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TWIN PICKS: DISENTANGLING THE DETERMINANTS OF RISK-TAKING IN HOUSEHOLD PORTFOLIOS

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

Laurent E. Calvet and Paolo Sodini

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ABSTRACT

This paper investigates the determinants of financial risk-taking in a panel containing the asset holdings of Swedish twins. We measure the impact of a broad set of demographic, financial, and portfolio characteristics, and use yearly twin pair fixed effects to control for genes and shared background. We report a strong positive relation between risky asset market participation and financial wealth. Among participants, the average financial wealth elasticity of the risky share is significantly positive and estimated at 22%, which suggests that the average individual investor has decreasing relative risk aversion. 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, and increases with habit, real estate wealth and household size. As a consequence, the elasticity of the aggregate demand for risky assets to exogenous wealth shocks is close to, but does not coincide with, the elasticity 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, lifestyle, mental and physical health, the intensity of communication between twins, and measures of social interactions.

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An online appendix is available at:
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focus (CRRA)

1. Introduction

Does financial wealth drive the share of risky assets in the portfolios of individual investors? Is the financial wealth elasticity of the risky share homogenous across investors or does it vary with their demographic, financial and portfolio characteristics? How does the aggregate demand for risky assets respond to changes in the wealth distribution? 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.[1] These theories also predict that the financial wealth elasticity of the risky share should vary with household characteristics, including financial wealth itself. Furthermore, a growing literature investigates how at the aggregate level, the demand for risky assets relates to the distribution of household preferences and characteristics.[2]

The empirical household finance literature provides only partial evidence on these mechanisms. 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, 2009*a*, 2009*b*).[3] In addition, the risky share has a negative cross-sectional relation to 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 2009*a*, 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 the comparison of the financial portfolios held by twins. The analysis is made possible by a novel dataset

[1] For instance, a positive relation between financial wealth and risk-taking originates from an internal habit in Constantinides (1990), an external habit in Campbell and Cochane (1999), borrowing constraints in Paxson (1990), leverage constraints and housing in Cocco (2005) and Yao and Zhang (2005), portfolio insurance in Brennan and Schwartz (1988), or a "capitalist" taste for wealth in Carroll (2000, 2002).

[2] Examples include Calvet, Grandmont and Lemaire (2005), Constantinides (1982), Gollier (2001), Hara, Huang and Kuzmics (2007), Jouini and Napp (2007), and Rubinstein (1974).

[3] 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).

containing the disaggregated portfolios and detailed characteristics of 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. 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 on the set of participants. As in the earlier literature, we begin by running pooled cross-sectional regressions of a household's risky share on its 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. It is an open question whether these cross-sectional estimates capture the direct impact of financial wealth on the risky share, or are instead driven by latent traits that are correlated with financial wealth.

We next consider linear panel specifications with yearly twin pair fixed effects, which is our main innovation. These specifications 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 therefore associated with a $2.0 - 2.2\%$ proportional increase in its risky share. We report that the cross-sectional variance of the twin pair fixed effect is of the same magnitude as the variance of the predicted component obtained from characteristics. Moreover, the adjusted R^2 coefficient is twice as high in twin panel regressions as in pooled cross-sections. Twin pair fixed effects are therefore important and explain a substantial fraction of the observed variation of the risky share.

Second, we investigate the impact of demographic, portfolio, and other financial characteristics. In both cross-sectional and twin regressions, the risky share is positively related to the risky portfolio's Sharpe ratio, but is negatively related to leverage, entrepreneurship, the risky portfolio's systematic exposure, household size, and a measure of habit. One interesting difference is that income risk and education, which are significant in cross-sectional regressions, become insignificant in twin pair regressions. These findings suggest that in traditional pooled cross-sectional regressions, income risk and education variables capture a fixed effect, for instance related to risk aversion or upbringing, that has 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. The elasticity sharply decreases with financial wealth and increases with a measure of habit, as theoretical models of habit formation would predict. The financial wealth elasticity of the risky share is also high for large households with low human capital or high real estate wealth.

Fourth, we verify the robustness of our results to alternative estimation methods and

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interpretations. We assess the role of zygosity by reestimating the regressions separately on identical and fraternal twins. We obtain similar coefficients, but as one would expect, the predicted variation of the risky share and the cross-sectional variance of the twin pair fixed effects are substantially higher for identical twins. We investigate the impact of communication between twins by separately reestimating the regressions on the group of twins who communicate frequently with each other and the group of twins who communicate infrequently. Consistent with intuition, the predicted variation is smaller for twins who communicate frequently. The financial wealth elasticity of the risky share is approximately the same in both groups, which suggests that the positive relation between financial wealth and risk-taking is unlikely to be primarily driven by differences in information. We check the robustness of our results to social interactions by including business and municipality dummies, as well as the average log risky share and financial wealth of other households in the municipality. We also consider the possibility of a reverse causality between the risky share and financial wealth, i.e. the possibility that risk-tolerant investors happened to have both a high risky share and high financial wealth at the end of the bull market of the nineties. A twin with high financial wealth in 1999 is found 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 alone, and strongly suggest that individual investors exhibit *decreasing* relative risk aversion.

Fifth, we verify that our results are not contaminated by individual fixed effects specific to each twin in a pair, such as different levels of 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 variables on each twin. Another strategy is to dynamically estimate the financial wealth elasticity of the risky share by following households over time, excluding twin pair fixed effects from consideration; specifically, 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. With either method, the elasticity has an average of about 22% and decreases with financial wealth, which suggests that the twin difference regressions are not severely contaminated by individual fixed effects.

Sixth, we use our micro estimates to compute how the aggregate demand for risky assets responds to exogenous changes in the distribution of financial wealth. 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, which have low elasticities and high initial risky shares, aggregate risky wealth grows only slightly faster than aggregate financial wealth. Overall, the elasticity of the aggregate demand for risky assets to a homogenous wealth shock is estimated to be slightly above unity. Thus, the negative relation between financial wealth and the elasticity of the risky share at the micro level implies that the aggregate demand for risky assets is close to, but does not coincide with, the demand of a CRRA representative investor.

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 is taken into account.

Twin comparisons are a true and tried method for disentangling family fixed effects from individual characteristics. In labor economics, they have been frequently applied to disentangle the relative effect of education and ability on earnings.[4] A similar approach seems fruitful for household finance. In recent studies, Barnea, Cronqvist and Siegel (2010) 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) on the positive link between IQ and stockmarket participation.

The dynamic estimates reported in this paper complement 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 (2009*a*) replicate the OLS results of Brunnermeier and Nagel and Chiappori and Paiella. They also 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 (2009*a*) estimate an adjustment model of portfolio rebalancing, the

[4] See for instance Ashenfelter and Krueger (1994), Ashenfelter and Rouse (1998), Behrman and Rosenzweig (2002), 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).

dynamic section of this paper focuses on a slightly more parsimonious, reduced-form specification.

The organization of the paper is as follows. Section 2 presents the Swedish dataset. In Section 3, we report cross-sectional and twin regressions of the risky share on financial wealth and other characteristics. In Section 4, we estimate how the financial wealth elasticity of the risky share varies with financial wealth itself as well as with other variables. Section 5 investigates the impact of measurement error, lagged financial wealth, and health and lifestyle variables. 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 2010), 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 impact of smoking and alcohol consumption on the health of Swedish residents. It consists of two surveys: 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, and STAGE between May 2005 and March 2006. Response rates for those eligible (still alive and living in Sweden) were 65% for the 1886-1925 cohort, 74% for the 1926-1958 cohort, and 59.6% for the 1959-1990 cohort.

