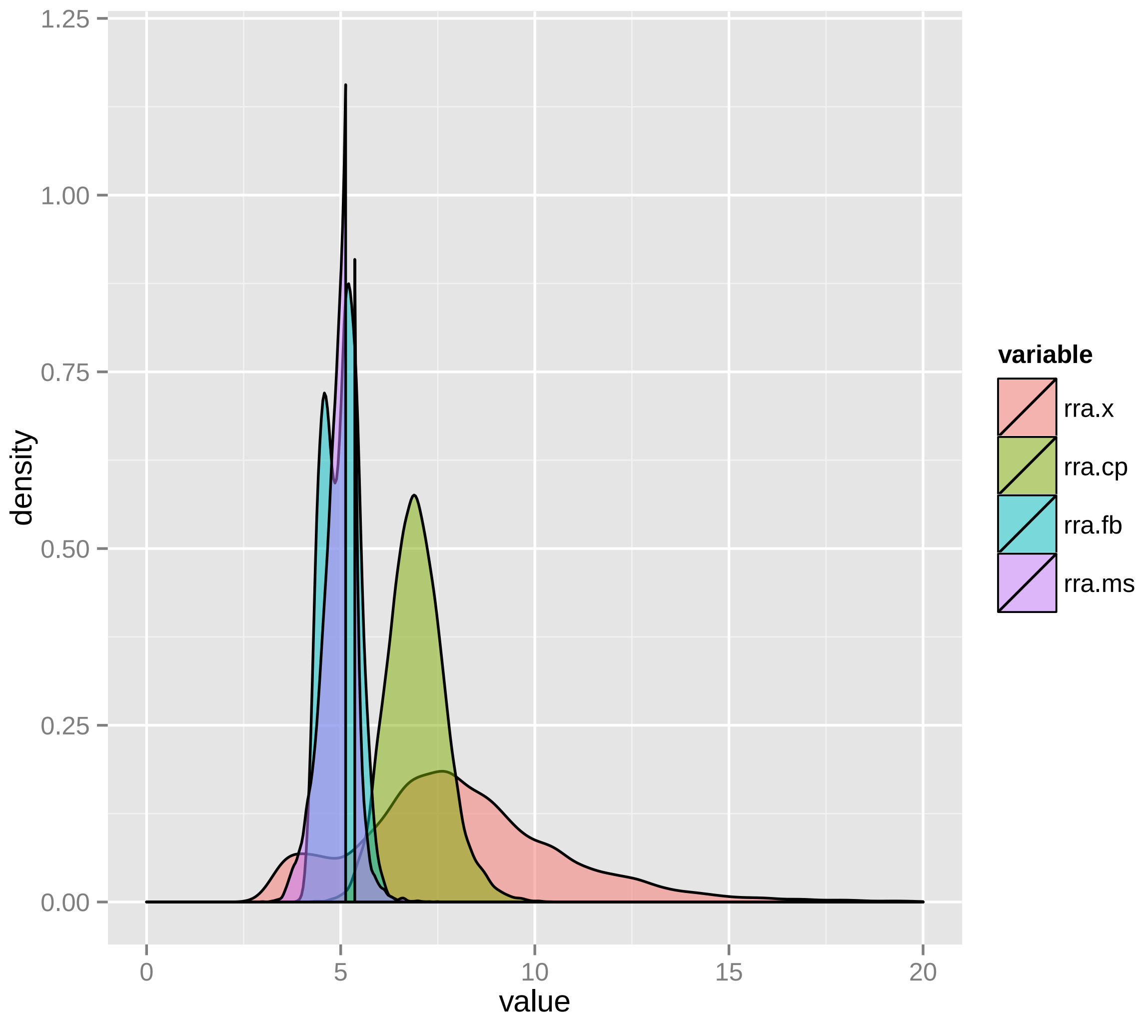
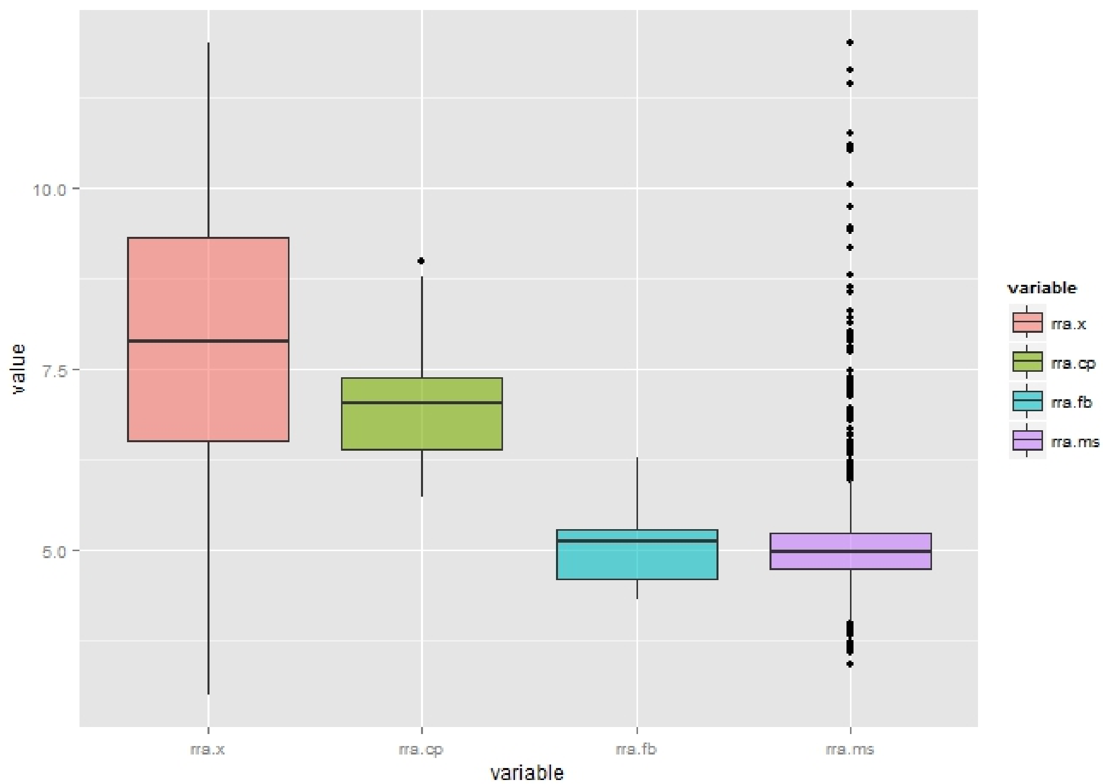


