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

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ABSTRACT

This paper investigates risk-taking in the liquid portfolios held by a large panel of Swedish twins. We document that the portfolio share invested in risky assets is an increasing and concave function of financial wealth, leading to different risk sensitivities across investors. Human capital, which we estimate directly from individual labor income, also drives risk-taking positively, while internal habit and expenditure commitments tend to reduce it. Our micro findings lend strong support to decreasing relative risk aversion and habit formation preferences. Furthermore, heterogeneous risk sensitivities across investors help reconcile individual preferences with representative-agent models.

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How does the asset allocation of individual investors depend on their main financial and demographic characteristics? Portfolio choice theory provides normative answers to this question under a wide range of risk preferences and financial circumstances (see, e.g., Campbell and Viceira (2002)). Among the many mechanisms investigated in the literature, the relation between risk-taking and wealth is of primary importance, because it distinguishes constant relative risk aversion (CRRA) utility from increasingly popular alternatives. As noted by Samuelson (1969), a CRRA investor selects the same asset allocation at all wealth levels in the absence of market frictions. By contrast, an investor with decreasing relative risk aversion (DRRA) invests a higher proportion of her wealth in risky assets as she gets richer. DRRA has many possible sources, including subsistence consumption (Carroll (2000) and Wachter and Yogo (2010)), habit formation (Campbell and Cochrane (1999) and Constantinides (1990)), committed expenditures (Chetty and Szeidl (2007, 2010)), or a "capitalist" taste for wealth (Bakshi and Chen (1996) and Carroll (2002)). Because DRRA produces higher risk aversion in bad times than in good times, it naturally generates countercyclical risk premia, which motivate its growing use in consumption-based asset pricing.[1] More generally, attitudes toward risk form the foundations of the portfolio choice and macro-finance literatures, and one would like to know which specifications are actually valid at the micro level.

The relation between risk-taking and financial variables is challenging to pin down empirically because individual investors have heterogeneous risk attitudes and other hidden traits impacting their investments. This latent diversity is the source of severe identification problems. For instance, a number of studies document a positive correlation between financial wealth and risk-taking in the cross-section of households (see, e.g., Calvet Campbell and Sodini ("CCS", 2007), and Carroll (2002)).[2] One interpretation is that investors have heterogeneous CRRA utilities and that their risk tolerance coefficients are positively correlated to socioeconomic status in the cross-section; an exogenous wealth change does not alter individual asset allocations under this scenario. Another interpretation is that investors have decreasing relative risk aversion; households select higher risky shares as they get wealthier, for instance in response to an exogenous shock. Cross-sectional data do not permit researchers to disentangle the two scenarios. In addition, cross-sectional studies typically account for less than 10% of the variance of portfolio asset allocations and are therefore of limited use in household finance.

A more recent empirical strategy relates time variations in a household's asset allocation to time variations in the household's financial wealth and characteristics (see, e.g., Chiappori and Paiella (2011)). A new set of identification problems must then be addressed. The portfolio dynamics may reflect the arrival of new information and investment opportunities, and not just changes in characteristics. In addition, households exhibit inertia in portfolio rebalancing, which induces endogeneity problems requiring the use of instruments. The conclusions of panel studies are highly sensitive to the choice of instruments (Brunnermeier and Nagel (2008) and CCS (2009*a*)),[3] so that the link between risk-taking and wealth at the micro level remains an open empirical question.

The present paper makes five contributions to the literature. First, we solve the identification problem by using a panel of twins.[4] The analysis is based on a high-quality and uniquely comprehensive panel containing the disaggregated portfolios and detailed characteristics of twins in Sweden. The panel contains about 23,000 twins observed at the end of each year over the 1999-2002 period. Because twins are much more closely related than random individuals in the population, the dataset allows us to control for latent forms of heterogeneity, such as attitudes toward risk, ability, genes, shared background, and expected inheritance, among others. We accordingly run portfolio regressions in which yearly twin pair fixed effects are included in the set of the explanatory variables. This method offers several advantages. Yearly twin pair fixed effects pick up the impact of latent characteristics and increase explanatory power relative to standard methods. Twin regressions can be implemented equally well on a single or on multiple years of data, and do not require the use of instruments. Furthermore, we can analyze how highly persistent variables such as human capital may impact investment, a mechanism that would be challenging to measure in a standard panel.