For each twin pair, we observe zygosity (fraternal or identical),[5] and the intensity of communication between the twins. We have also obtained for each twin in SALT a set of physiological and lifestyle variables: weight, height, blood pressure, self-assessed physical health, mental health, and smoking, alcohol and coffee habits. We refer the reader to Lichtenstein et al. (2006) and Pedersen et al. (2002) for detailed descriptions of the Swedish Twin Registry.

Swedish Wealth Registry. The Swedish Twin Registry allows us to identify twin pairs in the Swedish Wealth Registry, which we have used in earlier work (CCS 2007, 2009*a*, 2009*b*). Statistics Sweden has a parliamentary mandate to collect highly detailed information on the household finances of all Swedish residents. The information available on each resident in the Swedish Wealth Registry can be grouped into three main categories: demographic characteristics, income, and disaggregated wealth.

[5] Zygosity is determined by DNA markers or, when not available, 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?". The answer to this question has been shown to be consistent with DNA evidence in 99% of pairs.

Demographic information includes age, gender, marital status, nationality, birthplace, education, municipality, as well as household composition and an identification number.[6] All tax returns are filed individually in Sweden since the tax code does not allow the possibility of joint filing. However, the household identification number allows us to group residents by living units and thus investigate finances at the family level. The education variables include high school and post-high school dummies for every household member.

The income data comprises disposable income, as well as income reported by individual source. For capital income, the database reports the interest or dividend that has been earned on each bank account or each security. For labor income, the database reports gross labor income and business sector. The household head is defined as the individual with the highest income.

The Swedish Wealth Registry 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.

We have merged the Swedish Twin Registry with the Swedish Wealth Registry. Because financial theory suggests that investment decisions should be studied at the household level, the results presented in this paper are based on households with an adult twin during the 1999-2002 period. In unreported work, we have verified that our main results are qualitatively similar when we only consider twins living alone.

Throughout the paper, we group households with an adult twin into pairs, and conduct our investigation on the set of pairs where all characteristics are available. We impose no constraint on the risky asset market participation status of these households, but require that both households in a pair 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 highest earner in the household must be at least 25 years old.

3. What Drives the Risky Share?

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

[6] In order to protect privacy, Statistics Sweden provided us with a scrambled version of the household identification number.

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. Portfolio characteristics, family composition, human capital, and habit formation can also impact the risky share and its elasticity. We now summarize how we measure these effects, and refer the reader to the online appendix for more detailed descriptions.

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

Portfolio Characteristics. A household's risky share may be driven by the systematic exposure of its risky portfolio to aggregate market risk. As in CCS (2007), we measure systematic risk by computing the risky portfolio's beta coefficient relative to a global equity index under an international version of the CAPM.

A household with a diversified portfolio of risky securities may feel more confident in stockmarket investing and therefore be more willing to invest a higher fraction of its financial wealth in risky assets. Diversification may also proxy for the household's sophistication (CCS 2009*b*) or self-assessment of its investment skills (CCS 2007), which can in turn impact risk-taking. For this reason, we will include the ex-ante Sharpe ratio of the risky portfolio in our set of explanatory variables.

Family Composition. Gender is known to affect economic decision-making (e.g. Croson and Gneezy 2008) and may impact the asset allocation of the risky portfolio. In Sweden, each resident declares the fraction of the household's assets that it owns, and this information is available in the Swedish Wealth Registry. We define a *gender index* of economic power within the household as the share of the household's gross financial and real estate wealth owned by adult men. The gender index ranges between zero and one. It is close to unity if gross wealth is primarily controlled by 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 labor income specification used in Cocco, Gomes and Maenhout (2005):

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

where $L_{h,t}$ denotes real income in year t, a_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, $b'(x_{h,t} - x_{h,t-1})$. We also estimate the sample correlation ρ_h between the income growth residual $u_{h,t}$ and the historical excess return on the household's risky portfolio in year t.

Expected 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 at 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. The interest rate is set equal to $r = 3\%$ per year, and we have verified that our results are strongly robust to alternative choices of r. 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 throughout the remainder of the paper: (a) expected 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 imply 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 a CRRA investor, $X_{h,t}$ is an 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,

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

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 household income in household h's municipality. The twin sample has been excluded from the households sampled in each peer group.

For the remainder of this paper, we investigate the determinants of the risky share on the set of twin pairs in which both siblings participate in risky asset markets. In Table 1, we report summary statistics for the set of participating twins, as well as for a random sample from the population of participating households. For the twin sample, the education, entrepreneur and unemployment dummies refer to the twin in the household, while all other characteristics are computed at the household level. To facilitate international comparisons, we convert all financial quantities into U.S. dollars. Specifically, the Swedish krona traded at \$0.1127 at the end of 2002, and this fixed conversion factor is used throughout the paper. A household in the twin sample selects on average a slightly higher risky share, has slightly higher financial and real estate wealth, is slightly more educated, has lower human capital, is more likely to be unemployed and is less leveraged than the average Swedish household. Differences in the means across the two samples are modest, except for the leverage ratio. The correlation of characteristics within twin pairs is positive, and ranges from 0.001 for the Sharpe ratio to 0.484 for human capital.

In the Appendix, we report summary statistics for the risky share and the characteristics of identical and fraternal twins. Pairwise correlations are generally higher for identical twins than for fraternal twins, which suggests that these variables have a genetic component. We also report the results of an ACE decomposition, an additive model of genetic effects that has been widely employed in medicine and is now starting to be used in household finance (e.g. Barnea, Cronqvist and Siegel 2010; Cesarini et al. 2009*a*, 2009*b*). ACE provides a decomposition of the cross-sectional variance of a characteristic into a genetic component, a common component, and an idiosyncratic component, which is conveniently estimated from the pairwise correlations of identical and fraternal twins. We verify that the risky share, financial wealth and most characteristics have a substantial genetic component according to ACE.

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, and $x_{h,t}$ is a vector of characteristics. We now examine the evidence on a pooled cross-section of Swedish households.

Financial and Portfolio Characteristics. In the first two columns of Table 2, we regress the log risky share on log financial wealth and yearly fixed effects. The financial wealth coefficient η is highly significantly positive and estimated at 0.212. 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 financial wealth is excluded from the pooled regression with yearly dummies. 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 financial wealth coefficient η increases slightly to 0.223. Real estate wealth, which represents a large fraction of the overall wealth of most households, is negatively related to the risky share in the cross-section. The real estate wealth coefficient is estimated at -0.005, which is much smaller than the financial wealth coefficient, but is strongly significant. These results are consistent with Cocco (2005), who documents that homeowners tend to select lower levels of financial risk in the 1989 wave of 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 conservative portfolios, consistent with previous empirical evidence (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 nominal debt might have more experience of financial markets or might be more risk-tolerant, which would explain why they choose leveraged positions in risky assets. Like debt, private pension investing is positively related to the risky share and may be a proxy for financial experience and literacy.

