Twin Picks: Disentangling the Determinants of Risk-Taking in Household Portfolios*

Laurent E. Calvet and Paolo Sodini

This draft: October 2009
First version: August 2009

*Calvet: Department of Finance, HEC Paris, 1 avenue de la Libération, 78351 Jouy-en-Josas, France; and NBER, calvet@hec.fr. Sodini: Department of Finance, Stockholm School of Economics, Sveavägen 65, Box 6501, SE-113 83 Stockholm, Sweden, Paolo.Sodini@hhs.se. We received helpful comments from John Campbell, Mariassunta Giannetti, Jacques Olivier, and seminar participants at HEC Paris and the 2009 SAET Ischia Conference. We thank Statistics Sweden and the Swedish Twin Registry for providing the data. The project benefited from excellent research assistance by Krister Ahlersten and Tomas Thörnqvist. This material is based upon work supported by the Agence Nationale de la Recherche under a Chaire d'Excellence to Calvet, BFI under a Research Grant to Sodini, the HEC Foundation, Riksbank, and the Wallander and Hedelius Foundation.

Abstract

This paper investigates the determinants of risk-taking in household portfolios by comparing the asset holdings of Swedish twins. We report a strong positive relation between financial wealth and risk-taking, as measured by participation and the risky share. Among participants, the average elasticity of the risky share with respect to financial wealth is estimated at 22%. This result is strongly significant and suggests that the average individual investor has *decreasing* relative risk aversion. The risky share also increases with financial experience and sophistication, and decreases with leverage, entrepreneurial activity, household size and a measure of habit. Furthermore, the financial wealth elasticity of the risky share itself is heterogeneous across investors and varies strongly with characteristics. The elasticity decreases with financial wealth and human capital, increases with habit, real estate wealth, and household size, and is a hump-shaped function of age. As a result, the response of the aggregate demand for risky assets to exogenous wealth shocks is similar to, but does not coincide with, the response of a representative investor with *constant* relative risk aversion. We confirm the robustness of our results by running time-differenced instrumental variable regressions, and by controlling for zygosity, age, lifestyle, mental and physical health, the intensity of communication between twins, and measures of social interactions.

Keywords: Asset allocation, communication, habit formation, human capital, labor income, leverage, participation, risk-taking, social interactions.

JEL Classification: D5, D9, E3, O1.

1. Introduction

Does financial wealth drive the share of risky assets in the portfolio of individual investors? Is the financial wealth elasticity of the risky share homogenous across investors or is it impacted by their demographic, financial and portfolio characteristics? How does the aggregate demand for risky assets respond to changes in the wealth distribution? These questions have profound implications for portfolio selection and asset pricing. In portfolio choice theory, mechanisms such as habit formation, borrowing constraints, decreasing relative risk aversion, portfolio insurance, or a "capitalist" taste for wealth, all imply that richer households allocate a higher fraction of their financial wealth to risky investments. The empirical investigation of household portfolios can help us determine if these linkages do exist in practice. The shape of the utility function also plays a central role in our understanding of the equity premium and business-cycle variations in asset returns (e.g. Boldrin Christiano and Fisher 2001, Campbell and Cochrane 1999, Constantinides 1990, Dybvig 1995, Jermann 1998).

The household finance literature provides partial empirical evidence on the relation between household characteristics and risk-taking. In cross-sections, richer and more educated investors are known to allocate a higher proportion of their financial wealth to risky assets than less sophisticated households (e.g. Campbell 2006, Calvet Campbell and Sodini, "CCS" 2007, CCS 2009b).[1] In addition, the risky share has a negative cross-sectional relation with real estate holdings (Cocco 2005, Flavin and Yamashita 2002), leverage (Guiso Jappelli and Terlizzese 1996), and internal consumption habit (Lupton 2002). It is unclear, however, whether these variables directly impact portfolio choice, or simply proxy for latent traits such as ability, genes, risk aversion, or upbringing. Several recent papers suggest that panel data offer a possible solution to this identification problem when the characteristic of interest exhibits sufficient time variations (e.g. Brunnermeier and Nagel 2008, CCS 2009a, Chiappori and Paiella 2008). One difficulty with the dynamic panel approach is that the researcher needs to control for household inertia by using instruments, and the results are sensitive to the validity of the instruments.

In this paper, we consider an alternative estimation strategy based on comparing the financial portfolios held by twins. The analysis is made possible by a novel dataset containing the disaggregated portfolios and detailed characteristics of all twins in Sweden. We observe the worldwide assets owned by each twin at the end of a tax year, including bank accounts, mutual funds and stocks but excluding retirement accounts.

[1] See Alessie, Hochguertel and van Soest (2002), Ameriks and Zeldes (2004), Banks and Tanner (2002), Bertaut and Starr-McCluer (2002), Carroll (2002), Cohn, Lewellen, Lease and Schlarbaum (1975), Eymann and Börsch-Supan (2002), Friend and Blume (1975), Guiso and Jappelli (2002), Guiso, Jappelli and Terlizzese (1996), King and Leape (1987, 1998), Lupton (2002), Perraudin and Sørensen (2000), and Vissing-Jorgensen (2002b).

All holdings are reported at the asset level for the 1999-2002 period.

Our main results are the following. First, we estimate the average financial wealth elasticity of the risky share in the population. As in the earlier literature, we begin by running pooled cross-sectional regressions of a household's risky share on financial wealth and yearly fixed effects. The elasticity of the risky share ranges from 21% in the absence of controls to 23% when a large set of a demographic and financial variables is included. These results are difficult to interpret, because financial wealth may simply proxy for latent traits such as risk aversion or ability.

We next consider linear panel specifications with yearly twin pair fixed effects, which is our main innovation. The model can be estimated by regressing twin differences in the risky share on twin differences in characteristics. The financial wealth elasticity of the risky share is measured at 20% in the absence of controls and at 22% in the presence of controls. A 10% proportional increase in a household's financial wealth is associated with a $2.0 - 2.2\%$ proportional increase in its risky share. The adjusted R^2 coefficient is twice higher in the panel regressions with yearly twin pair fixed effects than in the cross-sectional regressions, which confirms that twin pair fixed effects explain a substantial fraction of the observed variation of the risky share.

Second, we investigate the impact of demographic, portfolio, and other financial characteristics on the risky share. In both cross-sectional and twin regressions, the risky share is positively related to financial experience and the risky portfolio's Sharpe ratio, but is negatively related to leverage, entrepreneurial activity, the risky's portfolio systematic exposure, household size, and a measure of habit. Education and income risk, which are significant in the cross-section, are found to be insignificant in the twin pair regressions. These findings suggest that education variables and income risk capture a fixed effect in traditional pooled cross-sectional regressions, but have no direct effect on the risky share.

Third, we show that the financial wealth elasticity of the risky share itself is heterogeneous across households and varies strongly with characteristics, which, to the best of our knowledge, is new to the literature. The elasticity strongly decreases with financial wealth and increases with a measure of habit, as theoretical models of habit formation would predict. Furthermore, human capital tends to reduce the elasticity, while real estate wealth and household size tend to increase it. The elasticity is also a hump-shaped function of age. These findings highlight that the financial wealth elasticity of the risky share varies with characteristics and is substantially heterogeneous across households.

Fourth, we conduct a number of robustness checks. We obtain similar coefficients when we estimate the regressions separately on identical twins and on fraternal twins. The predicted variation, however, is substantially higher for identical twins. We separately reestimate the regressions on the group of twins that communicate frequently with each other and on the group of twins that communicate infrequently. The estimated coefficients are approximately the same in both groups. The predicted variation is smaller for households that communicate frequently, suggesting that communication attenuates the importance of demographic and financial differences. We check the robustness of our results to social interactions by including as controls the business and municipality of each household, as well as the average log risky share and financial wealth of other households in the municipality. We also consider the alternative interpretation that at the end of the bull market of the nineties, risk-tolerant investors happened to have both a high risky share and a high financial wealth. We verify that a household with high financial wealth in 1999 tended to have a high risky share in 2002, even if one controls for the 1999 risky share. These empirical regularities cannot be explained by constant relative risk aversion (CRRA) utility or inertia, and strongly suggest that individual investors exhibit *decreasing* relative risk aversion.

Fifth, we verify that our results are not contaminated by individual fixed effects that are specific to each twin in a pair, such as differences in risk aversion. Since drinking and smoking habits have been previously related to risk tolerance (e.g. Barsky Juster Kimball and Shapiro 1997), one strategy is to expand the twin regressions by including physiological and lifestyle control variables, such as height, weight, measures of mental health and physical health, frequency of exercise, and the consumption of coffee, alcohol and tobacco. Another strategy is compute dynamic estimates of the elasticity by following a given household over time. We correct for inertia in portfolio rebalancing by running the instrumental variable regression of changes in a household's log risky share on changes in its log financial wealth. The elasticity has an estimated average of 23% and decreases with financial wealth in both cases. Thus, our twin difference regressions do not seem to be severely contaminated by individual fixed effects. Furthermore, the dynamic panel, cross-sectional and twin difference methods all provide very similar estimates of the average incremental impact of financial wealth on the risky share.

Sixth, we compute how exogenous changes in household financial wealth affect the aggregate demand for risky assets. We take security prices as given and consider several scenarios. When financial shocks are concentrated on low and medium wealth households, their incremental demand for risky assets is substantial because their risky shares, which are initially low, are highly elastic. In proportional terms, aggregate risky wealth grows almost as quickly as aggregate financial wealth. When instead the wealth shocks are concentrated on the richest households, their risky wealth grows only slightly quicker than their exogenous financial wealth. As a result, aggregate risky wealth grows only slightly faster than aggregate financial wealth in the entire population. Overall, the elasticity of the aggregate demand for risky assets to a homogenous wealth shock is estimated to be slightly above unity. The aggregate implications of our microeconomic specification are therefore close to, but do not coincide with, the demand elasticity of a representative agent with constant relative risk aversion. In further research, it would be interesting to examine if these deviations provide support for alternative benchmarks, such as the aggregate habit formation models of Constantinides (1990) and Campbell and Cochrane (1999).

Finally, we investigate the decision to participate in risky asset markets. The probability that a household owns risky assets is found to increase with financial wealth and human capital, and to decrease with measures of habit, leverage, and income risk. Education and household size, which are significant in the pooled regression, are insignificant when we control for twin pair fixed effects. We use these results to recompute the aggregate elasticity of the risky share to exogenous wealth changes when entry to or exit from risky asset markets are taken into account.

The dynamic panel estimation reported in this paper complements several recent empirical studies. Brunnermeier and Nagel (2008) and Chiappori and Paiella (2008) run ordinary least squares (OLS) regressions of changes in a household's risky share on changes in its financial wealth and other controls, and find no evidence of a link between wealth and risk-taking. Brunnermeier and Nagel reach the same conclusion when they control for measurement error and inertia by instrumenting financial wealth with income growth and inheritance receipts. CCS (2009a) consider a different set of instruments, derived from the returns on the assets held by a household at the beginning of a period, and instead find evidence of a positive relation between financial wealth and the risky share. While CCS (2009a) estimate an adjustment model of portfolio rebalancing, the dynamic approach reported in this paper focuses on a slightly more parsimonious, reduced-form specification.

Twin comparisons are a true and tried method for disentangling family fixed effects from individual characteristics, which have been extensively employed in medicine, epidemiology, and psychology. In economics, twin studies have been mostly applied to labor economics, often to disentangle the relative effect of education and ability on earnings.[2] A similar approach seems fruitful for household finance. In recent studies, Barnea, Cronqvist and Siegel (2009) and Cesarini et al. (2009*a*, 2009*b*) compare the choices of identical and fraternal twins and show that risk aversion is in part an inherited trait. Their findings suggest that the results reported in the present paper control, at least partially, for differences in risk aversion. More generally, data on siblings can be useful in household finance, as exemplified by the recent work of Grinblatt, Keloharju, and Linnainmaa (2009) showing a positive link between IQ and stockmarket participation.

The organization of the paper is as follows. Section 2 presents the Swedish dataset.

[2] See for instance Ashenfelter and Krueger (1994), Ashenfelter and Rouse (1998), Behrman and Rosenzweig (2000), Behrman and Taubman (1989), Bronars and Grogger (1994), and Taubman (1976). Another influential line of research considers instead adoptees, as in the work of Björklund, Lindahl, and Plug (2006), Björklund, Jäntti, and Solon (2007), Plug and Vijverberg (2003), and Sacerdote (2002, 2007). Other contributions on the interplay between genetics and economics include Guiso, Sapienza, and Zingales (2009) and Murray (2002).