Second, we document that financial wealth has a strong positive impact on the *risky share*, defined as the proportion of the liquid financial portfolio invested in risky assets. The positive relationship holds both for the decision to participate in risky asset markets and for the selected risky share conditional on participation. We demonstrate it by running regressions of the participation status (or the log risky share) on yearly twin pair fixed effects, financial wealth, and other observable characteristics. We then focus on the asset allocation conditional on participation, so that the financial wealth elasticity of the risky share is well-defined. The average elasticity is close to 0.2 and highly significant in all specifications. In particular, the elasticity is invariant to the frequency of communication between the twins. For instance even when identical twins meet in person at least twice a week *and* interact by mail, phone or e-mail at least five times a week, the wealthier twin selects a significantly higher risky share than its poorer sibling, whether or not one controls for a large set of observable characteristics. These findings imply that financial wealth does not merely act as a proxy for information differences across investors in risky share regressions. The measured impact of financial wealth on risk-taking is remarkably robust across specifications and provides strong evidence that households exhibit decreasing relative risk aversion.

Third, the Swedish dataset allows us to investigate the investment impact of an unprecedented set of explanatory variables, including, most notably, human capital. Earlier empirical investigations of portfolio choice over the life-cycle highlight the difficulty of disentangling cohort, time and age effects in cross-sectional or panel data, and as a result strong additional identification assumptions must be used (Ameriks and Zeldes (2004) and Fagereng, Gottlieb and Guiso (2011)). By contrast, our dataset allows us to estimate directly the labor income process and then measure how expected human capital drives the risky share, which, to the best of our knowledge, is new to the household finance literature. Moreover, the twin methodology naturally controls for time, cohort and age effects along with observable and latent family characteristics. We document that financial risk-taking is positively related to expected human capital, as theory predicts; interestingly, the relation is significant only on the subsample of identical twins, in which our method best controls for latent heterogeneity. Educational attainment, which is strongly significant in the cross-section, becomes insignificant in twin regressions. Income risk, leverage, entrepreneurship, household size, and a measure of internal habit tend to reduce the risky share, consistent with financial theory.[5] The adjusted R^2 of the twin regression is 19% on the full sample of identical and fraternal twins, and reaches 40% on the subsample of identical twins who communicate often with each other. These levels of explained variation are exceptionally high for household finance, which illustrates the benefits of using a twin panel with a comprehensive set of characteristics.

Fourth, we document for the first time that the sensitivity of risk-taking to financial wealth is highly heterogeneous across households. Consistent with DRRA and habit formation preferences, the financial wealth elasticity of the risky share strongly decreases with financial wealth itself and increases with habit, whether or not leverage and a large set of characteristics are included as controls. When an investor gets closer to her habit level, her asset allocation become more sensitive to additional liquid wealth. Our results imply that the risky share is an increasing and concave function of financial wealth. Furthermore, we report that the financial wealth elasticity of the risky share increases with residential real estate and family size and decreases with human capital. These novel empirical regularities are intuitive since housing and children can be viewed as proxies for consumption habit or as commitments to future expenditures. Until now, however, portfolio theory has not explicitly related residential real estate and family composition to the financial wealth elasticity of the risky share, and we provide new facts that this literature may seek to match.

Finally, we show that the measured heterogeneity in the financial wealth elasticity of the risky share has key implications for aggregate risk-taking. Using our empirical micro estimates, we compute how the total demand for risky assets from the household sector responds to exogenous changes in the cross-sectional distribution of wealth.[6] When shocks are positive and 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 shares, aggregate risky wealth grows only slightly faster than total financial wealth. For the same reason, the elasticity to a homogenous shock is also slightly (but significantly) above unity. Moreover, the heterogeneous elasticity specification implies that aggregate risk-taking is less sensitive to the wealth distribution across investors than a heterogeneous CRRA counterfactual would entail; heterogeneous elasticities thus help reconcile the micro evidence with the predictions of representative-agent models.