The risky portfolio's Sharpe ratio has a positive coefficient, while beta has a negative coefficient. Both estimates are strongly significant. In a cross-section, households holding diversified portfolios with low systematic exposure also tend to select high risky shares.

Demographic Characteristics. The level of education has a positive cross-sectional relation with the risky share. One possibility is that education has a direct impact on risk-taking. Another is that education proxies for latent traits such as ability and upbringing that are also associated with higher risk-taking.

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 Houthakker 1955).

Households in which men control a large share of financial wealth have a slight tendency to select a lower risky share. In unreported work, we obtain that male-dominated households invest a higher share of their risky portfolios directly in stocks. 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).

Human Capital, Income Risk and Habit. In the third set of columns, we add human capital and measures of habit to the set of predictors. Expected human capital has a positive but insignificant coefficient. Income risk, on the other hand, is negatively related to financial risk-taking, as captured by the negative coefficients on the variance of the permanent and transitory components of income. Entrepreneurs tend to invest less aggressively than the rest of the population. A high correlation between income innovation and the household's risky portfolio return is associated with a high risky share. These results confirm the findings of Palia, Qi and Wu (2009) and Vissing-Jørgensen (2002b) on income risk, Heaton and Lucas (2000) on entrepreneurship, and Massa and Simonov (2006) on the correlation of labor income and portfolio return.

The measures of internal and external habit are both negatively related to the risky share, as theory predicts, but with different significance levels. 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 proxy habit with average income, the internal habit coefficient may be due to cash on hand effects, as in Haliassos and Bertaut (1995) and Haliassos and Michaelides (2002).

Municipality and Business Dummies. In the last set of columns of Table 2, 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. The previously reported coefficients are almost unchanged when we control for these effects.

Overall, Table 2 confirms earlier empirical findings. As in Carroll (2002), the risky share is substantially larger for households with higher financial wealth, which is by far the most significant regressor. While earlier research is typically based on fragmentary data, the Swedish dataset allows us to simultaneously measure the relation between the risky share and a large number of household characteristics. To the best of our knowledge, this paper is the first to combine human capital, leverage, and habit into a single regression. In addition, we consider portfolio characteristics and document that in a cross-section, the risky share is positively related to the risky portfolio's Sharpe ratio and negatively related to its systematic risk. The inclusion of portfolio characteristics, however, does not impact the cross-sectional relation between the risky share and other financial and demographic variables.

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 predict. 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 endogeneity and inertia, as will be explained in Section 5.4. 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 twin j's household, $j \in \{1, 2\}$, 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 common impact of time, stock market performance, genes, shared background, common upbringing, and expected inheritance, among others, on the twin's risky shares. The elasticity η is assumed to be the same for all households and can therefore be viewed as the average elasticity in the population. In Section 4, we will consider a more flexible specification in which the financial wealth elasticity of the risky share can vary across pairs.

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

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

where $\Delta_j(y_{i,j,t}) = y_{i,2,t} - y_{i,1,t}$ denotes the twin difference of a variable y, and $\varepsilon_{i,t} = \varepsilon_{i,2,t} - \varepsilon_{i,1,t}$. The two methods provide nearly identical estimates and $t-$statistics of η and γ, but different R^2 coefficients. We will see that twin difference regressions (3.6) have substantially lower R^2 coefficients than the regressions in levels (3.5), as one would expect if pair fixed effects are important.

The contribution of the pair fixed effect to the cross-sectional variance of the risky share is given by:

$$\omega_\alpha^2 = \frac{Var(\alpha_{i,t})}{Var(\ln w_{i,j,t})}.$$

Since the residuals $u_{i,j,t} = \ln(w_{i,j,t}) - \eta f_{i,j,t} - \gamma' x_{i,j,t}$ satisfy $Cov(u_{i,1,t}; u_{i,2,t}) = Var(\alpha_{i,t})$, we estimate the cross-sectional variance of the fixed effect, $Var(\alpha_{i,t})$, by the pairwise covariance of the regression residuals.

We are also interested in comparing the relative effects of the fixed effect and household characteristics, and in measuring their correlation. The coefficient of determination can be decomposed as:

$$\rho^2 = \frac{Var(\alpha_{i,t} + \eta f_{i,j,t} + \gamma' x_{i,j,t})}{Var(\ln w_{i,j,t})} = \omega_\alpha^2 + \omega_c^2 + 2\rho_{c,\alpha}\omega_\alpha\omega_c, \tag{3.7}$$

where $\omega_c^2 = Var(\eta f_{i,j,t} + \gamma' x_{i,j,t})/Var(\ln w_{i,j,t})$ denotes the contribution of observable characteristics, and $\rho_{c,\alpha} = Corr(\alpha_{i,t}; \eta f_{i,j,t} + \gamma' x_{i,j,t})$. Because the number of parameters increases linearly with the number of pairs, ρ^2 is consistently estimated by the adjusted R^2 of the panel regression in levels. We estimate ω_c^2 by taking the ratio of the sample variances of $\eta f_{i,j,t} + \gamma' x_{i,j,t}$ and $\ln w_{i,j,t}$, and infer from (3.7) an estimate of the correlation $\rho_{c,\alpha}$ between the fixed effect and the predictor of the risky share computed from characteristics.

In the first two columns of Table 3, 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 2. 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), 0.220 when we add human capital, income risk and habit measures (third set), and 0.217 when we also include municipality and industry dummies (last set of columns). These estimates are remarkably stable and confirm the cross-sectional findings that the average financial wealth elasticity of the risky share is strictly positive and close to 0.22.

The twin regressions confirm that households with real estate holdings, leverage, large family size, a risky portfolio with high systematic exposure, or a high habit, tend to invest conservatively. Diversification and proxies for financial experience and sophistication are positively related to the risky share, while expected human capital is insignificant. The positive Sharpe ratio coefficient confirms the explanation proposed in CCS (2007, 2009*b*) that households are more prone to purchase risky assets when they are more competent about stockmarket investing.

One interesting difference between the pooled and twin regressions is that the education level and income risk are significantly related to the risky share in the cross-section, but are insignificant in the twin regression. These results indicate that education and income risk proxy for a fixed effect in traditional cross-sectional regressions. For instance, education could capture the impact of ability and upbringing, while income risk could be correlated with risk tolerance. Able, risk-tolerant individuals may have a propensity to choose both aggressive financial portfolios and risky and skilled professions, but the panel regressions indicate that income risk and education have no direct bearing on the risky share. One caveat is that we do not control for the field of study. In a recent dynamic panel investigation, Christiansen, Joensen and Rangvid (2008) provide evidence that conditional on risky asset market participation, no field of study at the university level seems to have a causal impact on the risky share. Our results confirm that the causal relation between education and the risky share is either weak or difficult to measure.

Yearly twin pair fixed effects and financial wealth explain most of the predicted variation in the risky share. The adjusted R^2 coefficient of the panel regression (3.5), 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 23.0% when all other characteristics are included as explanatory variables.