In Section 3, we report cross-sectional and twin regressions of the log risky share on log financial wealth and other characteristics. In Section 4, we estimate how the wealth elasticity of the risky share varies with financial wealth itself as well as with other variables. Section 5 investigates the impact of social interactions, health, behavior and age. We also dynamically estimate the elasticity of the risky share in a broad panel of households. In Section 6, we investigate the participation decision in the presence of twin pair fixed effects, and compute the aggregate financial wealth elasticity of the risky share. Section 7 concludes. An Appendix available online (Calvet and Sodini 2009) presents details of data construction and estimation methodology.

2. The Swedish Dataset

Swedish Twin Registry. The Swedish Twin Registry (STR) was founded to study the health impact of smoking and alcohol consumption. We have obtained two surveys from the STR: SALT for twins born between 1886 and 1958, and STAGE for twins born between 1959 and 1990. The SALT survey was conducted between March 1998 and March 2002. Response rates for those eligible (still alive and living in Sweden) were 65% for the cohort between 1886 and 1925, and 74% for the cohort between 1926 and 1958. The STAGE survey was conducted between May 2005 and March 2006, and had a total response rate of 59.6%.

The STR data allows us to identify twin pairs in our panel of Swedish households, which we describe below. We also use a wide range of variables from the STR: the zygosity of each twin pair (fraternal or identical),[3] the intensity of communication between twins, and the weight, height, health condition (self-assessed health, blood pressure), behavior (smoking, alcohol and coffee habits), and mental health of each twin. We refer the reader to Lichtenstein et al. (2006) and Pedersen et al. (2002) for more detailed descriptions of the Swedish Twin Registry.

Swedish Wealth Registry. We have merged the Swedish Twin Registry with the Swedish Wealth Registry, which we have used in earlier work (CCS 2007, 2009*a*, 2009*b*). Because Swedish households pay taxes on both income and wealth, Statistics Sweden has a parliamentary mandate to collect highly detailed information on household finances. We compiled the data supplied by Statistics Sweden into a panel covering four years (1999-2002) and the entire population of Sweden. The information available on each resident can be grouped into three main categories: demographic characteristics, income, and disaggregated wealth.

[3] Zygosity is determined by responses to the question: "During your childhood, were you and your twin partner alike as two peas in a pod or not more alike than siblings in general?". This method has been shown to be highly reliable. For instance, the zygosity classification has been validated using 13 DNA markers, and has proved correct in 99% of pairs.

Demographic information includes age, gender, marital status, nationality, birthplace, education, household size, and municipality. The household head is defined as the individual with the highest income. The education variable includes high school and post-high school dummies for the household head.

Income is reported by individual source. For capital income, the database reports the income (interest, dividends) that has been earned on each bank account or each security. For labor income, the database reports gross labor income and business sector.

The panel contains highly disaggregated information on household wealth. We observe the worldwide assets owned by each resident on December 31 of each year, including bank accounts, mutual funds and stocks. The information is provided for each individual account or each security. The database also records contributions made during the year to private pension savings, as well as debt outstanding at year end and interest paid during the year.

The results presented in this paper are based on households that exist throughout the 1999-2002 period. We impose no constraint on the participation status of these households, but require that they satisfy the following financial requirements at the end of each year. First, disposable income must be at least 1,000 Swedish kronor ($113) each year. Second, the value of all financial assets must be no smaller than 3,000 kronor ($339). Third, the household head must be at least 25 years old.

3. What Drives the Risky Share?

In this section, we analyze the main determinants of risk-taking in household portfolios. We describe the main variables, report cross-sectional evidence with time fixed effects, and then estimate regressions that also control for twin pair fixed effects.

3.1. Definitions and Construction of Variables

We will use the following definitions throughout the paper. Cash consists of bank account balances and money market funds. Risky financial assets include directly held stocks and risky mutual funds. For every household h, the *risky portfolio* is defined as the portfolio of risky financial assets. We measure *financial wealth* $F_{h,t}$ as the sum of holdings in cash, risky financial assets, capital insurance products, and directly held bonds, excluding from consideration illiquid assets such as real estate or consumer durables, and defined contribution retirement accounts. Also, our measure of wealth $F_{h,t}$ is gross financial wealth and does not subtract mortgage or other household debt.

The *risky share* $w_{h,t}$ at date t is the weight of risky assets in the household's portfolio of cash and risky financial assets. A *participant* is a household with a positive risky share. In the rest of this section and in Sections 4 and 5, we examine the determinants of the risky share in the portfolios held by participants. The participation decision is investigated in Section 6.

The *financial wealth elasticity of the risky share* is defined as:

$$\eta_{h,t} = \frac{d\ln(w_{h,t})}{df_{h,t}}, \tag{3.1}$$

where $f_{h,t} = \ln(F_{h,t})$ denotes the household's log financial wealth. Portfolio choice theory suggests that the elasticity $\eta_{h,t}$ is zero if the household has isoelastic utility and there are no market frictions. The elasticity $\eta_{h,t}$ can be positive, however, if the household exhibits decreasing relative risk aversion or faces leverage constraints. Financial sophistication, family composition, human capital, and habit formation can also impact the risky share. We now explain how we measure these effects.

Leverage. Risk-taking can be impacted by current borrowing, for instance through a mortgage, and the likelihood of facing borrowing constraints in the future. Cvitanic and Karatzas (1992), Grossman and Vila (1992), Paxson (1990), Teplá (2000), Cocco (2005), and Yao and Zhang (2005) develop portfolio choice models with this feature. We measure the effect of borrowing through the leverage ratio, which is defined as total debt divided by the sum of financial and real estate wealth.

Portfolio characteristics. A household's assessment of its investment skills might affect its willingness to invest in risky assets (CCS 2007). We proxy investment competence with the ex-ante Sharpe ratio of the household risky portfolio. The risky share may also be driven by systematic risk, which is measured by the beta coefficient of the risky portfolio. In the appendix we explain the methodology used to estimate the Sharpe ratio and beta.

Family composition. We compute the gross wealth of each adult household member, where gross wealth is defined as the sum of financial and real estate wealth. We define the gender index as the share of the household's gross wealth owned by adult men.

Human capital. Future income can be viewed, at least partly, as a nontraded bond. Households with substantial human capital may therefore tilt their financial portfolios toward risky financial assets, as in the theoretical models of Bodie, Merton and Samuelson (1992), Cocco, Gomes and Maenhout (2005), and Wachter and Yogo (2009). The risky share may also depend on the variance of labor income growth, and on the correlation between the household's income growth and its risky portfolio.

We estimate the specification of labor income used in Cocco, Gomes and Maenhout (2005):

$$\ln(L_{h,t}) = \alpha_h + \beta' x_{h,t} + \nu_{h,t} + \varepsilon_{h,t},$$

where $L_{h,t}$ denotes real income in year t, α_h is a household fixed effect, $x_{h,t}$ is a vector of characteristics, $\nu_{h,t}$ is an idiosyncratic permanent component, and $\varepsilon_{h,t}$ is an idiosyncratic temporary shock distributed as $\mathcal{N}(0, \sigma^2_{\varepsilon,h})$. The permanent component $\nu_{h,t}$ follows the random walk:

$$\nu_{h,t} = \nu_{h,t-1} + \xi_{h,t},$$

where $\xi_{h,t} \sim \mathcal{N}(0, \sigma^2_{\xi,h})$ is the shock to permanent income in period t. The Gaussian innovations $\varepsilon_{h,t}$ and $\xi_{h,t}$ are white noise and are uncorrelated with each other at all leads and lags.

We estimate the income process of each household by using its yearly series between 1993 and 2002. Let $u_{h,t}$ denote the difference between the income growth, $\ln(L_{h,t}/L_{h,t-1})$, and the fitted value, $\beta'(x_{h,t} - x_{h,t-1})$. We compute the sample correlation ρ_h between the income growth innovation $u_{h,t}$ and the historical excess return on the portfolio of risky assets held by the household in year t.

Human capital is defined by:

$$\sum_{n=0}^{T_h} \pi_{h,t,t+n} \frac{\mathbb{E}_t(L_{h,t+n})}{(1+r)^n},$$

where T_h denotes the difference between 100 and the age of household h in date t, and $\pi_{h,t,t+n}$ denotes the probability that the household head h is alive at $t+n$ conditional on being alive at t. We make the simplifying assumption that no individual lives longer than 100. The survival probability is estimated using the life table provided by Statistics Sweden. We refer the reader to the Appendix for a detailed discussion of the estimation of labor income and human capital.

We use the following variables in the remaining of the paper: (a) human capital expressed in year t prices; (b) the variance of the transitory component of real income, $\sigma^2_{\varepsilon,h}$; (c) the variance of the permanent component of real income, $\sigma^2_{\xi,h}$; and (d) the correlation between income and the risky portfolio excess return, ρ_h.

Internal and external habit. The risky share can be impacted by lagged values of consumption, either by the household itself or by a peer group. For instance, a large class of additive habit formation models implies that the optimal risky share is of the form:

$$w_{h,t} = w^*_{h,t} \left(1 - \frac{\lambda_{h,t} X_{h,t}}{F_{h,t}}\right), \tag{3.2}$$

where $w^*_{h,t}$ is the risky share of the CRRA investor, $X_{h,t}$ is the (internal or external) habit, and $\lambda_{h,t}$ is the shadow value of the habit. In the internal habit model of Constantinides (1990) and the external habit specification of Campbell and Cochrane (1999), $\lambda_{h,t} X_{h,t}$ represents the cost of supporting the habit over an infinite horizon.

Equation (3.2) implies that households have a positive financial wealth elasticity of the risky share. Let $y_{h,t} = \lambda_{h,t} X_{h,t}/F_{h,t}$ denote the present value of the cost of maintaining the (internal or external) habit relative to financial wealth. The financial wealth elasticity of the risky share,

$$\eta_{h,t} = \frac{y_{h,t}}{1 - y_{h,t}}, \tag{3.3}$$

is positive. It is arbitrarily large when financial wealth is close to the present value of the habit, and declines to zero for large values of financial wealth.

Since we do not observe individual consumption, we proxy the internal habit of household h at date t by its average disposable income in years $t-2$, $t-1$ and t, excluding private pension savings from consideration. Similarly, we proxy the external habit by the three-year average income in household h's municipality. The twin sample has been excluded from the households sampled in each peer group.

3.2. Cross-Sectional Evidence

In household finance, it is common to consider pooled cross-sections of the risky share:

$$\ln(w_{h,t}) = \delta_t + \eta f_{h,t} + \gamma' x_{h,t} + \varepsilon_{h,t}, \tag{3.4}$$

where δ_t is a time fixed effect, $f_{h,t}$ is the log financial wealth of household h, and $x_{h,t}$ is a vector of characteristics. We now examine the evidence on a pooled cross-section of Swedish households.

In the first two columns of Table 1, we regress a household's log risky share on its log financial wealth and yearly fixed effects. The financial wealth elasticity of the risky share, η, is estimated at 0.212 and is highly significant. The pooled regression has an R^2 coefficient of 9.7%. In unreported work, we have found that R^2 is only 1.6% when time dummies are included but financial wealth is excluded from the pooled regression. Financial wealth therefore explains most of the predicted variation in the risky share.

In the next two columns, we include additional financial variables and demographic characteristics. The estimate of the financial wealth elasticity η increases slightly to 0.222. Real estate wealth, which represents a large fraction of the overall wealth of most households, is cross-sectionally related to the asset allocation of the financial portfolio. The real estate wealth elasticity of the risky share is negative and estimated at -0.005. Its magnitude is much smaller than financial wealth elasticity, but is strongly significant. Households with real estate wealth tend to select lower levels of financial risk. This result confirms the findings of Cocco (2005), who also finds a negative cross-sectional relation between housing and the risky share in the U.S. Panel Study of Income Dynamics (PSID). This empirical regularity could be explained by the risk of real estate investments, as in the portfolio choice models of Cocco (2005), Flavin and Yamashita (2002), and Yao and Zhang (2005), or by a household fixed effect.

Households with high leverage ratios tend to select a lower risky share, consistent with the empirical evidence in other countries (e.g. Guiso, Jappelli, and Terlizzese 1996). A high level of debt in kronor, however is associated with a higher risky share. Households with high levels of debt might be more risk-tolerant, which would also explain why they choose leveraged positions of risky assets. Another explanation is that debt is a proxy for financial experience and literacy. Like debt, private pension investing is positively related to the risky share, and could also be a proxy for financial experience.

Portfolio diversification has a strongly significant and positive effect on the risky share. Households with a high Sharpe ratio might be confident in their investment ability and thus take more risk (CCS 2007), or might simply be less risk averse than average. Beta has a significantly negative coefficient. In the cross-section, households with substantial systematic exposure in their risky portfolios tend to select low risky shares.