The paper complements the growing literature that attempts to tease out the role of genes in risk-taking (Barnea, Cronqvist and Siegel (2010) and Cesarini et al. (2009), (2010)) and savings decisions (Cronqvist and Siegel (2011)) through variance decomposition techniques. In our study, twin pair fixed effects are quantitatively important, which can be attributed both to the common genetic makeup and the common background of twin siblings. We document that communication has a dramatic impact on the explanatory power of yearly twin pair fixed effects, which indicates that twin fixed effects are not purely driven by genes. Interestingly, communication is also found to have a strong influence on the so-called genetic component when we estimate variance decompositions of the type considered in earlier research. We do not attempt to disentangle between nature and nurture in the paper because a growing literature in genetics, medicine and experimental psychology documents substantial interactions between them (Ridley (2003)). Another key result of our paper is that observable characteristics explain a substantial fraction of the cross-sectional variation of the risky share. Individual investors do not simply select genetically predetermined portfolios but instead aggressively respond to their own financial circumstances and their interactions with others, often in accordance with the prescriptions of portfolio theory.

The organization of the paper is as follows. Section I presents the Swedish twin dataset and constructs the main variables. Section II investigates how the risky share relates to financial wealth and other characteristics conditional on risky asset market participation. In Section III, we document the empirical properties of the financial wealth elasticity of the risky share. Section IV reports robustness checks. In Section V, we investigate the participation decision and derive the aggregate implications of the micro findings. Section VI concludes. The Internet Appendix presents details of data construction and estimation methodology.

I. Data and Definitions

A. The Swedish Dataset

The Swedish Twin Registry, which is administered by the Karolinska Institute in Stockholm, is the largest twin database in the world. It provides the genetic relationship (fraternal or identical) of each twin pair,[7] and the intensity of communication between the twins. We refer the reader to Lichtenstein et al. (2006) and Pedersen et al. (2002), as well as the Internet Appendix, for detailed descriptions.

The twin database allows us to identify twin siblings in the Swedish Wealth Registry, an administrative dataset compiled by Statistics Sweden which we have used in earlier work (CCS (2007), (2009*a*), (2009*b*)). For tax purposes, Statistics Sweden and the tax authority had until recently a parliamentary mandate to collect highly detailed information on every resident, including age, gender, marital status, nationality, birthplace, education, municipality, income and disaggregated wealth. The wealth data include the worldwide assets owned by the resident on December 31 of each year, including real estate, bank accounts, mutual funds and stocks. Holdings are provided for each property, account or security. The database also records debt outstanding at year end and contributions made during the year to private pension savings.

Statistics Sweden provides a household identification number for each resident, which allows us to group residents by living units.[8] Because financial theory suggests that investment decisions should be studied at the family level, the results presented in this paper are based on households with an adult twin during the 1999-2002 period. In the Internet Appendix, we verify that most of our household-level results also hold when we ignore living units and consider finances at a purely individual level.

Throughout the paper, we pair households with related adult twins and conduct our investigation on the set of pairs for which all characteristics are available. We impose no constraint on their risky asset market participation status, 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). Second, the value of all financial assets must be no smaller than 3,000 kronor ($339). Third, the household head, defined as the individual with the highest income, must be at least 25 years old. Overall, we obtain an unbalanced panel containing 85,532 observations over the 1999-2002 period, corresponding to 11,721 distinct twin pairs.

B. *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* $F_{h,t}$ at date 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. Residential real estate consists of primary and secondary residences, while commercial real estate consists of rental, industrial and agricultural property. The *leverage ratio* is defined as a household's total debt divided by the sum of its financial and real estate wealth.

The *risky share* $w_{h,t}$ is the proportion of risky assets in the household's portfolio of cash and risky financial assets. A participant is a household with a positive risky share. Habit formation models imply that the risky share is affected by lagged values of consumption, either by the household itself or by a peer group. 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 external habit by the three-year average income of households (without an adult twin) in the same municipality.