Figure 2: Relative Risk Aversion Estimates Comparison 1



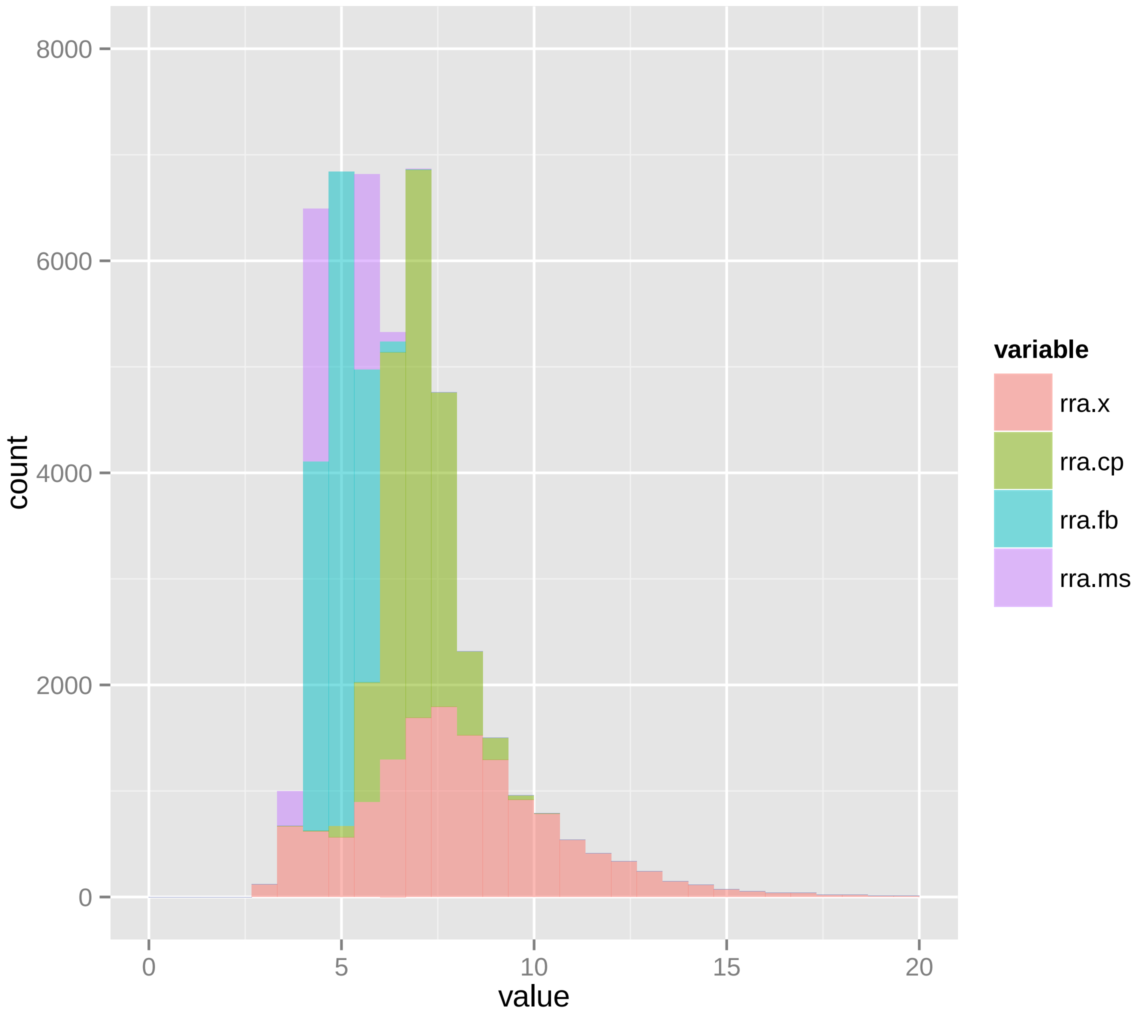
1. rra.x is the RRA estimates of this paper; rra.fb is the RRA estimates of Friend and Blume (1975); rra.ms is the RRA estimates of Morin and Suarez (1963) and rra.cp is the RRA estimates of Chiappori and Paiella (2011). 2. All methods apply to the same HFCS data. 3. the maket price of risk $\mathbf{E}(r_m - r_f)/\sigma_m^2$ is 2 with risk premium $\mathbf{E}(r_m - r_f) = 0.08$ and maket volatility $\sigma_m^2 = 0.04$.