Education is associated with a higher risky share in the cross-section. Larger households take less financial risk, consistent with the substantial background risk caused by the random needs of the members of a large family. A complementary interpretation is that larger households behave like poorer households of smaller size, as in consumption models based on household equivalence scales (e.g. Calvet and Comon 2003; Deaton, 1974; Jorgenson and Slesnick 1987; Lewbel and Pendakur, 2008; Prais and Houthaker 1955). Households in which men control a large share of financial wealth have a slight tendency to select a lower risky share. In an unreported work, we obtain that male-dominated households tend to invest directly in stocks a higher share of their risky portfolios. These results are in line with the evidence that gender differences in risk taking vary with the gamble payoff structure and the type of task (e.g. Croson and Gneezy 2008, Feng and Seasholes 2007, Haliassos and Bertaut 1995).

In the third set of columns, we add human capital and measures of habit to the set of explanatory variables. Expected human capital has a positive but insignificant relation with the risky share. Income risk, on the other hand, is negatively related, as captured by the negative coefficients on the permanent and transitory components of income. These results are consistent with the findings of Palia, Qi and Wu (2009) and Vissing-Jørgensen (2002b). As in Heaton and Lucas (2000), entrepreneurs are less prone to selecting a large fraction of risky assets in their financial portfolios, consistent with the widely heterogeneous performance of private businesses (e.g. Moskowitz and Vissing-Jørgensen 2002). A high correlation between income innovation and the household's risky portfolio return tends to be associated with a high risky share, as in the work of Massa and Simonov (2006) on Swedish households.

The measures of internal and external habit are both negatively related to the risky share, as theory predicts, but with different significance levels. The internal habit is strongly significant: Households with higher average income (a proxy for own consumption habit) are less prone to financial risk. Lupton (2002) obtained a similar result on US consumption data. The external habit coefficient is insignificant, suggesting that income differences across Swedish municipalities provide only limited explanations of the risky share. Our cross-sectional evidence is based on a short history and should be interpreted with caution. External habit-formation models are primarily used to explain time series variations in asset returns and risk premia, not the cross-section of the risky share. Furthermore, given that we regress the risky share on average income, our results may also be due to cash on hand, as in Haliassos and Bertaut (1995) and Haliassos and Michaelides (2002).

In the last set of columns of Table 1, we include dummies for the household's municipality and the household head's industry. These variables may matter because households in different municipalities and business sectors may have access to different information or have different expectations about future economic conditions and stock market performance. We obtain no major difference in the estimated coefficients once we control for these effects.

Overall, our results confirm the cross-sectional findings obtained with other datasets. As in Carroll (2002), the risky share is substantially larger for households with high financial wealth and is by far the most significant regressor. Financial wealth has a strong positive cross-sectional correlation with the risky share that ranges from 0.21 in the absence of controls to 0.23 in the presence of controls. The risky share tends to be lower for households with high levels of real estate wealth, the leverage ratio, family size, internal habit, income risk, or a low correlation between income risk and portfolio return. Education and portfolio diversification are positively related to risk-taking. One advantage of the Swedish dataset is that we can simultaneously measure the relation between the risky share and a large number of household characteristics, while earlier research is typically based on fragmentary data. To the best of our knowledge, this paper is the first to combine human capital, leverage, and habit in a single regression.

While compelling, these results are difficult to interpret, because financial wealth and household characteristics play a dual role in the pooled cross sectional regressions (3.4). On the one hand, the regressors may have a direct impact on risk-taking, as financial theory would suggest. On the other hand, household characteristics can be viewed as proxies for a latent fixed effect. One might consider resolving these issues by including a household fixed effect in (3.4). This is difficult to do in practice, however, because important variables such as gender and education are either constant or very persistent, and therefore difficult to distinguish from a fixed effect. Even when there is sufficient variation, one must control for inertia, as will be explained in Section 5.5. The

Swedish twin dataset offers the possibility of an alternative estimation strategy, which we now explain.

3.3. Twin Regressions

We assume that for every twin pair i, the risky share of each twin j can be expressed as:

$$\begin{aligned} \ln(w_{i,1,t}) &= \alpha_{i,t} + \eta f_{i,1,t} + \gamma' x_{i,1,t} + \varepsilon_{i,1,t}, \\ \ln(w_{i,2,t}) &= \alpha_{i,t} + \eta f_{i,2,t} + \gamma' x_{i,2,t} + \varepsilon_{i,2,t}. \end{aligned} \tag{3.5}$$

The intercept $\alpha_{i,t}$ is a fixed effect specific to twin pair i in year t. It captures the impact of time, stock market performance, genes, shared background, common upbringing, and expected inheritance, among others.

Specification (3.5) can be estimated using standard panel techniques. Equivalently, we can difference the two equations and estimate by OLS:

$$\Delta_j \ln(w_{i,j,t}) = \eta \Delta_j (f_{i,j,t}) + \gamma' \Delta_j (x_{i,j,t}) + \varepsilon_{i,t}, \tag{3.6}$$

where $\Delta_j(y_{i,j,t}) = y_{i,2,t} - y_{i,1,t}$ denotes the twin difference of a variable y, and $\varepsilon_{i,t} = \varepsilon_{i,2,t} - \varepsilon_{i,1,t}$. Both methods provide the same estimates and $t-$statistics of η and γ, but they have different R^2 coefficients. To facilitate comparison with the pooled cross-sectional regressions, we will report the R^2 coefficient for (3.5). Twin difference regressions (3.6) have substantially lower R^2 coefficients than (3.5), as one would expect if pair fixed effects are important.

In first two columns of Table 2, we regress the risky share on financial wealth and yearly twin pair fixed effects. Financial wealth has a strong positive coefficient, and the estimated elasticity η is now 0.196, as compared to 0.212 in the pooled regression reported in Table 1. The elasticity of the risky share with respect to financial wealth is estimated at 0.212 when we include financial and demographic characteristics (second set of columns), 0.221 when we add human capital, income risk and habit measures (third set), and 0.218 when we also include municipality and industry dummies (last set of columns). These estimates are remarkably stable and confirm the findings from cross-sectional regressions that the financial wealth elasticity of the risky share is strictly positive and close to 0.22.

The twin regressions confirms some of the other main results of the pooled cross-sections. Households with real estate holdings, leverage, large family size, risky assets with high systematic exposure, risky income, or a high habit, tend to take less financial risk. Diversification and proxies for financial experience and sophistication are positively related to the risky share, while expected human capital is insignificant. The positive impact of the Sharpe ratio confirms the explanation proposed in CCS 2007 that households are more prone to purchase risky assets when they are more competent about stockmarket investing. One interesting difference between pooled and twin regressions is that education is positively related to the risky share in the cross-section, but is insignificant in the twin regression. Education variables have sample standard deviations of similar magnitudes in the level and twin differences. These findings suggest that education variables capture a fixed effect in traditional cross-sectional regressions, but have no direct relation to the risky share.

Yearly twin pair fixed effects and financial wealth explain most of the predicted variation in the risky share. The adjusted R^2 coefficient, which equals 9.7% in the pooled cross-section of the risky share on financial wealth, increases to 18.0% in the presence of yearly twin pair fixed effects, and to 22.8% when all other characteristics are included as explanatory variables.

Our estimates of the financial wealth elasticity of the risky share can be readily interpreted in the context of habit formation models. Since the average elasticity is $\eta \approx 0.2$, we infer from (3.3) that the present value of maintaining the (internal or external) habit relative to financial wealth is approximately $\eta/(1+\eta) \approx 1/6$. The habit thus represents on average one sixth of the household's financial wealth.

We conduct a number of robustness checks in the Appendix. First, we consider the impact of zygosity. The variance of the risky share is substantially smaller within pairs of identical twins than within pairs of fraternal twins. We also reestimate the yearly twin pair regressions separately on monozygotic and dizygotic twins. The financial wealth elasticity of the risky share is estimated at 0.17 for monozygotic twins and 0.227 for dizygotic twins, and adjusted R^2 coefficients are 31.4% and 21.7%, respectively[4]. Consistent with intuition, yearly twin pair fixed effects and financial wealth capture a higher fraction of the observed variation of the risky share when we focus on identical twins. The financial wealth elasticity of the risky share is close 0.2 in both groups, and remains strongly significant despite the smaller size of each subsample.

Second, it is sometimes suggested that genetic effects matter less with age. In the Appendix, we classify twin pairs by age and reestimate the twin regressions in each group. The financial wealth elasticity of the risky share is 0.161 for twins younger than 35, 0.246 for twins between 35 and 45, 0.211 for twins between 45 and 55, and 0.181 for twins above 55. The elasticity remains significantly positive for all groups and is hump-shaped with age. The effect of other characteristics is generally robust, but tends to be less significant due to the smaller size of the groups. Leverage, family size, income risk, and (external and internal) habit have a negative impact on the risky share. The correlation between the income growth innovation and the risky portfolio return, ρ_h, is

[4] The pooled cross sectional regressions have adjusted R^2 of 16.97% and 16.16% for monozygotic and dizygotic twins, respectively.

positively related to risk-taking in two age groups ($35-45$ and above 55) and negatively related in the other two (less than 25 and $45-55$). Furthermore, the correlation effect is strongly significant only for the older group.

Third, one might worry that working with pairs of twins creates additional difficulties. For example, the insignificant education coefficients can be interpreted as evidence that education cannot explain risk-taking, or alternatively that twin communicate frequently enough to overcome the impact of education differences on their risk-taking behavior. In the Appendix, we separately reestimate our regressions on the set of twins that communicate rarely and the set of twins that communicate often. The regression coefficients reported for each group are remarkably similar to the ones reported in Table 2. Interestingly, the adjusted R^2 for twins with infrequent contacts is more than double the R^2 for twins that communicate often, suggesting that communication tends to reduce differences in risk-taking. We leave to future research the investigation of such issue.

Fourth, we have so far assumed that individual choices are driven by individual preferences and characteristics, and we have devoted only limited attention to the potential impact of social interactions. Because residents in different areas of Sweden may imitate the asset allocation of their neighbors, we have included municipality and business dummies in the last column of Tables 1 and 2, and we have verified that these variables do not impact our main results. In the Appendix, we provide further evidence on the role of local interactions. We report that the standard deviation of the risky share (in logs or in levels) within Swedish municipalities is at least five times larger than the standard deviation of the average risky share between municipalities, which suggests that local interactions are not the main drivers of risk-taking. We also reestimate the twin difference regressions by including as controls the average log risky share and the average log financial wealth of households in the same municipality, while keeping municipality fixed effects as controls. The financial wealth elasticity is again estimated at 0.22, and the main results of Table 2 remain unchanged. The log risky share has a positive and significant coefficient of about 0.76. This result should naturally be taken cautiously, since regressing a variable on group means is fraught with difficulties such as the reflection principle (e.g. Manski, 1993). While we leave the full investigation of social interactions in risk-taking for further research, we conclude that social interactions within municipalities do not alter our main findings.

In the above analysis, we have not controlled for individual fixed effects that are specific to each twin and impact the risky share in addition to the pair fixed effect. We provide a detailed treatment of this issue in Section 5. Another limitation is that we have assumed that the financial wealth elasticity of the risky share is constant across households. Financial theory suggests, however, that the elasticity can vary with household characteristics, including financial wealth. For this reason, we now investigate the determinants of the elasticity of the risky share.

4. What Drives the Financial Wealth Elasticity of the Risky Share?

We have so far assumed that the financial wealth elasticity of the risky share is constant, and we have estimated it by regressing twin differences of the risky share on twin differences of financial wealth. We now consider the extended specification:

$$\Delta_j \ln(w_{i,j,t}) = \eta_{i,t}\Delta_j(f_{i,j,t}) + \gamma'\Delta_j(x_{i,j,t}) + \varepsilon_{i,t}, \tag{4.1}$$

where $\eta_{i,t}$ is pair-dependent. We will allow $\eta_{i,t}$ to be a function of the characteristics of the pair.[5]

In Table 3, we classify twin pairs into quartiles of the average log financial wealth $f_{i,t} = (f_{i,1,t} + f_{i,2,t})/2$, and estimate the elasticity of the risky share in each bin. We do not include any other characteristics in the first set of columns. The measured elasticity is 0.29 in the first financial wealth quartile, 0.22 in the second quartile, 0.15 in the third quartile, and 0.10 in the fourth quartile. The elasticity $\eta_{i,t}$ is therefore a decreasing function of financial wealth $f_{i,t}$. In the second set of columns of Table 3, we also include all the other characteristics as controls. The estimates of elasticity in each quartile increase slightly, but the elasticity still decreases strongly with financial wealth.