These results can be readily interpreted by estimating the decomposition (3.7) of the adjusted R^2. When financial wealth is the only explanatory variable (first set of column of Table 3), yearly twin pair fixed effects and financial wealth account, respectively, for $\omega_\alpha^2 = 9.6\%$ and $\omega_c^2 = 6.9\%$ of the variance of the risky share; the correlation between financial wealth and the fixed effect, $\rho_{c,\alpha}$, is correspondingly equal to 8.5%. We obtain almost identical estimates of ω_α^2, ω_c^2, and $\rho_{c,\alpha}$ in the presence of demographic characteristics, human capital, income risk, and habit variables (second and third set of column of Table 3). When municipality and business dummies are included as well, the share of the fixed effects ω_α^2 increases to 12.1%, and the share ω_c^2 to 15.7%, with an implied correlation $\rho_{c,\alpha} = -17.4\%$ (last set of columns of Table 3). In all specifications, twin pair fixed effects therefore explain a substantial fraction of the observed variation of the risky share. We refer the reader to the Appendix for the comprehensive set of results.

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 $\eta/(1+\eta) \approx 1/6$. If the habit is internal, Table 1 indicates that that its proxy, the three-year average value of disposable income, is about two thirds of financial wealth. The present value of maintaining the internal habit over an infinite horizon therefore represents about one sixth of financial wealth and one quarter of disposable income.

We conduct a number of robustness checks in the Appendix, which we summarize below.

Identical vs. Fraternal Twins. The measured variance of the risky share within pairs is substantially smaller for identical twins than for fraternal twins. We reestimate the yearly twin pair regressions separately on both groups and report that characteristics capture a higher fraction of the observed variation of the risky share for identical twins.

For instance, the adjusted R^2 coefficients are 31.6% and 21.8%, respectively, for identical and fraternal twins, as compared to 23.0% in Table 3.[7] The contribution of the fixed effect is also more than twice as high for identical twins ($\omega_\alpha^2 = 16.0\%$) as for fraternal twins ($\omega_\alpha^2 = 7.2\%$). These findings confirm the intuition that the twin pair fixed effect has a genetic component.

The financial wealth elasticity of the risky share is estimated at 0.18 for identical twins and 0.20 for fraternal twins when financial wealth is the only observable characteristic, and and at 0.17 and 0.23, respectively, in the presence of all characteristics. Thus, the financial wealth elasticity of the risky share is close to 0.2 in both groups, and remains strongly significant despite the smaller size of each subsample.

Random Matching. We verify that the measured pair fixed effects are not spurious by reestimating the regressions on a panel of randomly matched pairs. The coefficients of all characteristics in the difference regressions with random pairs are very similar to the ones obtained from pooled cross-sections. In particular, income risk and education remain significant. The adjusted R^2 declines to 16.8%, compared to 23.0% with actual twin pairs. The share of the cross-sectional variance explained by the pseudo twin pair fixed effect, ω_α^2, ranges between 2% and 4% across specifications. These estimates of ω_α^2 are of the same order as the contribution of yearly fixed effects and are substantially smaller than the values obtained with properly matched twins. These findings confirm the empirical importance of yearly twin pair fixed effects in our actual dataset.

Age. 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 remains significantly positive and close to 0.22 for all groups, and we cannot reject that the null hypothesis that the elasticity is constant 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 and habit have a negative impact on the risky share. The correlation between the income growth innovation and the risky portfolio return, ρ_h, is positively related to risk-taking in two age groups ($35 - 45$ and above 55) and insignificant in the other two (less than 25 and $45 - 55$). Furthermore, the correlation effect is strongly significant only for the oldest group.

Frequency of Communication Between Twins. The insignificant education coefficients in Table 3 can be interpreted as evidence that education cannot explain risk-taking, or alternatively that twins communicate frequently enough to overcome the

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

impact of education differences. In the Appendix, we separately reestimate our regressions on the set of twins who communicate often with each other and the set of twins who communicate rarely. The regression coefficients reported for each group are very similar to the ones reported in Table 3. The adjusted R^2 is twice as high for twins with infrequent contacts as for twins with frequent contacts, suggesting that communication tends to reduce differences in risk-taking.

Social Interactions. We have so far focused on the impact of individual preferences and characteristics on individual choices, and have devoted only limited attention to the influence of social interactions. Because investors may imitate the asset allocation of their neighbors, we have included municipality and business dummies in the last column of Tables 2 and 3. These variables do not impact the regression coefficients of other characteristics.

In the Appendix, 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. Thus, local interactions do not appear to be the main drivers of risk-taking.

We 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 other results of Table 3 remain unchanged. The municipality log risky share has a positive and significant coefficient of about 0.76, which suggests that a household's risky share is influenced by households in the same geographical area. This result should be taken with caution, however, since the econometric analysis of social interactions is fraught with difficulties (e.g. Manski, 2000). We leave for further research the full investigation of this topic.

Our findings on communication and social interactions complement earlier research on the link between information and risk-taking (e.g. Guiso and Jappelli 2006; Peress 2004). We document that while social interactions and information asymmetries seem to play a substantial role, they do not significantly affect the positive relation between financial wealth and the risky share.

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 will provide a detailed treatment of this issue in Section 5.

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

Economic theory suggests that the financial wealth elasticity of the risky share can vary with wealth and other household characteristics. For this reason, we 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 specific to the pair and may be a function of its characteristics.[8]

In Table 4, 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 include no other characteristic 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 4, we also include all the other characteristics as controls. The elasticity increases slightly in each quartile compared to the previous specification, and remains a strongly decreasing function of 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 conveniently estimated.

In a habit formation model, the elasticity increases with habit and decreases with financial wealth, as can be seen from (3.3). In the first set of columns of Table 5, we estimate a version of (4.2) in which the financial wealth elasticity of the risky share is driven only by log financial wealth and log internal habit. We focus on the internal habit because our measure of external habit is noisy and less significant in previous tables. Consistent with theory, the elasticity is a decreasing function of financial wealth and an increasing function of habit. The first result is consistent with the bin regressions in Table 4, while the second result is new.

We interpret the regression coefficients by loglinearizing (3.3) around $\overline{\ln(y_{h,t})}$:

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

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 5, we have estimated that the coefficient of financial wealth and habit are -0.09 and 0.13,

[8] Equation (4.1) is a direct implication of the specification $\ln(w_{i,j,t}) = \alpha_{i,t} + \eta_{i,t} f_{i,j,t} + \gamma' x_{i,j,t} + \varepsilon_{i,j,t}$. Ashenfelter and Rouse (1998) consider a similar approach to modeling heterogeneity in the context of labor economics.

respectively. These estimates are approximately the negative of each other, and their magnitudes are about half of the predicted theoretical values. Our analysis represents 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 nonlinearities in financial wealth and other characteristics.

In the second set of columns of Table 5, 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. Consistent with the household equivalence scales literature, family size has a direct negative impact on the risky share and a positive impact on its elasticity. Thus, large households behave 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. Conversely, the risky portfolio's beta and Sharpe ratio, which have a significant direct impact on the risky share, do not significantly affect the elasticity.

In the Appendix, we investigate the relation between the elasticity $\eta_{i,t}$ and the propensity to take risk. We reestimate the twin difference regression when the set of explanatory variables of $\eta_{i,t}$ includes the twin pair fixed effect $\alpha_{i,t}$ obtained from the regression reported in Table 5. The coefficient of $\alpha_{i,t}$ is negative and significant: households with a high propensity to take risk tend to have a small financial wealth elasticity of the risky share.