Figure 3: Relative Risk Aversion Estimates Comparison 2



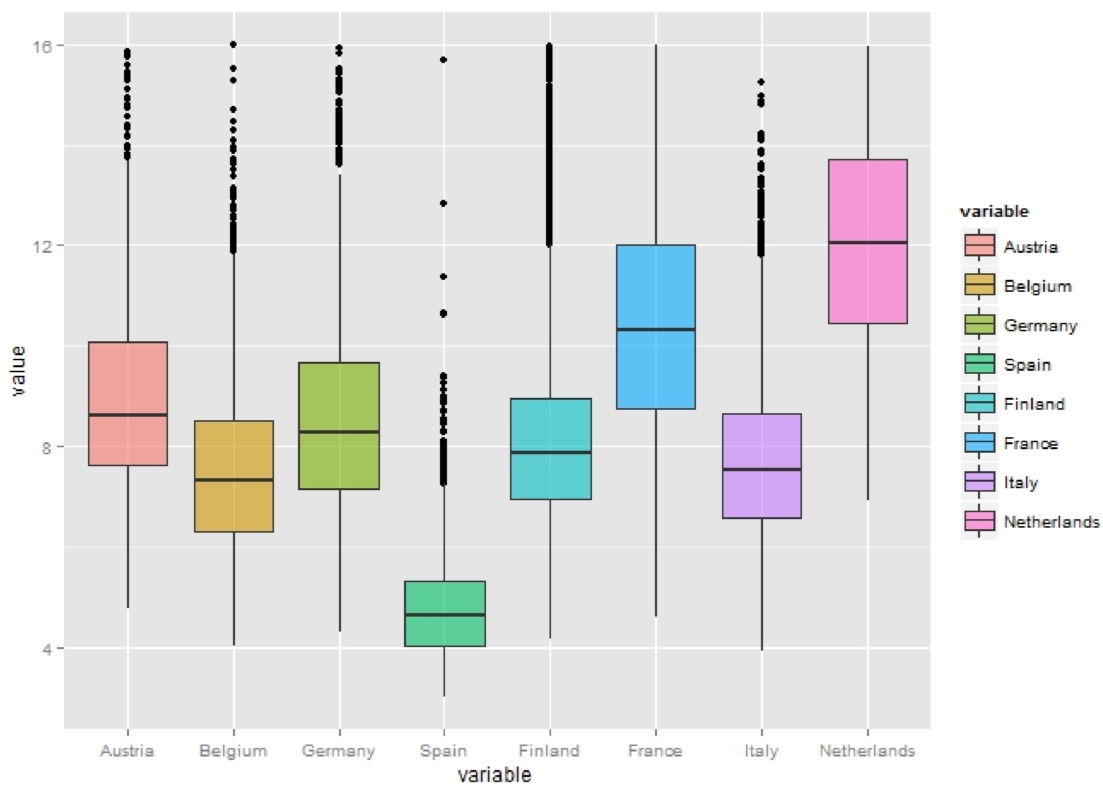
1. rra.x is the RRA estimates of this paper; rra.fb is the RRA estimates of Friend and Blume (1975); rra.ms is the RRA estimates of Morin and Suarez (1963) and rra.cp is the RRA estimates of Chiappori and Paiella (2011). 2. All methods apply to the same HFCS data. 3. the maket price of risk $\mathbf{E}(r_m - r_f)/\sigma_m^2$ is 2 with risk premium $\mathbf{E}(r_m - r_f) = 0.08$ and maket volatility $\sigma_m^2 = 0.04$.