We next assume that the elasticity is a linear function of log financial wealth and other characteristics:

$$\eta_{i,t} = \eta_0 + \eta_1 f_{i,t} + \psi' x_{i,t},$$

where $x_{i,t}$ denotes the average vector of characteristics in pair i. The variables $f_{i,t}$ and $x_{i,t}$ are demeaned year by year. This specification implies:

$$\Delta_j \ln(w_{i,j,t}) = (\eta_0 + \eta_1 f_{i,t} + \psi' x_{i,t})\Delta_j(f_{i,j,t}) + \gamma'\Delta_j(x_{i,j,t}) + \varepsilon_{i,t}, \tag{4.2}$$

which can be estimated by running an OLS regression of $\Delta_j \ln(w_{i,j,t})$ on $\Delta_j(f_{i,j,t})$, $f_{i,t}\Delta_j(f_{i,j,t})$, $x_{i,t}\Delta_j(f_{i,j,t})$, and $\Delta_j(x_{i,j,t})$.

In a habit formation model, the elasticity (3.3) increases with the habit and decreases with financial wealth. In the first set of columns of Table 4, we therefore consider that the financial wealth elasticity of the risky share is driven by these two variables. The elasticity of the risky share is a decreasing function of financial wealth and an increasing function of the habit. The first result is consistent with the bin regressions in Table 3, while the second result is new. Our findings are readily interpreted. We loglinearize $\eta_{h,t}$ around $\overline{\ln(y_{h,t})}$ and obtain:

$$\eta_{h,t} \approx \bar{\eta} + \eta_1 \left(f_{h,t} - \bar{f}_{h,t}\right) - \eta_1 \left[\ln(X_{h,t}) - \overline{\ln(X_{h,t})}\right],$$

[5] We can derive (4.1) from the specification $\ln(w_{i,j,t}) = \ln(w_{i,t}) + \eta_{i,t}(f_{i,j,t} - f_{i,t})$, as in Ashenfelter and Rouse (1998).

where $\eta_1 = \bar{\eta}^2 / e^{\overline{\ln(y_{h,t})}}$. Since $\bar{\eta} \approx 0.2$, we infer that $\eta_1 \approx 0.24$. In regression (1) of Table 4, we have estimated that the coefficient of financial wealth and the habit are -0.091 and 0.13, respectively. These estimates are approximately the negative of each other, and their magnitudes are about half of the predicted theoretical values. Our analysis is of course a rough assessment of habit formation, since our measures of habit and financial wealth are contaminated by measurement error and we have ignored substantial nonlinearities in financial wealth and other characteristics. We leave the full assessment of the microeconomic implications of habit formation for further research.

In the second set of columns of Table 4, we allow the elasticity to depend on the full set of demographic and financial characteristics. The elasticity decreases with financial wealth and human capital, and increases with real estate wealth and leverage. Family size not only has a direct negative impact on the risky share but also increases the elasticity of financial wealth. Larger households have lower effective wealth and are in fact behaving like poorer households of smaller size. It is noteworthy that human capital, whose direct impact on the risky share is insignificant, becomes significant when it is interacted with financial wealth. Portfolio diversification has a positive and significant direct impact on the risky share but does not affect the elasticity with respect to financial wealth.

5. Robustness Checks

5.1. Measurement Error

Because financial wealth is observed with measurement error, we now consider an instrumental variable estimation of the twin specification (3.5). We begin with some definitions. The *passive risky return* $r_{h,t}$ is the proportional change in value of a household's risky portfolio if the household does not trade risky assets during the year. *Log passive financial wealth* is defined as:

$$f^p_{h,t} = \phi(F_{h,t-1}, w_{h,t-1}, r_{h,t}, r_{f,t}),$$

where

$$\phi(F, w, r, r_f) = \ln\{[w(1+r) + (1-w)(1+r_f)]F\}.$$

In Table 5, we instrument log financial wealth with log passive financial wealth. In the first set of columns, we consider a constant elasticity η and estimate it at 0.29, which is slightly higher than the values reported in earlier tables. Thus, the presence of measurement error causes our OLS estimates to exhibit a downward bias.

In the second set of columns of Table 5, we estimate separate values of the elasticity η in different financial wealth quartiles. Consistent with Section 4, the measured elasticity strongly decreases with financial wealth. We also observe that the impact of our other characteristics is qualitatively unchanged, but internal habit has a negative significant impact on the risky share compared to the OLS twin difference regressions reported in Tables 2 to 4. Overall, the empirical regularities documented in Sections 3 and 4 do not seem to be invalidated by the presence of measurement error in financial wealth.

5.2. Impact of Lagged Financial and Portfolio Characteristics

Consistent with earlier research, we have shown that there is a positive relation between financial wealth and the risky share. One interpretation of this result, which we have emphasized until now, is that richer households tend to select a higher risky share. An alternative interpretation, however, is that at the end of the bull market of the nineties, investors with high equity investments happened to have larger financial wealth than other households. In an economy populated with CRRA investors, we would indeed observe a positive cross-sectional correlation between the risky share and financial wealth after a prolonged period of positive excess stock returns.

In order to distinguish between these two explanations, we define the *passive risky share* $w^p_{h,t}$ as the risky share at the end of year t if the household does not trade risky assets during the year. The passive share is given by:

$$w^p_{h,t} = \frac{w_{h,t-1}(1 + r_{h,t})}{w_{h,t-1}(1 + r_{h,t}) + (1 - w_{h,t-1})(1 + r_f)},$$

where $r_{h,t}$ is the passive return on the risky portfolio previously defined. The *passive change in the log risky share* is then defined as $\ln(w^p_{h,t}) - \ln(w_{h,t-1})$. These definitions readily extend to periods of inactivity of n years.

In Table 6, we report twin regressions of the log risky share in 2002 on the usual characteristics and: (a) the log risky share in 1999; (b) the passive change in the log risky share between 1999 and 2002; (c) log financial wealth in 1999; and (d) the passive change in log financial wealth. The coefficient of the risky share and its passive change are both positive and significant, which confirms that the propensity to take risk is persistent over time and that there is inertia in portfolio rebalancing.

Perhaps more importantly, we obtain that 1999 log financial wealth has a positive and significant coefficient. That is, richer households in 1999 have a higher risky share in 2002, even when we control for their risky share at the end of 1999. This result is important, because one would not expect it to hold if investors have CRRA utilities (with or without inertia). In the CRRA specification, risk-tolerant investors have high financial wealth in 1999 because of the bull market, a high risky share in 1999, and therefore a high risky share in 2002. We thus expect a positive relation between the risky share in 1999 and 2002. This mechanism cannot explain, however, the positive relation between the 1999 financial wealth and the 2002 risky share. We conclude that the measured positive relation between financial wealth and risk-taking is not mechanically implied by the bull market of the 1990's. Instead, it suggests that individual investors exhibit decreasing relative risk aversion and inertia in portfolio rebalancing.

5.3. Health and Lifestyle

Twin difference regressions may be contaminated by individual fixed effects that are specific to each twin in the pair. For instance, twins may have different levels of risk aversion. One strategy is to include additional control variables that are known to be related to risk aversion. For instance, Barsky et al. (1997) show that risk aversion and asset allocation decisions are related to behavioral variables such as smoking and drinking.

In Table 7, we include as controls data on the lifestyle and physical and mental health of each twin. Because we have only obtained these variables for the SALT survey, we reestimate the risky share regression on the subset of twins born between 1886 and 1958. The empirical regularities documented in Sections 3 and 4 are robust to the inclusion of these new variables. The average financial wealth elasticity of the risky share is again estimated at 0.21. The new control variables are mainly insignificant at the 5% level, but this is partly due to the fact that we are using a smaller number of observations. Alcohol drinking is positively related to risk-taking, but the coefficient is only significant at the 10% level. High blood pressure and depression symptoms have a negative impact at higher significance levels. Coffee drinking, tobacco, regular physical exercise, height, and weight have insignificant coefficients. In unreported work we find that the adjusted R^2 increases only marginally when the physiological and lifestyle characteristics are added to the pooled cross sectional regression whether or not we control for yearly pair fixed effects. Overall, these new regressions confirm the robustness of our results, and also show that risk-taking is positively related to alcohol consumption and negatively related to depression and high blood pressure.

5.4. Dynamic Panel Estimation

We can also control for individual fixed effects by following over time the risky share of of a given household (e.g. Brunnermeier and Nagel 2008; Chiappori and Paiella 2008; CCS 2009*a*). Given the specification $\ln(w_{h,t}) = \delta_{0,t} + \alpha_h + \eta f_{h,t} + \varepsilon_{h,t}$, we eliminate the household fixed effect by taking the first time-difference:

$$\Delta_t \ln(w_{h,t}) = \delta_t + \eta \Delta_t(f_{h,t}) + \Delta_t(\varepsilon_{h,t}). \tag{5.1}$$

This estimation method can naturally be applied to any subsample of households in the overall Swedish population, and not simply households with a twin. As discussed in CCS (2009a), the estimation of (5.1) must control for two related problems. First, because households display inertia in household rebalancing, we need to include variables that capture passive variations in the risky share. Second, the regressor $\Delta_t(f_{h,t})$ and the error term $\Delta_t(\varepsilon_{h,t})$ are correlated in equation (5.1), since the innovation $\varepsilon_{h,t-1}$ has an impact on the following period's financial wealth $f_{h,t}$. A natural solution is to instrument changes in financial wealth.

In the first set of columns of Table 8, we estimate the specification:

$$\Delta_t \ln(w_{h,t}) = \delta_t + \eta\Delta_t(f_{h,t}) + \zeta\Delta_t \ln(w^p_{h,t}) + \Delta_t(\varepsilon_{h,t}).$$

We instrument changes in financial wealth, $\Delta_t(f_{h,t})$, and changes in the passive risky share, $\Delta_t \ln(w^p_{h,t})$, with: (a) the change in financial wealth in the absence of period $t-1$ rebalancing, $\phi(F_{h,t-1}, w^p_{h,t-1}, r_{h,t}, r_{f,t}) - f_{h,t-1}$;[6] and (b) the period $t-1$ log passive risky share, $\ln(w^p_{h,t-1})$. In CCS (2009a), we have followed a similar method to estimate an adjustment model of portfolio rebalancing, in which the financial wealth elasticity of the target risky share is assumed to be constant.

The elasticity of the risky share with respect to financial wealth is estimated at 0.22. This result is consistent with the twin difference regressions of Section 3, and is also in line with the financial wealth elasticity of the target risky share reported in CCS (2009). The change in the log passive share has a significant and positive coefficient, which confirms that there is inertia in household portfolio rebalancing.

In the second set of columns, we let η vary across financial wealth quartiles, which is a methodological innovation. As in the twin difference regressions, the wealth elasticity of the risky share strongly decreases with financial wealth itself. The coefficient of $\Delta_t \ln(w^p_{h,t})$ is significantly positive in both specifications, which confirms the presence of inertia in portfolio rebalancing.

In the third and fourth set of columns, we reestimate these specifications in the presence of all controls. We use the level of these controls at the end of year $t-1$ in order to avoid endogeneity problems. The average elasticity of the risky share slightly increases to 0.23, and the elasticity is still a strongly decreasing function of financial wealth.

The dynamic panel estimation confirms all the main results of the twin difference regressions. The two approaches are strongly complementary. The dynamic method controls for household fixed effects, but requires valid instruments, which is a source of concern. The technical complexity of dynamic models might hamper their applicability to a large class of explanatory variables. While dynamic panel estimation requires instruments, twin difference equations can be estimated by OLS. Furthermore, the results

[6] The instrument coincides with the passive log return on the complete portfolio,

$$\ln[w^p_{h,t-1}(1 + r_{h,t}) + (1 - w^p_{h,t-1})(1 + r_f)].$$

of the section suggest that twin difference regression are not severely contaminated by household fixed effects.

6. Participation and Aggregate Implications

In the previous sections, we have focused on households that own risky assets. We now investigate the decision to participate in risky assets markets, and provide estimates of the elasticity of the aggregate risky share to changes in the wealth distribution.

6.1. Determinants of the Participation Decision

We begin by measuring the cross-sectional correlation between participation, financial wealth, and other characteristics. In the first two columns of Table 9, we run a pooled logit regression of the participation regression on household characteristics:

$$\mathbb{E}(y_{h,t}|x_{h,t}) = \Lambda(\delta_t + \gamma' x_{h,t}).$$

Richer households with high human capital and education are more likely to own risky assets. The effect of financial wealth is especially significant. Households with other experience of financial markets, for instance because they have debt or invest in the private pension system, are also more likely to participate. Conversely, participation is less likely for larger households that have a high leverage ratio, a high external or internal habit, or high income risk. The negative relation between household size and participation is consistent with the concept of equivalence scale, or with the background risk induced by the random needs of a large family. These cross-sectional results confirm earlier findings (e.g. Bertaut and Starr-McCluer 2002; CCS 2007; Guiso and Jappelli 2002; Vissing-Jørgensen 2002b). The reported negative correlation between participation and (internal and external) habit measures are, to the best of our knowledge, new to the literature.