This analysis shows that there is substantial heterogeneity in the financial wealth elasticity of the risky share, which tends to strongly decrease with financial wealth itself. We investigate in the next section the robustness of these results to alternative specifications, and derive in Section 6 their implications for the aggregate demand for risky assets.

5. Robustness Checks

5.1. Measurement Error

Financial wealth and the risky share are observed with measurement error, for instance because of high-frequency variation in cash balances at the end of the year. For this reason, we now consider the 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 6, we instrument log financial wealth with log passive financial wealth. In the first set of columns, we estimate the average elasticity η at 0.29, which is slightly higher than the values reported in earlier tables.

In the second set of columns of Table 6, 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. The impact of other characteristics is qualitatively unchanged, but internal habit now has a negative significant impact on the risky share.

In the Appendix, we consider the instrumental variable estimation of the linear elasticity specifications (4.2). The internal habit coefficient is measured to be larger and more significant than in Table 5. Overall, we document the results of Sections 3 and 4 even more strongly when we control for measurement error in financial wealth.

5.2. Reverse Causality between the Risky Share and Financial Wealth

We have hitherto viewed the positive empirical cross-sectional correlation between financial wealth and risk-taking as evidence that richer households tend to select a higher risky share. An alternative interpretation 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* $w_{h,t}^p$ as the risky share at the end of year t if the household does not trade during the year. It is given by:

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

where $r_{h,t}$ denotes the risky portfolio's passive return defined in Section 5.1. The *passive change in the log risky share* is the difference $\ln(w_{h,t}^p) - \ln(w_{h,t-1})$. These definitions readily extend to periods of inactivity of n years.

In Table 7, 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 lagged risky share and the passive change both have significantly positive coefficients, which confirms that the propensity to take risk is persistent and that there is inertia in portfolio rebalancing.

Lagged financial wealth has a positive and significant coefficient: households with larger financial wealth in 1999 have a higher risky share in 2002, even though we control for the 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 an economy of heterogeneous CRRA investors, households with high risk tolerance would both have high risky shares and high financial wealth at the end of the bull market of the 1990's, which would generate a positive cross-sectional correlation between financial wealth and the risky share in 1999. Heterogeneity in risk tolerance cannot explain, however, why the 2002 risky share is positively related to both 1999 financial wealth and the 1999 risky share, as shown in Table 7.

The measured positive relation between financial wealth and risk-taking is not mechanically implied by the bull market of the 1990's. Instead, Table 7 strongly suggests that individual investors exhibit both *decreasing* relative risk aversion and inertia.

5.3. Health and Lifestyle

Twin difference regressions may be contaminated by individual fixed effects that are specific to each twin in the pair, such as individual differences in risk aversion. Barsky et al. (1997) show that risk aversion and asset allocation decisions are empirically related to lifestyle variables such as smoking and drinking. In Table 8, we verify the robustness of our results to individual fixed effects by including data on the lifestyle and health of each twin as controls. 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 the health and lifestyle 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, which is partly due to the smaller number of observations. Alcohol drinking is positively related to risk-taking at the 10% significance level. High blood pressure and depression have a negative impact at higher significance levels. Coffee drinking, tobacco, regular physical exercise, height, and weight have insignificant coefficients. Overall, these new regressions confirm the robustness of our elasticity estimates, and 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 relating time variations in a household's risky share to time variations in its financial wealth (e.g. Brunnermeier and Nagel 2008; Chiappori and Paiella 2008; CCS 2009*a*). This method can naturally be applied to any sample of households, and not just to households with a twin.

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:

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

As discussed in CCS (2009*a*), the estimation of (5.1) must control for two related problems. First, households display inertia in portfolio rebalancing. When a household saves in the form of cash during the year and only partially rebalances its financial portfolio, its risky share tends to fall mechanically. For this reason, 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 to the period $t-1$ risky share, $\varepsilon_{h,t-1}$, 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 9, 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, $\phi(F_{h,t-1}, w^p_{h,t-1}, r_{h,t}, r_{f,t}) - f_{h,t-1}$;[9] and (b) the period $t-1$ log passive risky share, $\ln(w^p_{h,t-1})$. In CCS (2009*a*), we followed a similar method to estimate an adjustment model of portfolio rebalancing, in which the financial wealth elasticity of the target risky share was assumed to be constant.

The average elasticity of the risky share with respect to financial wealth is estimated at 0.22 in the dynamic panel. 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*a*). 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. As in the twin difference regressions, the wealth elasticity of the risky share strongly decreases with financial wealth itself. 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 once again a strongly decreasing function of financial wealth.

The dynamic panel and twin difference regressions are strongly complementary. The dynamic method controls for household fixed effects but requires valid instruments,

[9] The instrument coincides with the passive log return on the portfolio of cash and risky financial assets, $\ln[w^p_{h,t-1}(1 + r_{h,t}) + (1 - w^p_{h,t-1})(1 + r_f)]$.

which is a source of concern and can hamper applicability to a large class of explanatory variables. Twin difference regressions, on the other hand, can be estimated by least squares, and the results of this section suggest that they are not severely contaminated by individual fixed effects. Overall, the robustness checks reported in this section confirm that the financial wealth elasticity of the risky share has a positive average and strongly decreases with financial wealth among participants.

6. Participation and Aggregate Implications

In this section, we investigate the decision to participate in risky assets markets. We then combine our micro findings to compute the response of the aggregate demand for risky assets to changes in the wealth distribution.

6.1. Determinants of Risky Asset Market Participation

We begin by measuring the cross-sectional relation between risky asset market participation, financial wealth, and other characteristics. In the first two sets of columns of Table 10, we report the results of pooled logit regressions:

$$\mathbb{E}(y_{h,t}|x_{h,t}) = \Lambda(\delta_t + \theta f_{h,t} + \gamma' x_{h,t}), \tag{6.1}$$

where $y_{h,t}$ equals unity if household h holds risky assets at the end of year t. In a cross-section, richer households with high human capital and education are more likely to own risky assets. Other experience of financial markets, as measured for instance by debt or investments in the private pension system, is also positively related to participation. Conversely, large households that have a high leverage ratio, a high external or internal habit, or high income risk are less likely to own risky assets. These cross-sectional results confirm earlier empirical 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 last two sets of columns of Table 10, we report the results of logit regressions with yearly twin pair fixed effects:

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

Financial wealth, human capital, and proxies for financial experience all have strong positive coefficients, while leverage, income risk and external habit have negative coefficients. Interestingly, some of these variables, such as external habit, have stronger magnitudes than in the cross-sectional regression. Thus, some of the main theories of financial market participation remain empirically valid when one controls for yearly twin pair fixed effects (e.g., Haliassos and Bertaut 1995; Heaton and Lucas 1999; Vissing-Jørgensen 2002a; Calvet, Gonzalez-Eiras and Sodini, 2004).

Education variables, internal habit, and household size, which are significant in the pooled regression (6.1), become insignificant in the presence of yearly twin pair fixed effects. The general level of education seems to impact neither the risky share nor risky asset market participation. One caveat is that in these regressions, we do not take into account the field of training received by investors. Our results therefore complement the work of Christiansen, Joensen and Rangvid (2008), who show on a dynamic panel that getting an education in economics can have a causal impact on risky asset market participation, while training in other fields does not.