Figure 4: Relative Risk Aversion Estimates Comparison 3



1. rra.x is the RRA estimates of this paper; rra.fb is the RRA estimates of Friend and Blume (1975); rra.ms is the RRA estimates of Morin and Suarez (1963) and rra.cp is the RRA estimates of Chiappori and Paiella (2011). 2. All methods apply to the same HFCS data. 3. the maket price of risk $\mathbf{E}(r_m - r_f)/\sigma_m^2$ is 2 with risk premium $\mathbf{E}(r_m - r_f) = 0.08$ and maket volatility $\sigma_m^2 = 0.04$.

Figure 5: Relative Risk Aversion Estimates Country Comparison



1. This predicted relative risk aversion in eight European countries from the pooled estimation. 2. The maket price of risk $\mathbf{E}(r_m - r_f)/\sigma_m^2$ is 2 with risk premium $\mathbf{E}(r_m - r_f) = 0.08$ and maket volatility $\sigma_m^2 = 0.04$.

References

Altonji, J. G., H. Ichimura, and T. Otsu (2012). Estimating derivatives in nonseparable models with limited dependent variables. *Econometrica 80*(4), 1701–1719.

Attanasio, O., J. Banks, and S. Tanner (2002). Assets holding and consumption volatility. *Journal of Political Economy 4*(110), 771–792.

Attanasio, O. P. and M. Paiella (2011). Intertemporal consumption choices, transaction costs and limited participation in financial markets: reconciling data and theory. *Journal of Applied Econometrics 26*(2), 322–343.

Barro, R. J. (2006). Rare disasters and asset markets in the twentieth century. *The Quarterly Journal of Economics 121*(3), 823–866.

Barsky, R. B., F. T. Juster, M. S. Kimball, and M. D. Shapiro (1997). Preference parameters and behavioral heterogeneity: An experimental approach in the health and retirement study. *The Quarterly Journal of Economics*, 537–579.

Brunnermeier, M. K. and S. Nagel (2008). Do wealth fluctuations generate time-varying risk aversion? micro-evidence on individuals' asset allocation. *The American Economic Review 98*(3), 713–736.

Calvet, L. E. and P. Sodini (2013). Twin picks: Disentangling the determinants of risk-taking in household portfolios. *The Journal of Finance*.

Campbell, J. Y. (2006). Household finance. *The Journal of Finance 61*(4), 1553–1604.

Chernozhukov, V. (2005). Extremal quantile regression. *Annals of Statistics 33*(2), 806–839.

Chernozhukov, V. and I. Fernández-Val (2011). Inference for extremal conditional quantile models, with an application to market and birthweight risks. *The Review of Economic Studies 78*(2), 559–589.

Chiappori, P.-A. and M. Paiella (2011). Relative risk aversion is constant: Evidence from panel data. *Journal of the European Economic Association 9*(6), 1021–1052.

Christiansen, C., J. S. Joensen, and J. Rangvid (2008). Are economists more likely to hold stocks? *Review of Finance 12*(3), 465–496.