In the third set of two columns of Table 9, we report the results of a logit regression with yearly twin pair fixed effects:

$$\mathbb{E}(y_{i,j,t}|x_{i,j,t}) = \Lambda(\alpha_i + \delta_t + \gamma' x_{i,j,t}).$$

Financial wealth, human capital, and proxies for financial experience all have strong positive coefficients, while leverage, income risk and the external habit have negative coefficients. Interestingly, some of these variables, such as the external habit, have stronger magnitudes that in the cross-sectional regression. Internal habit, education, and household size are now insignificant.

The results of the fixed effect regression is that financial wealth is once again a strong determinant of risk-taking. As in Section 3, the impact of leverage, human capital, habit, and income risk is also significant. Our findings thus that confirm some of the main theories of financial market participation (e.g. Calvet, Gonzalez-Eiras and Sodini, 2004; Heaton and Lucas 1999; Vissing-Jørgensen 2002a) still hold when one controls for yearly twin pair fixed effects.

6.2. Aggregate Implications

We now investigate how exogenous changes in household financial wealth can impact the aggregate demand for risky assets. We take asset prices are fixed and neglect general equilibrium effects, local interactions, and changes in the habit. At the end of a given year, households are characterized by their risky share w_h, their log financial wealth $f_h = \ln(F_h)$, and their other characteristics x_h. For simplicity, we neglect time indices in this section. We consider an exogenous change in the cross-sectional distribution of financial wealth, which for every household h is specified by the growth rate $\Delta(f_h)$.The household's new financial wealth is therefore $F_h' = F_h e^{\Delta(f_h)}$.

We focus for now on the set of households that initially hold risky assets, and do not consider participation changes. Let F denote the aggregate financial wealth of participants, and $F_R = \sum_h w_h F_h$ the aggregate wealth invested in risky assets. We define the elasticity of aggregate risky wealth as:

$$\xi = \frac{\Delta \ln(F_R)}{\Delta \ln(F)}.$$

Since prices are exogenous, ξ quantifies how the aggregate demand for risky assets responds to exogenous changes in aggregate wealth. We will see that ξ generally depends on the individual growth rates $\Delta(f_1), ..., \Delta(f_H)$, and not simply on the aggregate growth rate $\Delta \ln(F)$.

If the aggregate demand for risky assets is driven by a representative agent with constant relative risk aversion (CRRA), the aggregate risky share F_R/F is constant, and the elasticity is equal to unity: $\xi = 1$.

We also consider micro-level imputation methods that use the initial share w_h of each household. After the wealth shock, the risky share is given by:

$$\ln(w_h') = \ln(w_h) + \eta_h \Delta(f_h),$$

where η_h denotes the financial wealth elasticity of the risky share considered in earlier sections. We consider three possible choices for the elasticity η_h:

- $\eta_h = 0$ for all h, as is the case where each household has its own CRRA utility;
- $\eta_h = \eta > 0$ for all h, that is, households have a positive identical financial wealth elasticity of the risky share;

- $\eta_h = \eta(f_h, x_h)$ for all h, which corresponds to the case where the elasticity of each household is a linear function of its financial wealth and characteristics.

The scenario $\eta_h = 0$ implicitly assumes that households have heterogeneous risk aversion coefficients, which determine their initial risky share w_h. We can easily verify that the elasticity ξ is equal to unity if all households have the same initial risky share ($w_1 = ... = w_H$). We will see, however, that ξ can be either larger or smaller than 1 when households have heterogeneous initial shares. In the scenario $\eta_h = \eta > 0$, the constant elasticity is obtained from the yearly twin difference regression of the risky share on log financial wealth. In the last scenario, the linear elasticity $\eta(f_h, x_h)$ is obtained by also including characteristics as regressors. It is the most plausible specification given the micro-level evidence of Section 4.[7]

In Figure 1, we consider 20 financial wealth quantiles, and report for each quantile the value of ξ corresponding to an exogenous wealth shock that affects only households in the quantile: $\Delta(f_h) = g$ if h in the quantile, and $\Delta(f_h) = 0$ otherwise. All the results are reported for year 2001 and in the Appendix we show that the results are qualitatively similar in other years. The yellow line corresponds to the benchmark representative investor. The aggregate risky wealth $F'_R = \sum_h w'_h F'_h$ and the elasticity ξ are higher when the wealth increase is concentrated on households with higher initial risky share. For this reason, when households have heterogeneous but fixed levels of risk aversion (green line), the elasticity ξ is monotonic, is less than 1 for low and medium quantiles and exceeds unity only for the very top quantiles. When households have a strictly positive elasticity η (pink line), risky financial wealth grows faster, as one would expect, and reaches 1.4 for the highest quantile. When instead the elasticity is a linear function of financial wealth (blue line), the aggregate demand for risky assets has an elasticity that remains close to unity for a wide range of middle quantiles. For high quantiles, however, the financial wealth elasticity of the risky share of individual households is close to zero, and the aggregate elasticity ξ coincides almost exactly with the aggregate elasticity of the heterogeneous CRRA investors. Thus, the linear elasticity specification is consistent with micro evidence, and generates an aggregate demand for risky assets that can be approximately represented by, but does not exactly coincide with, a CRRA representative investor.

We next investigate participation effects. Let $\mathcal{N}$ denote the set of households that do not initially participate in financial markets. The probability that a household participates is given by the yearly cross-sectional logit model $\Lambda(f_h; x_h)$. The probability

[7] We have checked that our results are robust when we estimate the elasticity from the pooled cross-section.

that a household in $\mathcal{N}$ enters is 0 if $\Delta f_h \leq 0$, and is otherwise:

$$e_h = \frac{\Lambda(f_h + \Delta f_h; x_h) - \Lambda(f_h; x_h)}{1 - \Lambda(f_h; x_h)}.$$

If the household enters, we assume that it selects the risky share $w'_h = w(f_h + \Delta f_h; x_h)$, which is imputed from the cross-sectional regression of the log risky share on characteristics. Aggregate risky financial wealth is then $F'_R = \sum_{h \in \mathcal{N}} e_h w'_h F'_h + \sum_h w_h e^{\eta_h g_h} F'_h$.

In Figure 2, we illustrate the elasticity of aggregate risky wealth with respect to aggregate financial wealth in the population of participating and nonparticipating twins. By a slight abuse of notation, this new elasticity is also denoted by ξ. In low quantiles, participation is low, so ξ is close to zero for all imputation methods. With the linear elasticity method (blue line), poor investors have a higher elasticity of the risky share η than average, so ξ tends to be higher than with the constant elasticity method (pink line). The linear elasticity eventually goes down and the two lines cross. Because rich investors have an elasticity η close to zero, they behave like heterogeneous CRRA investors. Thus, the linear elasticity specification, which was estimated in Section 4, implies that the aggregate elasticity ξ is close to unity on a wide range of wealth quantiles.

We also investigate the impact of homogenous shocks to the wealth distribution: $\Delta(f_h) = g$ for all h. When investor have CRRA utilities, the elasticity ξ is 1 when the set of participants is fixed, and 1.02 in 2001 when entry or exit is taken into account. The corresponding estimates are 1.22 and 1.25 when households have a constant η, and 1.07 and 1.1 when households have a linear elasticity $\eta(f_h, x_h)$.

Overall, this section illustrates the benefits of considering a risky share specification in which the elasticity $\eta(f_h, x_h)$ decreases with financial wealth. First, this approach is empirically consistent with micro data, as was shown in Section 4. Second, such a specification generates an aggregate demand for risky assets that is consistent, but does not exactly coincide, with the demand of a representative agent with CRRA utility. Third, the aggregate elasticity of such a group of investors is remarkably stable, whether one considers homogenous shocks or shocks that only affect a concentrated group of households. We anticipate that these results will stimulate further research on the specification of the representative agent. For instance, it is open question if the deviations from the CRRA benchmark are negligible or could instead be used to provide support for alternative benchmarks, such as the aggregate habit formation models of Constantinides (1990) and Campbell and Cochrane (1999). Our estimates could also have implications for consumption-based asset pricing. We leave these questions for further research.

7. Conclusion

The determinants of risk-taking have been the subject of an extensive literature in portfolio choice theory and empirical household finance. In this paper, we have used a novel empirical methodology, the comparison of the portfolios held by twins, to investigate the risky share and its elasticity with respect to financial wealth. We have considered an unprecedented set of control variables, including portfolio characteristics, real estate wealth, debt, leverage, human capital, labor income risk, household size, age, and measures of internal and external habit. The average elasticity of the risky share with respect to financial wealth is estimated at 22%.

This paper confirms that the findings of several strands of the literature are qualitatively robust to the inclusion of twin pair fixed effects. Most explanatory variables have a similar impact on the risky share in the cross-sectional and twin difference regressions. The risky share is positively related to diversification and financial experience, and negatively related to income risk, real estate, leverage, household size and a measure of habit. Education, however, significantly affects the risky share in the cross section but becomes insignificant in the twin difference regression.

We document substantial heterogeneity in the financial wealth elasticity of the risky share across households. The elasticity decreases with financial wealth and human capital, is unaffected by education and diversification, and increases with leverage and a measure of habit. The present value of the cost of maintaining the habit represents 1/6 of financial wealth on average, but is higher for poorer households.

Intuition suggests that twin pair fixed effects control for factors such as genes, ability, risk aversion, common upbringing, or expected inheritance. One might worry, however, that twin difference regressions may be contaminated by fixed effects that are specific to each twin in the pair. We confirm our findings by regressing time variations of a household's log risky share on time variations of its log financial wealth. We also verify that our results are unchanged when we control for communication between twins and variables typically associated with risk taking, like drinking, smoking behavior, and other lifestyle and physiological characteristics.

Our household-level results provide support for decreasing relative risk aversion, habit formation, and a negative relation between financial wealth and the financial wealth elasticity of the risky share. We also consider exogenous shocks to the wealth distribution, and show that the aggregate demand for risky assets behave close to, but does not coincide with, the aggregate demand of a representative investor with CRRA utility. In further research, it would be interesting to examine if these deviations provide support for alternative benchmarks, such as the aggregate habit formation models of Constantinides (1990) and Campbell and Cochrane (1999).

References

[1] Alessie, Rob, Stefan Hochguertel, and Arthur Van Soest, 2002, Household portfolios in the Netherlands, in Luigi Guiso, Michael Haliassos and Tullio Jappelli eds. *Household Portfolios*, MIT Press, Cambridge, MA.

[2] Ameriks, John, and Stephen Zeldes, 2004, How do household portfolio shares vary with age?, working paper, Columbia University.

[3] Ashenfelter, Orley, and Alan Krueger, 1994, Estimates of the economic return to schooling from a new sample of twins, *American Economic Review* 84(5), 1157–1173.

[4] Ashenfelter, Orley, and Cecilia Rouse, 1998, Income, schooling, and ability: Evidence from a new sample of identical twins, *Quarterly Journal of Economics* 113, 253-284.

[5] Banks, James, and Sarah Tanner, 2002, Household portfolios in the United Kingdom, in Luigi Guiso, Michael Haliassos and Tullio Jappelli eds. *Household Portfolios*, MIT Press, Cambridge, MA.

[6] Barnea, Amir, Henrik Cronqvist, and Stephan Siegel, 2009, Nature or nurture: What determines investor behavior?, working paper, Claremont McKenna College and University of Washington.

[7] Barsky, Robert, Thomas Juster, Miles Kimball, and Matthew Shapiro, 1997, Preference parameters and behavioral heterogeneity: An experimental approach in the Health and Retirement Study, *Quarterly Journal of Economics* 112(2), 537-579.

[8] Behrman, Jere, and Mark Rosenzweig, 2002, Does increasing women's schooling raise the schooling of the next generation?, *American Economic Review* 92(1), 323-334.

[9] Behrman, Jere, and Paul Taubman, 1989, Is schooling mostly in the genes? Nature-nurture decomposition using data on relatives, *Journal of Political Economy*, 97, 1425-1446.

[10] Bertaut, Carol, and Martha Starr-McCluer, 2002, Household portfolios in the United States, in Luigi Guiso, Michael Haliassos and Tullio Jappelli eds. *Household Portfolios*, MIT Press, Cambridge, MA.

[11] Björklund, Anders, Markus Jäntti, and Gary Solon, 2007, Nature and nurture in the intergenerational transmission of socioeconomic status: Evidence from Swedish

children and their biological and rearing parents, *B.E. Journal of Economic Analysis and Policy* 7.

[12] Björklund, Anders, Mikael Lindahl, and Erik Plug, 2006, The origins of intergenerational associations: Lessons from Swedish adoption data, *Quarterly Journal of Economics* 121, 999-1028.

[13] Bodie, Zvi, Robert C. Merton, and William Samuelson, 1992, Labor supply flexibility and portfolio choice in a life cycle model, *Journal of Economic Dynamics and Control* 16, 427-49.