Every Swedish resident is required to declare the fraction of the household's assets that it owns. We define the *gender index* of economic power as the share of the household's gross financial and real estate wealth owned by adult men. The gender index is close to unity if gross wealth is primarily controlled by men.

Human Capital. We consider the labor income specification used in Cocco, Gomes and Maenhout (2005):

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

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 on its yearly series between 1993 and 2002 using the procedure of Carroll and Samwick (1997). Let $u_{h,t}$ denote the difference between income growth, $\log(L_{h,t}/L_{h,t-1})$, and the fitted value, $b'(x_{h,t} - x_{h,t-1})$. We measure the systematic risk in income by the beta coefficient β_h of the innovation $u_{h,t}$ relative to historical excess returns on the risky portfolio.

Expected human capital is defined by:

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

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 discount rate is set equal to $r = 3\%$ per year. In the Internet Appendix, we provide a detailed description of the human capital calculation and verify that our results are robust to alternative choices of r.

We use the following variables throughout the remainder of the paper: a) expected human capital $HC_{h,t}$; 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 beta of income growth relative to the risky portfolio, β_h.

C. Summary Statistics

In the remainder of the section and in sections II to IV, we consider pairs in which both twins participate in risky asset markets. The resulting panel contains 55,898 observations over the 1999-2002 period, corresponding to 8,394 distinct twin pairs. The participation decision is investigated in section V.

[Insert Table I about here]

Table I reports summary statistics for participating twins and for a random sample 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. Our estimates of income risk, which are based on the Carroll and Samwick (1997) OLS regressions, can take negative values, as has also been observed in U.S.

data (Campbell and Viceira (2002), ch. 7). Differences in the means between the two samples are modest, except for the leverage ratio. The correlation of characteristics within twin pairs is positive, ranging from 3% for permanent income risk to 48% for human capital. In the Internet Appendix, we report summary statistics separately for identical and fraternal twins and verify that pairwise correlations are generally higher for identical twins, as one expects.

II. What Drives the Risky Share?

A. Theoretical Motivation

We briefly review some of the main implications of financial theory for the portfolio asset allocation of an individual investor. We begin with a simple environment in which the agent's wealth is purely financial and fully liquid. If the agent has constant relative risk aversion (CRRA) and is unconstrained, the optimal risky share is independent of financial wealth and satisfies $w^*_{h,t} \approx S_{h,t}/(\gamma_h \sigma_{h,t})$, where γ_h is the agent's coefficient of relative risk aversion, $S_{h,t}$ is the risky portfolio's Sharpe ratio, and $\sigma_{h,t}$ is the standard deviation of its log excess returns (Samuelson (1969)).

By contrast, if the agent has decreasing relative risk aversion (DRRA), the optimal risky share increases with financial wealth. DRRA is frequently modelled by incorporating a subsistence or habit term into CRRA utility. Under a wide range of assumptions explained in the Internet Appendix (see, e.g., Brunnermeier and Nagel (2008), Campbell and Viceira (2002), and Constantinides (1990)), the optimal risky share is:

$$w_{h,t} = w^*_{h,t}\left(1 - \frac{\lambda_h X_{h,t}}{F_{h,t}}\right), \tag{2}$$

where $X_{h,t}$ is a subsistence or habit level in consumption and λ_h is a positive constant. The product $\lambda_h X_{h,t}$ is the present value of maintaining the habit over an infinite horizon. Equation (2) also holds in models of committed expenditures, in which current consumption choices impose a lower bound on future consumption and $\lambda_h X_{h,t}$ denotes the present value of future commitments (Dybvig (1995)). Habit formation and committed expenditures are closely related theories that can both be explained by adjustment costs in consumption (Chetty and Szeidl (2007, 2010)). For this reason and given the limitations of the data, we will not attempt to distinguish between habit, subsistence, and commitment, and we will generically refer to $X_{h,t}$ as the habit parameter.