6.2. Aggregate Implications

The micro findings on participation and the risky share reported in earlier sections allow us to assess how exogenous changes in household financial wealth can impact the aggregate demand for risky assets. We take security prices as fixed and neglect general equilibrium effects, local interactions, and habit changes. For simplicity, we remove time indices in this section.

At the end of a given year, each household h is characterized by its risky share w_h, log financial wealth $f_h = \ln(F_h)$, and other characteristics x_h. We consider an exogenous change in the cross-sectional distribution of financial wealth, which is specified by the individual growth rates Δf_h. Each household h now has new financial wealth $F'_h = F_h e^{\Delta f_h}$ and selects a new risky share w'_h, as we explain below.

Fixed Set of Participants. We focus for now on the set of households $\mathcal{P}$ that initially hold risky assets, and we do not consider participation changes. Let F denote the aggregate financial wealth of participants, and $F_R = \sum_{h\in\mathcal{P}} w_h F_h$ 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 asset prices are fixed, ξ is the elasticity of the aggregate demand for risky assets in response to exogenous changes in household wealth. The elasticity ξ generally depends on the households' initial risky shares $(w_h)_{h\in\mathcal{P}}$, initial levels of financial wealth $(F_h)_{h\in\mathcal{P}}$, growth rates $(\Delta f_h)_{h\in\mathcal{P}}$, and elasticities $(\eta_h)_{h\in\mathcal{P}}$.

If the demand for risky assets is driven by a representative agent with constant relative risk aversion (CRRA), the aggregate risky share F_R/F remains constant and the elasticity equals unity: $\xi = 1$. We view this case as an important benchmark.

We also employ imputation methods based on the initial share w_h of each household.

After the wealth shock, the risky share is given by:

$$\ln(w'_h) = \ln(w_h) + \eta_h \Delta f_h.$$

We consider three possible choices for the elasticity:

- $\eta_h = 0$ for all h, as is the case if households have CRRA utilities;
- $\eta_h = \eta > 0$ for all h, that is, all households have the same positive elasticity (as in Section 3);
- $\eta_h = \eta(f_h, x_h)$ is a function of the household's financial wealth and characteristics (as in Section 4).

Under all three specifications, the aggregate risky wealth after the shock satisfies:

$$F'_R = \sum_{h \in \mathcal{P}} w_h F_h e^{(1+\eta_h)\Delta f_h}. \tag{6.2}$$

Since $F' = \sum_{h \in \mathcal{P}} F_h e^{\Delta f_h}$, the aggregate elasticity ξ tends to be high when the wealth increase is concentrated on households with high initial risky shares or high elasticities.

The scenario $\eta_h = 0$ implicitly assumes that households have heterogeneous risk aversion coefficients, which determine their initial risky share w_h. By (6.2), the aggregate elasticity ξ equals unity if all households have the same initial risky share, but can otherwise be larger or smaller than unity. In the scenario $\eta_h = \eta > 0$, the common individual elasticity is obtained from the yearly twin difference regression of the risky share on log financial wealth. In the last scenario, the elasticity $\eta(f_h, x_h)$ depends on financial wealth and other characteristics. It is the most plausible specification given the micro-level evidence reported in Section 4.

In Figure 1, we consider twenty financial wealth quantiles, and report for each quantile the aggregate elasticity corresponding to an exogenous wealth shock affecting only households in the quantile: $\Delta f_h = g$ if h is in the quantile, and $\Delta f_h = 0$ otherwise. The growth rate g is set equal to 10%, and all the results are reported for year 2001. In the Appendix we verify that the results are qualitatively similar in other years. The yellow line corresponds to the benchmark representative investor.

When households have heterogeneous CRRA utilities (black line), the aggregate elasticity increases monotonically with the quantile on which the wealth shock is concentrated. The mechanism is that richer households have higher risky shares. ξ is less than 1 for low and medium quantiles and exceeds unity only for the very top quantiles.

When households have an identical and strictly positive elasticity of the risky share (blue line), the aggregate elasticity is again a monotonic function of the wealth quantile on which the shock is concentrated. As one would expect, the aggregate elasticity ξ is uniformly higher than in the heterogeneous CRRA case. It reaches 1.4 when the wealth shock impacts the richest households.

The red line corresponds to our preferred micro specification. Poor investors have a higher elasticity $\eta(f_h; x_h)$ than average. As a result, ξ is higher and closer to unity in low quantiles than under the CRRA and constant positive elasticity specifications. Conversely, because the linear elasticity $\eta(f_h; x_h)$ decreases with wealth, ξ is smaller and closer to unity in higher wealth quantiles than under the constant elasticity method. In top wealth quantiles, household elasticities are very close to zero, and the aggregate elasticity ξ coincides almost exactly with the aggregate elasticity of heterogeneous CRRA investors.

We now consider the impact of a homogenous wealth shock: $\Delta(f_h) = g$ for all h. When investors have CRRA utilities, ξ equals unity, as can be seen from (6.2).[10] The aggregate elasticity is 1.22 when households have a constant η, and 1.07 when households have a linear elasticity $\eta(f_h, x_h)$. The corresponding aggregate elasticity of the *risky share*, $\Delta \ln(F_R/F)/\Delta \ln(F)$, is therefore 0 in the heterogeneous CRRA case, 22% in the identical η case, and 7% in the preferred case. Thus, the heterogeneous 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, the demand of a CRRA representative investor.

Endogenous Participation. We next investigate participation effects. The probability that a household participates in risky asset markets is given by the yearly cross-sectional logit model $\Lambda(f_h; x_h)$. Let $\mathcal{N}$ denote the set of households that do not initially participate. The probability that a household in $\mathcal{N}$ enters after the shock is 0 if $\Delta f_h \leq 0$, and

$$p'_h = \frac{\Lambda(f_h + \Delta f_h; x_h) - \Lambda(f_h; x_h)}{1 - \Lambda(f_h; x_h)}$$

otherwise. We impute the risky share $w'_h = w(f_h + \Delta f_h; x_h)$ of an entering household from the cross-sectional regression of the log risky share on characteristics reported in Table 2. Conversely, a household in $\mathcal{P}$ remains a participant with probability:

$$p'_h = \min[1; \Lambda(f_h + \Delta f_h; x_h)/\Lambda(f_h; x_h)].$$

Aggregate risky financial wealth is then $F'_R = \sum_{h \in \mathcal{N}} p'_h w'_h F'_h + \sum_{h \in \mathcal{P}} p'_h w_h e^{\eta_h g_h} F'_h$.

In Figure 2, we illustrate the elasticity of aggregate risky wealth with respect to aggregate financial wealth in the population of participating and nonparticipating households. By a slight abuse of notation, this new elasticity is also denoted by ξ. We consider wealth shocks of 10% to each quantile of financial wealth in the population of households with a twin. In bottom quantiles, participation is low and new entrants select small risky

[10] By (6.2), $F'_R = e^g \sum_h w_h F_h = e^g F_R$, and therefore $\Delta \ln(F'_R) = \Delta \ln(F_R)$.

shares, so ξ is close to zero for all imputation methods. With the linear elasticity method (red line), the aggregate elasticity ξ remains close to unity on a range of intermediate wealth quantiles. We verify that the contribution of new entrants is generally small compared to changes in risky asset demand from preexisting participants.