[14] Boldrin, Michele, Lawrence Christiano, and Jonas Fisher, 2001, Habit persistence, asset returns, and the business cycle, *American Economic Review* 91 (1), 149-166.

[15] Bronars, Stephen, and Jeff Grogger, 1994, The economic consequences of unwed motherhood: Using twin births as a natural experiment, *American Economic Review* 84 (5), 1141-1156.

[16] Brunnermeier, Markus, and Stefan Nagel, 2008, Do wealth fluctuations generate time-varying risk aversion? Micro-evidence on individuals' asset allocation, *American Economic Review* 98 (3), 713-736.

[17] Calvet, Laurent E., John Y. Campbell and Paolo Sodini, 2007, Down or out: Assessing the welfare costs of household investment mistakes, *Journal of Political Economy* 115, 707-747.

[18] Calvet, Laurent E., John Y. Campbell and Paolo Sodini, 2009*a*, Fight or flight? Portfolio rebalancing by individual investors, *Quarterly Journal of Economics* 124, 301-348.

[19] Calvet, Laurent E., John Y. Campbell and Paolo Sodini, 2009*b*, Measuring the financial sophistication of households, *American Economic Review Papers and Proceedings* 99, 393–98.

[20] Calvet, Laurent E., and Etienne Comon, 2003, Behavioral heterogeneity and the income effect, *Review of Economics and Statistics* 85(3), 653-669.

[21] Calvet, Laurent E., Martín Gonzalez-Eiras and Paolo Sodini, 2004, Financial innovation, market participation and asset prices, *Journal of Financial and Quantitative Analysis* 39, 431–459.

[22] Calvet, Laurent E., and Paolo Sodini, 2009, Appendix to Twin picks: Disentangling the determinants of risk-taking in household portfolios, available online at http://www.hec.fr/calvet.

[23] Campbell, John Y., 2006, Household finance, *Journal of Finance* 61, 1553–1604.

[24] Campbell, John Y., and John Cochrane, 1999, By force of habit: A consumption based explanation of aggregate stock market behavior, *Journal of Political Economy* 107, 205-251.

[25] Carroll, Christopher D., 2000, Why do the rich save so much?, in J.B. Slemrod ed. *Does Atlas Shrug? The Economic Consequences of Taxing the Rich*, Harvard University Press, Cambridge, MA.

[26] Carroll, Christopher D., 2002, Portfolios of the rich, in Luigi Guiso, Michael Haliassos and Tullio Jappelli eds. *Household Portfolios*, MIT Press, Cambridge, MA.

[27] Carroll, Christopher D., and Andrew Samwick, 1997, The nature of precautionary wealth, *Journal of Monetary Economics* 40, 41-71.

[28] Cesarini, David, Christopher Dawes, Magnus Johannesson, Paul Lichtenstein, and Björn Wallace, 2009a, Genetic variation in preferences for giving and risk-taking, *Quarterly Journal of Economics* 124 (2), 809-842.

[29] Cesarini, David, Magnus Johannesson, Paul Lichtenstein, Sandewall Örjan and Björn Wallace, 2009b, Genetic variation in financial decision making, forthcoming, *Journal of Finance*.

[30] Chiappori, Pierre-André, and Monica Paiella, 2008, Relative risk aversion is constant: evidence from panel data, working paper, Columbia University and University of Naples.

[31] Cocco, Joao, 2005, Portfolio choice in the presence of housing, *Review of Financial Studies* 18 (2), 535-567.

[32] Cocco, Joao, Francisco Gomes, and Pascal Maenhout, 2005, Consumption and portfolio choice over the life cycle, *Review of Financial Studies* 18 (2), 491-533.

[33] Cohn, R. A., Wilbur G. Lewellen, Ronald C. Lease, and Gary G. Schlarbaum, 1975, Individual investor, risk aversion, and investment portfolio composition, *Journal of Finance* 39, 602-620.

[34] Constantinides, George, 1990, Habit formation: A resolution of the equity premium, *Journal of Political Economy* 98, 519-543.

[35] Croson, Rachel, and Uri Gneezy, 2008, Gender differences in preferences, *Journal of Economic Literature*, 47 (2), 1-27.

[36] Cvitanic, Jaksa, and Ioannis Karatzas, 1992, Convex duality in constrained portfolio optimization, *Annals of Applied Probability* 2(4), 767-818.

[37] Deaton, Angus, 1974, The analysis of consumer demand in the United Kingdom, 1900-1970, *Econometrica* 42 (2), 341-367.

[38] Dybvig, Philip H., 1995, Duesenberry's ratcheting of consumption: Optimal dynamic consumption and investment policies given intolerance for any decline in standard of living, *Review of Economic Studies* 62, 287–313.

[39] Eymann, Angelika, and Axel Börsch-Supan, 2002, Household portfolios in Germany, in Luigi Guiso, Michael Haliassos and Tullio Jappelli eds. *Household Portfolios*, MIT Press, Cambridge, MA.

[40] Feng, Lei and Marc Seasholes, 2007, Individual investors and gender similarities in an emerging stock market, *Pacific Basin Finance Journal* 16, 44-60.

[41] Flavin, Marjorie, and Takashi Yamashita, 2002, Owner-occupied housing and the composition of the household portfolio, *American Economic Review* 92 (1), 345-362.

[42] Friend, Irwin, and Marshall Blume, 1975, The demand for risky assets, *American Economic Review* 65(5), 900-922.

[43] Grinblatt, Mark, Matti Keloharju, and Juhani Linnainmaa, 2009, IQ and stock market participation, Working paper, UCLA, Helsinki School of Economics, and University of Chicago.

[44] Grossman, Sanford, and Jean-Luc Vila, 1992, Optimal dynamic trading with leverage constraints, *Journal of Financial and Quantitative Analysis* 27(2), 151-168.

[45] Guiso, Luigi, Michael Haliassos, and Tullio Jappelli, 2002, *Household Portfolios*, MIT Press.

[46] Guiso, Luigi, and Tullio Jappelli, 2002, Household portfolios in Italy, in Luigi Guiso, Michael Haliassos and Tullio Jappelli eds. *Household Portfolios*, MIT Press, Cambridge, MA.

[47] Guiso, Luigi, Tullio Jappelli, and Daniele Terlizzese, 1996, Income risk, borrowing constraints and portfolio choice, *American Economic Review* 86, 158-171.

[48] Guiso, Luigi, Paolo Sapienza, and Luigi Zingales, 2009, Cultural biases in economic exchange?, *Quarterly Journal of Economics* 124(3), 1095-1131.

[49] Haliassos, Michael, and Carol Bertaut, 1995, Why do so few hold stocks?, *Economic Journal* 105, 1110-1129.

[50] Haliassos, Michael, and Alexander Michaelides, 2002, Calibration and computation of household portfolio models, in Guiso, Haliassos and Jappelli (2002), 55-101.

[51] Heaton, John, and Deborah Lucas, 1999, Stock prices and fundamentals, in *NBER Macroeconomics Annual* Vol. 14, 213-242.

[52] Heaton, John, and Deborah Lucas, 2000, Portfolio choice and asset prices: The importance of entrepreneurial risk, *Journal of Finance* 55, 1163-1198.

[53] Hurst, Erik, Ming Ching Luoh, and Frank Stafford, 1998, The wealth dynamics of American families, 1984-94, *Brookings Papers on Economic Activity* 1998 (1), 267-329.

[54] Jermann, Urban, 1998, Asset pricing in production economies, *Journal of Monetary Economic*s 41 (2), 257-275.

[55] Jorgenson, Dale, and Daniel Slesnick, 1987, Aggregate consumer behavior and household equivalence scales, *Journal of Business and Economic Statistics* 5, 219-232.

[56] Juster, Thomas, James Smith, and Frank Stafford, 1999, The measurement and structure of household wealth, *Labor Economics* 6, 253—275.

[57] King, Mervyn A., and Jonathan I. Leape, 1987, Asset accumulation, information and the life cycle, NBER Working Paper 2392.

[58] King, Mervyn A., and Jonathan I. Leape, 1998, Wealth and portfolio composition: Theory and evidence, *Journal of Public Economics* 69, 155–193.

[59] Lewbel, Arthur, and Krishna Pendakur, 2008, Equivalence scales, entry for *The New Palgrave Dictionary of Economics*, 2nd Edition.

[60] Lichtenstein, Paul, Patrick F. Sullivan, Sven Cnattingius, Margaret Gatz, Sofie Johanson, Eva Carlström, Camilla Björk, Magnus Svartengren, Alicja Volk, Lars Klareskog, Ulf de Faire, Martin Schalling, Juni Palmgren, and Nancy L. Pedersen, 2006, The Swedish Twin Registry in the third millenium: An update, *Twin Research and Human Genetics* 9, 875-882.

[61] Lupton, Joseph, 2002, Household portfolio choice and the habit liability: Evidence from panel data, working paper, University of Michigan.

[62] Manski, Charles, 1993, Identification of endogenous social effects: The reflection problem, *Review of Economic Studies* 60, 531-542.

[63] Massa, Massimo, and Andrei Simonov, 2006, Hedging, familiarity and portfolio choice, *Review of Financial Studies* 19, 633-685.

[64] Moskowitz, Tobias, and Annette Vissing-Jørgensen, 2002, The returns to entrepreneurial investment: A private equity premium puzzle?, *American Economic Review* 92(4), 745-778.

[65] Murray, Charles, 2002, IQ and income inequality in a sample of sibling pairs from advantaged family backgrounds, *American Economic Review Papers and Proceedings* 92(2), 339-343.

[66] Palia, Darius, Yaxuan Qi, and Yangru Wu, 2009, Heterogeneous background risks, portfolio choice, and asset returns: Evidence from micro-level data, Working Paper, Concordia University and Rutgers Business School.

[67] Paxson, Christina, 1990, Borrowing constraints and portfolio choice, *Quarterly Journal of Economics* 105(2), 535-543.

[68] Pedersen, Nancy L., Paul Lichtenstein, and Pia Svedberg, 2002, The Swedish Twin Registry in the third millenium, *Twin Research and Human Genetics* 5, 427–432.

[69] Peress, Joël, 2004, Wealth, information acquisition, and portfolio choice, *Review of Financial Studies* 17, 879-914.

[70] Perraudin, William, and Bent Sørensen, 2000, The demand for risky assets: Sample selection and household portfolios, *Journal of Econometrics* 97, 117-144.

[71] Plug, Erik, and Wim Vijverberg, 2003, Schooling, family background, and adoption: Is it nature or is it nurture?, *Journal of Political Economy* 111, 611-641.

[72] Prais, S. J., and Hendrik Houthakker, 1955, *The Analysis of Family Budgets*, Cambridge University Press.

[73] Ravina, Enrichetta, 2007, Habit persistence and keeping up with the Joneses: Evidence from micro data, Working Paper, New York University.

[74] Sacerdote, Bruce, 2002, The nature and nurture of economic outcomes, *American Economic Review* 92, 344-348.

[75] Sacerdote, Bruce, 2007, How large are the effects from changes in family environment? A study of Korean American adoptees, *Quarterly Journal of Economics* 122, 119-157.

[76] Schlarbaum, Gary G., Ronald C. Lease, and Wilbur G. Lewellen, 1978, The common-stock-portfolio performance record of individual investors: 1964–1970, *Journal of Finance* 33, 429–441.

[77] Taubman, Paul, 1976, The determinants of earnings: Genetics, family, and other environments; A study of white male twins, *American Economic Review* 66(5), 858-870.

[78] Teplá, Lucie, 2000, Optimal portfolio policies with borrowing and shortsale constraints, *Journal of Economic Dynamics and Control* 24, 1623–39.

[79] Vissing-Jørgensen, Annette, 2002*a*, Limited asset market participation and the elasticity of intertemporal substitution, *Journal of Political Economy* 100, 825–853.

[80] Vissing-Jørgensen, Annette, 2002*b*, Towards an explanation of household portfolio choice heterogeneity: Nonfinancial income and participation cost structures, NBER Working Paper 8884.

[81] Yao, Rui, and Zhang, Harold, 2005, Optimal consumption and portfolio choices with risky housing and borrowing constraints, *Review of Financial Studies* 18(1), 197-239.

[82] Wachter, Jessica, and Motohiro Yogo, 2009, Why do household portfolio shares rise in wealth?, working paper, The Wharton School.