Cocco, J. F., F. J. Gomes, and P. J. Maenhout (2005). Consumption and portfolio choice over the life cycle. *Review of financial Studies 18*(2), 491–533.

Cohn, R. A., W. G. Lewellen, R. C. Lease, and G. G. Schlarbaum (1975). Individual investor risk aversion and investment portfolio composition. *The Journal of Finance 30*(2), 605–620.

Cook, D. O., R. Kieschnick, and B. McCullough (2008). Regression analysis of proportions in finance with self selection. *Journal of Empirical Finance 15*, 860–867.

Dohmen, T., A. Falk, D. Huffman, U. Sunde, J. Schupp, and G. G. Wagner (2011). Individual risk attitudes: Measurement, determinants, and behavioral consequences. *Journal of the European Economic Association 9*(3), 522–550.

Fagereng, A., C. Gottlieb, and L. Guiso (2013). Asset market participation and portfolio choice over the life-cycle. Technical report.

Fernandez, P., J. Aguirreamalloa, and L. C. Avendaño (2013). Market risk premium used in 82 countries in 2012: a survey with 7,192 answers. *Available at SSRN 2084213*.

Ferrari, S. and F. Cribari-Neto (2004). Beta regression for modelling rates and proportions. *Journal of Applied Statistics 31*(7), 799–815.

Friend, I. and M. E. Blume (1975). The demand for risky assets. *The American Economic Review 65*(5), 900–922.

Gomes, F. and A. Michaelides (2005). Optimal life-cycle asset allocation: Understanding the empirical evidence. *The Journal of Finance 60*(2), 869–904.

Guiso, L., P. Sapienza, and L. Zingales (2008). Trusting the stock market. *the Journal of Finance 63*(6), 2557–2600.

Haliassos, M. and C. C. Bertaut (1995). Why do so few hold stocks? *the Economic Journal*, 1110–1129.

Heaton, J. and D. Lucas (2000). Portfolio choice in the presence of background risk. *The Economic Journal 110*(460), 1–26.

Hoff, A. (2007). Second stage dea: Comparison of approaches for modelling the dea score. *European Journal of Operational Research 181*(1), 425–435.

Kieschnick, R. and B. D. McCullough (2003). Regression analysis of variates observed on (0, 1): percentages, proportions and fractions. *Statistical Modelling 3*(3), 193–213.

Love, D. A. (2010). The effects of marital status and children on savings and portfolio choice. *Review of Financial Studies 23*(1), 385–432.

Luttmer, E. G. (1999). What level of fixed costs can reconcile consumption and stock returns? *Journal of Political Economy 107*(5), 969–997.

Mehra, R. and E. C. Prescott (1985). The equity premium: A puzzle. *Journal of monetary Economics 15*(2), 145–161.

Merton, R. C. (1969). Lifetime portfolio selection under uncertainty: The continuous-time case. *Review of Economics and statistics 51*(3), 247–257.

Morin, Roger, A. and A. F. Suarez (1983). Risk aversion revisited. *The Journal of Finance 38*(4), 1201–1216.

Mulligan, C. B. and X. Sala-i Martin (2000). Extensive margins and the demand for money at low interest rates. *Journal of Political Economy 108*(5), 961–991.

Ospina, R. and S. L. Ferrari (2012). A general class of zero-or-one inflated beta regression models. *Computational Statistics & Data Analysis 56*(6), 1609–1623.

Paiella, M. (2007). The forgone gains of incomplete portfolios. *Review of Financial Studies 20*(5), 1623–1646.

Paolino, P. (2001). Maximum likelihood estimation of models with beta-distributed dependent variables. *Political Analysis 9*(4), 325–346.

Papke, L. E. and J. M. Wooldridge (1996). Econometric methods for fractional response variables with an application to 401 (k) plan participation rates. *Journal of Applied Econometrics 11*(6), 619–632.

Vissing-Jørgensen, A. (2002). Limited asset market participation and the elasticity of intertemporal substitution. *Journal of Political Economy 110*(4), 825–853.

Vissing-Jorgensen, A. (2004). Perspectives on behavioral finance: Does" irrationality" disappear with wealth? evidence from expectations and actions. In *NBER Macroeconomics Annual 2003, Volume 18*, pp. 139–208. The MIT Press.

Vissing-Jørgensen, A. and O. P. Attanasio (2003). Stock-market participation, intertemporal substitution, and risk-aversion. *The American Economic Review 93*(2), 383–391.