We now investigate the impact of a homogenous wealth shock: $\Delta(f_h) = g$ for all h. When investors have CRRA utilities, the elasticity ξ is 1.02 in 2001, which is slightly higher than the unit value in the fixed participation case. The aggregate elasticity estimates are 1.25 when households have a constant η, and 1.09 when households have a linear elasticity. These values exceed only slightly the fixed participation estimates.

Entry and exit generally imply that the aggregate elasticity ξ is not the same for a positive or negative shock. The difference remains small in practice, however, as is shown in the Appendix. The explanation is that participation turnover is limited and has only a modest impact on the aggregate elasticity.

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 consistent with the micro evidence reported in Section 4. Second, the aggregate elasticity is remarkably stable, whether one considers homogenous or concentrated shocks. The aggregate demand for risky assets is close to, but does not exactly coincide with, the demand of a representative agent with CRRA utility. It is an open question whether the deviations from the CRRA representative agent benchmark are negligible or could instead be used to provide support for alternative specifications, such as the aggregate habit formation models of Constantinides (1990) and Campbell and Cochrane (1999).

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 financial wealth elasticity of the risky share is strongly significant and estimated at 22%.

This paper confirms that the majority of the cross-sectional results obtained in the earlier literature are robust to the inclusion of twin pair fixed effects. The risky share is positively related to diversification and financial experience, and negatively related to leverage, entrepreneurship, the risky portfolio's beta, household size and a measure of habit. One interesting difference is that income risk and education, which are significantly related to the risky share in pooled cross sections, become insignificant in the twin difference regressions.

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 maintaining the habit over an infinite horizon represents 1/6 of financial wealth on average, and 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 verify that our results are unchanged when we control for communication between twins and lifestyle and physiological characteristics typically associated with risk-taking.

Our 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 at the micro level. We also consider exogenous shocks to the wealth distribution, and show that the aggregate demand for risky assets behaves 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). Our estimates also have implications for consumption-based asset pricing. We leave these questions for further research.

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TABLE 1. SUMMARY STATISTICS

	TWINS			RANDOM SAMPLE	
	Mean	Standard deviation	Pairwise correlation	Mean	Standard deviation
Financial and Portfolio Characteristics					
Risky share	0.543	0.291	0.185	0.513	0.296
Financial wealth ($)	46,782	72,718	0.312	45,067	73,774
Real estate wealth ($)	120,135	123,011	0.289	112,925	119,133
Leverage ratio	0.778	2.381	0.148	0.936	3.128
Total liability ($)	50,800	55,935	0.248	49,658	56,126
Private pension premia/income	0.043	0.094	0.058	0.042	0.211
Sharpe ratio of risky portfolio	0.289	0.056	0.001	0.285	0.061
Beta of risky portfolio	0.930	0.321	0.104	0.932	0.340
Demographic Characteristics					
High school dummy	0.843	0.364	0.365	0.807	0.395
Post-high school dummy	0.371	0.483	0.470	0.358	0.479
Number of adults	1.728	0.445	0.147	1.733	0.442
Number of children	1.005	1.107	0.403	0.992	1.096
Wealth-weighted gender index	0.542	0.325	0.135	0.547	0.324
Human Capital and Income Risk					
Human capital ($)	759,461	513,832	0.484	772,455	639,964
Permanent income risk	-0.002	0.089	0.029	-0.001	0.113
Transitory income risk	0.060	0.365	0.042	0.068	0.381
Correlation of income innovation and portfolio return	-0.003	0.308	0.040	-0.003	0.308
Entrepreneur dummy	0.036	0.186	0.128	0.037	0.190
Unemployment dummy	0.084	0.277	0.109	0.072	0.258
Habit					
Internal habit ($)	36,052	16,901	0.291	35,338	16,664
External habit ($)	26,135	3,319	0.449	26,215	3,328

Notes: The table reports summary statistics of the financial, portfolio, demographic, income, and habit characteristics of participating Swedish households. The first set of columns is based on the set of twin pairs in which both siblings participate in risky asset markets, and the last set of columns on a random sample of participating households. For each characteristic, we report the cross-sectional mean and standard deviation in each sample, as well as the correlation within twin pairs. The education, entrepreneur and unemployment dummies are computed for the twin in the household. All other characteristics are computed at the household level. Internal habit is proxied by the household's three-year average of disposable income, excluding private pension savings from consideration. External habit is proxied by the three-year average household income in the municipality. All nominal variables are winsorized at the 99th percentile.

TABLE 2. 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 participating 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 3. 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 participating households with an adult twin. We report the adjusted R^2 of the twin difference regressions, and the R^2 and adjusted R^2 of the corresponding linear panel regressions with yearly fixed effects specified by equation (3.5). 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. 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 of twin difference regression	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) financial wealth interacted with 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 5. 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 of twin difference regression	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, other household characteristics, and financial wealth interacted with 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 6. 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 of twin difference regression	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 7. LAGGED FINANCIAL AND PORTFOLIO CHARACTERISTICS

Twin pair fixed effects

	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 of twin difference regression	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 8. HEALTH AND LIFESTYLE 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 8 (cont.) HEALTH AND LIFESTYLE 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 of twin difference regression	13.8%		14.2%	
Number of observations	18,129		18,129	
Number of twin pairs	5,354		5,354	

Notes: This table reports the pooled twin difference regressions of the log risky share on health, lifestyle, and other characteristics, and: (1) financial wealth (first set of columns), and (2) financial wealth interacted with financial wealth dummies (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 9. 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 period and are the same as in the last set of columns of Table 3.