TABLE 1. POOLED CROSS-SECTIONAL REGRESSIONS OF THE LOG RISKY SHARE

Yearly fixed effects

	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Financial and Portfolio Characteristics								
Log financial wealth	0.212	43.20	0.223	39.80	0.234	36.50	0.233	36.60
Log real estate wealth			-0.005	-2.67	-0.004	-2.09	-0.003	-1.75
Leverage ratio			-0.021	-6.69	-0.020	-6.34	-0.020	-6.26
Log total liability			0.018	9.96	0.019	10.30	0.019	10.30
Private pension premia/income			0.108	1.05	0.154	1.31	0.148	1.29
Sharpe ratio of risky portfolio			0.027	16.50	0.027	16.10	0.027	16.40
Beta of risky portfolio			-0.093	-3.90	-0.083	-3.42	-0.081	-3.39
Demographic Characteristics								
High school dummy			0.109	5.01	0.105	4.84	0.110	5.14
Post-high school dummy			0.064	4.61	0.061	4.33	0.065	4.28
Number of adults			-0.207	-11.30	-0.175	-8.35	-0.180	-8.49
Number of children			-0.056	-8.32	-0.055	-7.21	-0.051	-6.55
Wealth-weighted gender index			-0.030	-1.42	-0.023	-1.10	-0.022	-1.06
Human Capital and Income Risk								
Log human capital					0.018	1.41	0.012	0.86
Permanent income risk					-0.116	-1.10	-0.079	-0.76
Transitory income risk					-0.061	-2.36	-0.052	-2.11
Correlation of income innovation and portfolio return					0.052	2.31	0.054	2.40
Entrepreneur dummy					-0.236	-5.82	-0.175	-4.23
Unemployment dummy					-0.078	-3.43	-0.071	-3.13
Habit								
Log internal habit					-0.091	-3.99	-0.095	-4.17
Log external habit					-0.036	-0.63	-0.365	-1.19
Municipality and Industry Dummies							Included	
Number of observations	55,898		55,898		55,898		55,898	
Number of twin pairs	8,394		8,394		8,394		8,394	
R^2	9.70%		13.70%		14.01%		15.81%	
Adjusted R^2	9.70%		13.68%		13.97%		15.31%	

Notes: This table reports pooled cross-sectional regressions of the log risky share on financial wealth and other characteristics. The estimation is based on all Swedish households with an adult twin. Yearly fixed effects are included in the cross-sectional regressions. The education, entrepreneur and unemployment dummies are computed for the twin in the household. All other characteristics are computed at the household level. Log human capital and the leverage ratio are winsorized at the 99th percentile.

TABLE 2. TWIN REGRESSIONS OF THE LOG RISKY SHARE

Yearly twin pair fixed effects

	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Financial and Portfolio Characteristics								
Log financial wealth	0.196	24.60	0.212	24.00	0.220	23.60	0.217	23.10
Log real estate wealth			-0.006	-2.56	-0.006	-2.28	-0.005	-1.95
Leverage ratio			-0.034	-4.85	-0.032	-4.58	-0.031	-4.45
Log total liability			0.017	6.52	0.018	6.95	0.017	6.64
Private pension premia/income			0.101	1.04	0.143	1.31	0.122	1.18
Sharpe ratio of risky portfolio			0.029	14.30	0.029	14.20	0.029	14.30
Beta of risky portfolio			-0.126	-3.90	-0.120	-3.70	-0.114	-3.55
Demographic Characteristics								
High school dummy			0.046	1.36	0.037	1.08	0.038	1.11
Post-high school dummy			0.043	1.77	0.035	1.43	0.032	1.29
Number of adults			-0.153	-6.01	-0.112	-3.74	-0.102	-3.34
Number of children			-0.069	-6.10	-0.058	-5.11	-0.057	-4.95
Wealth-weighted gender index			-0.074	-2.46	-0.061	-2.03	-0.054	-1.75
Human Capital and Income Risk								
Log human capital					-0.036	-1.19	-0.045	-1.47
Permanent income risk					-0.128	-0.97	-0.121	-0.93
Transitory income risk					-0.027	-0.93	-0.012	-0.42
Correlation of income innovation and portfolio return					0.069	2.34	0.068	2.27
Entrepreneur dummy					-0.292	-5.70	-0.252	-4.72
Unemployment dummy					-0.066	-2.25	-0.057	-1.97
Habit								
Log internal habit					-0.063	-1.81	-0.067	-1.89
Log external habit					0.035	0.39	-0.350	-0.65
Municipality and Industry Dummies							Included	
Number of observations	27,949		27,949		27,949		27,949	
Number of twin pairs	8,394		8,394		8,394		8,394	
Adjusted R^2 of twin difference regression	5.46%		9.43%		9.80%		11.25%	
R^2 with yearly twin pair fixed effects	59.00%		60.71%		60.88%		61.92%	
Adjusted R^2 with yearly twin pair fixed effects	17.99%		21.38%		21.69%		22.96%	

Notes: This table reports pooled twin difference regressions of the log risky share on financial wealth and other characteristics. The estimation is based on all Swedish households with an adult twin. The education, entrepreneur and unemployment dummies are computed for the twin in the household. All other characteristics are computed at the household level. Within differences in log human capital and the leverage ratio are winsorized at the 1st and 99th percentile.

TABLE 3. TWIN REGRESSIONS OF THE LOG RISKY SHARE

Financial wealth elasticity computed for quartiles of financial wealth

	Estimate	t-stat	Estimate	t-stat
Financial and Portfolio Characteristics				
Log financial wealth				
First quartile	0.289	18.10	0.308	17.30
Second quartile	0.224	15.80	0.232	15.90
Third quartile	0.150	10.90	0.173	12.30
Fourth quartile	0.101	7.68	0.147	10.40
Log real estate wealth			-0.004	-1.62
Leverage ratio			-0.019	-2.66
Log total liability			0.015	5.84
Private pension premia/income			0.148	1.33
Sharpe ratio of risky portfolio			0.028	14.20
Beta of risky portfolio			-0.108	-3.37
Demographic Characteristics				
High school dummy			0.033	0.97
Post-high school dummy			0.029	1.16
Number of adults			-0.134	-4.35
Number of children			-0.065	-5.61
Wealth-weighted gender index			-0.047	-1.56
Human Capital and Income Risk				
Log human capital			-0.047	-1.54
Permanent income risk			-0.109	-0.83
Transitory income risk			0.002	0.06
Correlation of income innovation and portfolio return			0.063	2.09
Entrepreneur dummy			-0.249	-4.67
Unemployment dummy			-0.050	-1.74
Habit				
Log internal habit			-0.029	-0.80
Log external habit			-0.351	-0.66
Adjusted R^2	6.12%		11.69%	
Number of observations	27,949		27,949	
Number of twin pairs	8,394		8,394	

Notes: This table reports the pooled twin difference regressions of the log risky share on: (1) dummies for financial wealth quartiles (first set of columns), and (2) other characteristics (second set of columns). The education, entrepreneur and unemployment dummies are computed for the twin in the household. All other characteristics are computed at the household level. Differences in log human capital and the leverage ratio are winsorized at the 1st and 99th percentile.

TABLE 4. FINANCIAL WEALTH ELASTICITY OF THE RISKY SHARE

Households with an adult twin

	Regression (1)				Regression (2)			
	Direct Effect		Interacted		Direct Effect		Interacted	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Financial and Portfolio Characteristics								
Log financial wealth	0.212	23.00	-0.090	-10.20	0.216	23.80	-0.083	-8.59
Log real estate wealth	-0.003	-1.37			-0.003	-1.14	0.008	2.91
Leverage ratio	-0.015	-2.11			-0.012	-1.30	0.011	1.91
Log total liability	0.014	5.57			0.013	5.07	0.004	1.38
Private pension premia/income	0.156	1.37			0.299	2.79	-0.260	-2.36
Sharpe ratio of risky portfolio	0.028	14.20			0.028	14.00	-0.003	-1.62
Beta of risky portfolio	-0.108	-3.39			-0.119	-3.75	-0.047	-1.44
Demographic Characteristics								
High school dummy	0.035	1.03			0.033	0.96	0.020	0.74
Post-high school dummy	0.026	1.06			0.021	0.85	-0.017	-0.80
Number of adults	-0.126	-4.05			-0.127	-4.11	0.130	3.95
Number of children	-0.065	-5.63			-0.077	-6.58	0.067	6.05
Wealth-weighted gender index	-0.043	-1.41			-0.031	-1.01	0.046	1.42
Human Capital and Income Risk								
Log human capital	-0.041	-1.33			-0.037	-1.23	-0.046	-2.95
Permanent income risk	-0.114	-0.87			-0.038	-0.28	-0.152	-0.88
Transitory income risk	0.003	0.10			0.018	0.58	-0.011	-0.25
Correlation of income innovation and portfolio return	0.062	2.07			0.056	1.86	0.067	1.94
Entrepreneur dummy	-0.256	-4.81			-0.239	-4.50	-0.045	-0.91
Unemployment dummy	-0.053	-1.84			-0.042	-1.47	0.021	0.65
Habit								
Log internal habit	-0.037	-1.03	0.130	5.61	0.002	0.06	0.030	1.00
Log external habit	-0.361	-0.68			-0.395	-0.75	-0.066	-0.81
Adjusted R^2	12.03%				12.89%			
Number of observations	27,949				27,949			
Number of twin pairs	8,394				8,394			

Notes: This table reports the pooled twin difference regressions of the log risky share on financial wealth and interacted characteristics. The education, entrepreneur and unemployment dummies are computed for the twin in the household. All other characteristics are computed at the household level. Differences in log human capital and the leverage ratio are winsorized at the 1st and 99th percentiles.

TABLE 5. IV ESTIMATION OF TWIN DIFFERENCE REGRESSIONS OF THE LOG RISKY SHARE

Yearly twin pair fixed effects

	Estimate	t-stat	Estimate	t-stat
Financial and Portfolio Characteristics				
Log financial wealth	0.289	24.10		
First quartile			0.469	15.40
Second quartile			0.284	10.90
Third quartile			0.235	9.64
Fourth quartile			0.180	9.22
Log real estate wealth	-0.003	-1.25	-0.002	-0.71
Leverage ratio	-0.008	-0.90	0.018	1.80
Log total liability	0.020	7.28	0.017	6.06
Private pension premia/income	-0.006	-0.10	0.028	0.37
Sharpe ratio of risky portfolio	0.028	12.10	0.027	11.70
Beta of risky portfolio	-0.187	-5.05	-0.182	-4.91
Demographic Characteristics				
High school dummy	0.031	0.83	0.024	0.64
Post-high school dummy	0.023	0.87	0.016	0.61
Number of adults	-0.088	-2.61	-0.139	-4.07
Number of children	-0.055	-4.35	-0.069	-5.45
Wealth-weighted gender index	-0.083	-2.49	-0.071	-2.15
Human Capital and Income Risk				
Log human capital	-0.056	-1.68	-0.059	-1.79
Permanent income risk	-0.113	-0.79	-0.104	-0.71
Transitory income risk	-0.018	-0.56	0.003	0.08
Correlation of income innovation and portfolio return	0.072	2.21	0.060	1.84
Entrepreneur dummy	-0.242	-3.95	-0.238	-3.91
Unemployment dummy	-0.050	-1.56	-0.041	-1.27
Habit				
Log internal habit	-0.153	-3.85	-0.097	-2.43
Log external habit	-1.108	-1.08	-1.120	-1.08
Adjusted R^2	8.8%		8.9%	
Number of observations	19,418		19,418	
Number of twin pairs	7,520		7,520	

Notes: This table reports the IV estimation of twin difference regressions of the log risky share on financial wealth and other characteristics. Differences in log human capital and the leverage ratio are winsorized at the 99th percentile.