TABLE 10. PARTICIPATION IN RISKY ASSET MARKETS

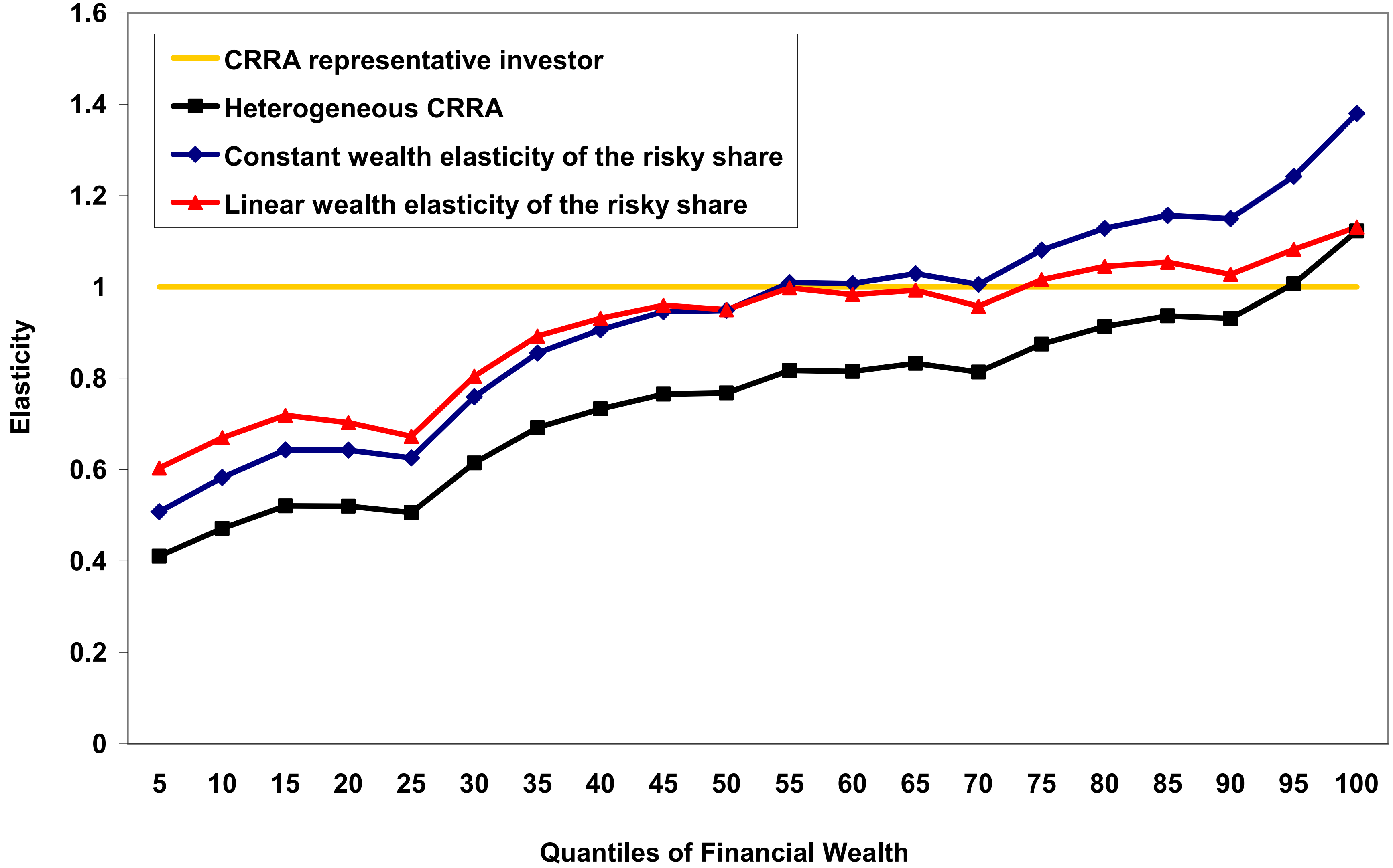
Logit regressions

	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.

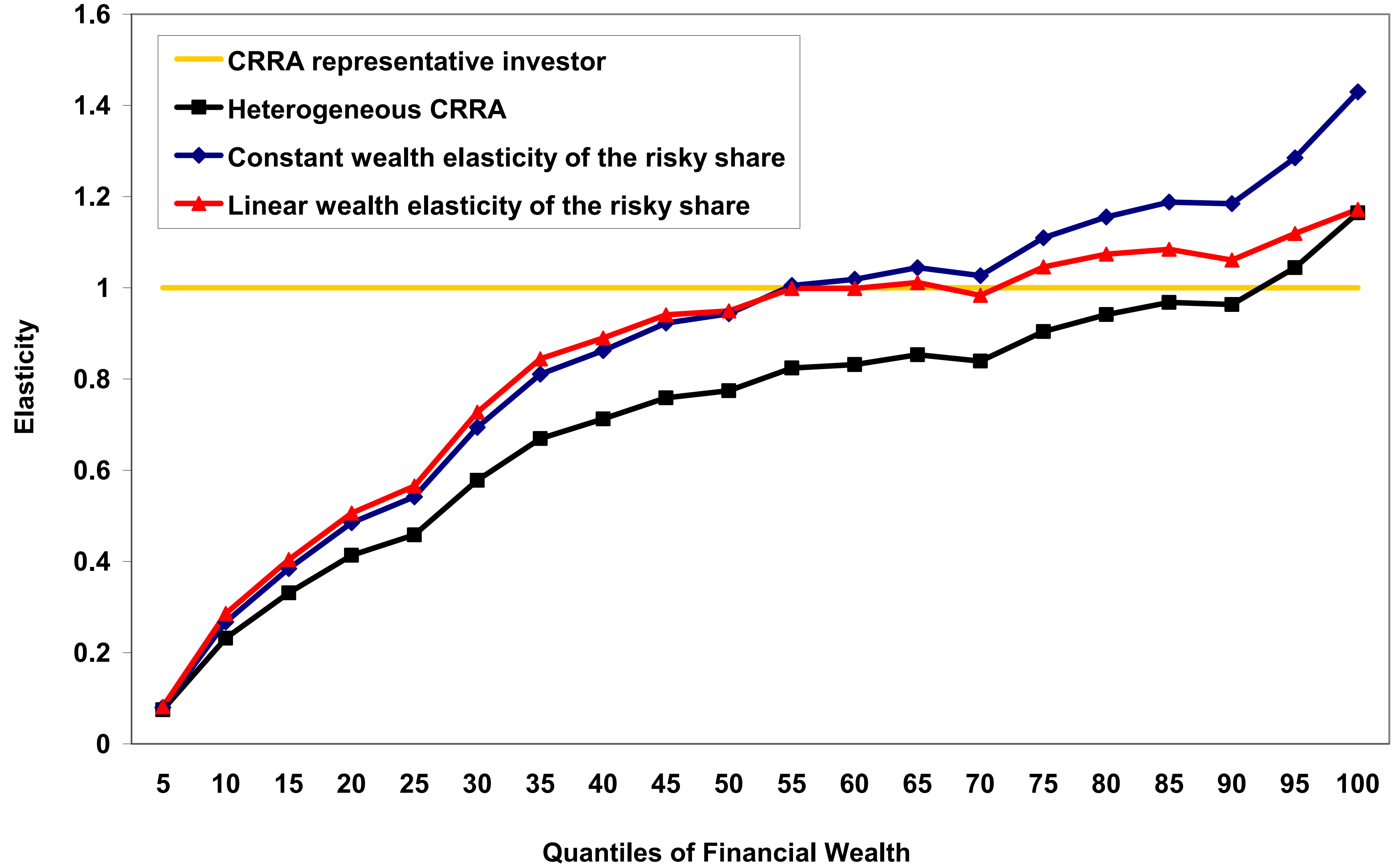
FIGURE 1. ELASTICITY OF AGGREGATE RISKY FINANCIAL WEALTH

Fixed set of participants (2001)



Notes: This figure illustrates the elasticity of aggregate risky financial wealth with respect to the aggregate financial wealth of participating households. We consider twenty financial wealth quantiles, and report for each quantile the aggregate elasticity corresponding to an exogenous wealth shock affecting only households in the quantile: $\Delta\ln(F_h) = g$ if h is in the quantile and $\Delta\ln(F_h) = 0$ otherwise. The set of participants is fixed and all results are reported for year 2001.

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



Notes: This figure illustrates the elasticity of aggregate risky financial wealth with respect to the aggregate financial wealth of participating and nonparticipating households. We consider twenty financial wealth quantiles, and report for each quantile the aggregate elasticity corresponding to an exogenous positive wealth shock affecting only households in the quantile: $\Delta\ln(F_h) = g$ if h is in the quantile and $\Delta\ln(F_h) = 0$ otherwise. The set of participants is endogenous and all results are reported for year 2001.