TABLE 6. LAGGED FINANCIAL AND PORTFOLIO CHARACTERISTICS

	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Financial and Portfolio Characteristics								
Log financial wealth in 99	0.132	15.50			0.132	15.50		
First quartile			0.173	10.10			0.172	10.10
Second quartile			0.113	8.16			0.112	8.11
Third quartile			0.149	10.60			0.150	10.70
Fourth quartile			0.096	8.22			0.095	8.19
Log risky share in 99	0.562	35.40	0.560	35.30	0.557	31.70	0.554	31.50
Log passive financial wealth change since 99					0.067	1.43	0.060	1.30
Log passive risky share change since 99					0.144	2.51	0.145	2.54
Log real estate wealth	-0.001	-0.35	-0.001	-0.37	-0.001	-0.44	-0.001	-0.45
Leverage ratio	-0.008	-0.90	-0.004	-0.40	-0.007	-0.86	-0.003	-0.38
Log total liability	0.008	3.86	0.008	3.65	0.008	3.85	0.008	3.63
Private pension premia/income	-0.012	-0.29	-0.007	-0.16	-0.012	-0.29	-0.007	-0.16
Sharpe ratio of risky portfolio	0.014	7.88	0.014	7.81	0.014	7.85	0.014	7.78
Beta of risky portfolio	-0.141	-4.06	-0.139	-3.99	-0.108	-2.93	-0.106	-2.90
Demographic Characteristics								
High school dummy	-0.010	-0.39	-0.010	-0.39	-0.010	-0.38	-0.010	-0.38
Post-high school dummy	0.045	2.22	0.043	2.08	0.045	2.22	0.043	2.09
Number of adults	-0.013	-0.50	-0.023	-0.86	-0.014	-0.55	-0.024	-0.90
Number of children	-0.016	-1.62	-0.018	-1.87	-0.015	-1.59	-0.018	-1.83
Wealth-weighted gender index	-0.049	-1.96	-0.047	-1.86	-0.050	-2.00	-0.048	-1.89
Human Capital and Income Risk								
Log human capital	-0.014	-0.53	-0.014	-0.54	-0.012	-0.44	-0.012	-0.44
Permanent income risk	-0.158	-1.07	-0.149	-1.00	-0.174	-1.18	-0.165	-1.12
Transitory income risk	-0.015	-0.56	-0.007	-0.28	-0.017	-0.64	-0.010	-0.36
Correlation of income innovation and portfolio return	0.022	0.87	0.022	0.86	0.024	0.92	0.023	0.91
Entrepreneur dummy	-0.078	-1.57	-0.080	-1.60	-0.079	-1.59	-0.080	-1.62
Unemployment dummy	-0.046	-1.86	-0.045	-1.83	-0.045	-1.80	-0.044	-1.78
Habit								
Log internal habit	-0.113	-3.64	-0.102	-3.24	-0.113	-3.62	-0.102	-3.23
Log external habit	-0.274	-0.31	-0.273	-0.31	-0.319	-0.36	-0.316	-0.35
Adjusted R^2	45.09%		45.21%		45.18%		45.30%	
Number of observations	17,355		17,355		17,355		17,355	
Number of twin pairs	6,312		6,312		6,312		6,312	

Notes: This table reports the IV regression of changes in the log risky share on lagged financial and portfolio characteristics. The estimation is based on households that participate in risky asset markets at the end of two consecutive years. Yearly fixed effects are included in all the regressions.

TABLE 7. HEALTH AND BEHAVIORAL VARIABLES

Yearly twin pair fixed effects

	Estimate	t-stat	Estimate	t-stat
Financial and Portfolio Characteristics				
Log financial wealth	0.210	18.60		
First quartile			0.290	13.70
Second quartile			0.203	12.50
Third quartile			0.178	9.57
Fourth quartile			0.146	8.56
Log real estate wealth	-0.005	-1.69	-0.005	-1.53
Leverage ratio	-0.064	-4.32	-0.046	-3.02
Log total liability	0.022	7.52	0.020	6.92
Private pension premia/income	0.238	1.75	0.272	1.99
Sharpe ratio of risky portfolio	0.031	12.30	0.031	12.20
Beta of risky portfolio	-0.214	-5.42	-0.208	-5.25
Demographic Characteristics				
High school dummy	0.036	0.93	0.031	0.79
Post-high school dummy	0.015	0.49	0.012	0.38
Number of adults	-0.098	-2.58	-0.127	-3.34
Number of children	-0.049	-3.48	-0.055	-3.90
Wealth-weighted gender index	-0.082	-2.13	-0.074	-1.92
Human Capital and Income Risk				
Log human capital	-0.059	-1.49	-0.058	-1.47
Permanent income risk	-0.063	-0.34	-0.057	-0.30
Transitory income risk	0.011	0.28	0.024	0.61
Correlation of income innovation and portfolio return	0.069	1.84	0.063	1.70
Entrepreneur dummy	-0.259	-4.05	-0.257	-4.00
Unemployment dummy	-0.101	-2.55	-0.098	-2.48
Habit				
Log internal habit	-0.096	-2.12	-0.063	-1.38
Log external habit	-1.011	-1.98	-1.007	-1.98

TABLE 7 (cont.) HEALTH AND BEHAVIORAL VARIABLES
Yearly twin pair fixed effects

Lifestyle				
Regular smoker	-0.02	-0.70	-0.02	-0.88
Alcohol drinker	0.06	1.79	0.05	1.64
Coffee drinker	0.02	0.32	0.02	0.39
Exercise level	0.00	-0.25	0.00	-0.26
Body Structure				
Height	0.00	-0.93	0.00	-1.04
Overweight	-0.03	-1.15	-0.04	-1.31
Obese	-0.04	-0.83	-0.04	-0.76
Mental Health				
Eating Disorder (EDNOS)	0.00	-0.17	0.00	-0.02
Anxiety (GAD)	0.07	0.77	0.06	0.69
Depression Symptoms	-0.07	-1.89	-0.07	-1.85
Major Depression	0.01	0.38	0.01	0.38
Health Conditions				
Indifferent or bad self-assessed health	-0.04	-1.16	-0.04	-1.04
Self-assessed health deterioration (last 5 years)	0.00	-0.01	0.00	0.03
Recurrent headaches, migrane	0.00	0.11	0.00	0.02
High Blood Pressure	-0.08	-2.29	-0.08	-2.37
Adjusted R^2	13.8%		14.2%	
Number of observations	18,129		18,129	
Number of twin pairs	5354		5354	

Notes: This table reports the pooled twin difference regressions of the log risky share on: (1) dummies for financial wealth quartiles (first set of columns), and (2) other characteristics (second set of columns). The education, entrepreneur and unemployment dummies are computed for the twin in the household. All other characteristics are computed at the household level. Differences in log human capital and the leverage ratio are winsorized at the 1st and 99th percentile.

TABLE 8. IV ESTIMATION OF YEARLY CHANGES IN THE LOG RISKY SHARE
Random sample of households

	No Controls				With Controls			
	Estimate	**t-stat**	**Estimate**	**t-stat**	**Estimate**	**t-stat**	**Estimate**	**t-stat**
Log financial wealth	0.218	4.77			0.229	4.75		
First quartile			0.441	2.75			0.467	2.76
Second quartile			0.413	3.09			0.372	2.80
Third quartile			0.333	3.35			0.346	3.45
Fourth quartile			0.029	0.57			0.031	0.55
Change in log passive share	0.093	3.07	0.084	2.69	0.101	3.47	0.091	3.01
Number of observations	38,496		38,496		38,496		38,496	

Notes: This table reports the IV regression of changes in the log risky share on changes in financial wealth, changes in the log passive share, and household characteristics. The estimation is based on households that participate in risky asset markets at the end of two consecutive years. Yearly fixed effects are included in all the regressions. Log human capital and the leverage ratio are winsorized at the 99th percentile. Characteristics are taken at the beginning of the year and are the same as in Table 1.

TABLE 9. PARTICIPATION IN RISKY ASSET MARKETS
Logit regressions

	POOLED CROSS-SECTION *Yearly Fixed Effects*				TWIN REGRESSION *Yearly Twin Pair Fixed Effects*			
	Estimate	**t-stat**	**Estimate**	**t-stat**	**Estimate**	**t-stat**	**Estimate**	**t-stat**
Financial Characteristics								
Log financial wealth	1.180	73.90	1.163	57.80	1.086	34.40	1.038	28.80
Log real estate wealth			0.006	1.45			0.006	0.80
Leverage ratio			-0.018	-5.14			-0.016	-2.21
Log total liability			0.059	10.50			0.047	4.81
Private pension premia/income			1.924	2.98			1.216	0.99
Demographic Characteristics								
High school dummy			0.243	5.17			0.115	1.14
Post-high school dummy			0.131	2.78			0.098	0.98
Number of adults			-0.195	-3.44			-0.096	-0.93
Number of children			-0.079	-3.42			-0.017	-0.41
Wealth-weighted gender index			-0.163	-3.10			-0.176	-1.82
Human Capital and Income Risk								
Log human capital			0.358	9.91			0.235	2.03
Permanent income risk			-1.002	-4.08			-1.226	-2.85
Transitory income risk			-0.207	-3.24			-0.171	-1.58
Entrepreneur dummy			-0.185	-1.60			-0.114	-0.52
Unemployment dummy			-0.038	-0.74			0.039	0.43
Habit								
Log internal habit			-0.221	-3.36			0.099	0.73
Log external habit			-0.705	-4.21			-0.895	-2.45
Number of observations	85,532		85,532		23,132		23,132	
Number of twin pairs	11,721		11,721		11,721		11,721	
Number of pairs with different participation decisions	.		.		4,477		4,477	

Notes: This table reports the pooled logit regression of a household's decision to participate in risky asset markets. The cross-sectional regressions are based on all Swedish households with an adult twin, and are run without and with characteristics (first two sets of columns). In the last sets of columns, we report a logit regression with a twin pair fixed effect. Yearly fixed effects are included in all regressions. The education, entrepreneur and unemployment dummies are computed for the twin in the household. All other characteristics are computed at the household level. Log human capital and the leverage ratio are winsorized at the 99th percentile.

FIGURE 1. ELASTICITY OF RISKY FINANCIAL WEALTH
Fixed set of participants (2001)

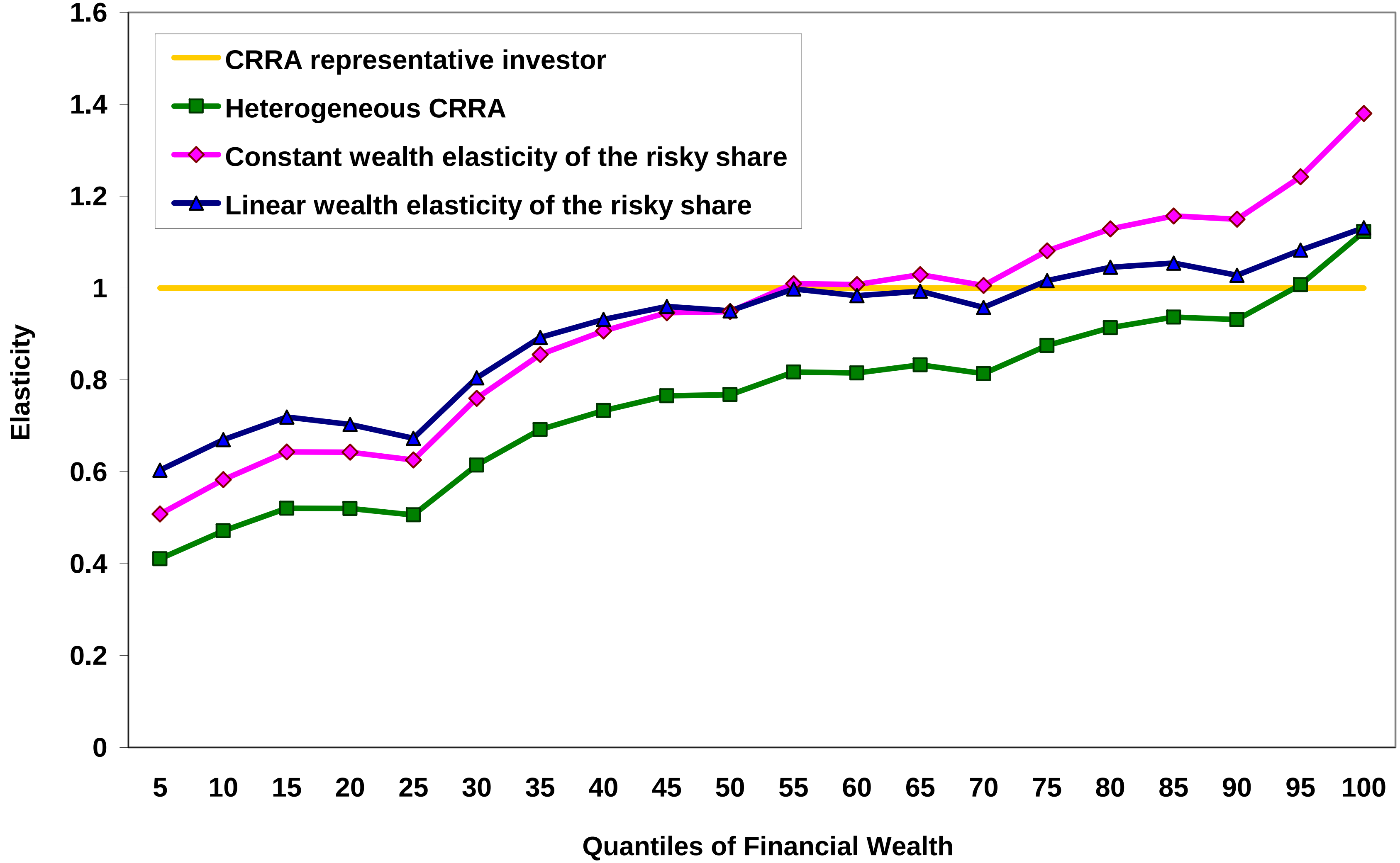

FIGURE 2. ELASTICITY OF RISKY FINANCIAL WEALTH
With entry or exit (2001)