The "spirit of capitalism" (Bakshi and Chen (1996) and Carroll (2000, 2002)) offers yet another motivation for DRRA. It proposes that household utility explicitly depend on the difference between own financial wealth and a benchmark. The optimal risky share is then:

$$w_{h,t} = \phi_h w^*_{h,t} \left(1 - \frac{\lambda_h F^*_{h,t}}{F_{h,t}}\right), \tag{3}$$

where ϕ_h and λ_h are fixed preference parameters and $F^*_{h,t}$ is a self-assessed subsistence wealth level.[9] The spirit of capitalism implies that financial wealth can impact the risky share through a different channel than the financial wealth-to-consumption habit ratio in (2). This observation motivates using financial wealth as a standalone variable in the empirical specification of the risky share.

The risky share (2) from habit formation models has the following testable properties.

Implication 1. *The risky share increases with financial wealth.*

Implication 2. *The risky share decreases with habit.*

Note that Implication 1 also holds under the "spirit of capitalism" specification (3).

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

$$\eta_{h,t} = \frac{d\log(w_{h,t})}{df_{h,t}}, \tag{4}$$

where $f_{h,t} = \log(F_{h,t})$ denotes the household's log financial wealth. The elasticity $\eta_{h,t}$ has key implications for the aggregate demand for risky assets and asset pricing, as will be shown in Section V. When the risky share is given by (2), the elasticity satisfies:

$$\eta_{h,t} = \frac{y_{h,t}}{1 - y_{h,t}} = \frac{\lambda_h X_{h,t}}{F_{h,t} - \lambda_h X_{h,t}}, \tag{5}$$

where $y_{h,t} = \lambda_h X_{h,t}/F_{h,t}$ denotes the cost of habit-to-financial wealth ratio. This leads to:

Implication 3. *The financial wealth elasticity of the risky share is positive, decreases with financial wealth and converges to zero when financial wealth is large.*

Implication 4. *The financial wealth elasticity of the risky share increases with habit.*

The twin dataset allows us to test these four predictions. In the case of a CRRA investor facing no market frictions, the elasticity $\eta_{h,t}$ is equal to zero and Implications 1 to 4 are all violated.

Human capital represents by far the largest form of wealth held by the average household (Table I) and is potentially another key determinant of the risky share. To the extent that future income can be viewed as a nontraded bond, households with substantial human capital select more aggressive financial portfolios than other households (Bodie, Merton and Samuelson (1992), Cocco, Gomes and Maenhout (2005), and Merton (1971)). For instance if the investor has a CRRA utility, the optimal risky share is an increasing function of the human capital-to-financial wealth ratio; the risky share is therefore expected to increase with human capital and *decrease* with financial wealth.

As the above analysis suggests, habit formation and human capital have conflicting implications for the relationship between financial wealth and the risky share. For this reason, it is useful to incorporate human capital into the habit models discussed above. If human capital $HC_{h,t}$ is both riskless and fully liquid, the investor allocates a fraction $w^*_{h,t}\left[1 - \lambda_h X_{h,t}/(F_{h,t} + HC_{h,t})\right]$ of *total wealth* to risky assets, which corresponds to a fraction

$$w_{h,t} = w^*_{h,t}\left(1 - \frac{\lambda_h X_{h,t}}{F_{h,t} + HC_{h,t}}\right)\frac{F_{h,t} + HC_{h,t}}{F_{h,t}}. \tag{6}$$

of *financial* wealth. Equation (6) illustrates that habit induces a *positive* relation between financial wealth and risky share, while human capital induces a *negative* relation between them through the total wealth-to-financial wealth ratio, $(F_{h,t} + HC_{h,t})/F_{h,t}$. We show in the Internet Appendix that the habit channel dominates if habit is sufficiently high. When income is risky, the habit channel dominates through a complementary mechanism. Because financial wealth and human capital must cover the habit cost with probability one, the risky share cannot exceed a binding upper bound, which is determined by the worst realization of human capital and asset returns. As financial wealth goes up, the constraint becomes progressively looser and the risky share increases (Polkovnichenko, 2007). Calibrated models show that the positive impact of habit prevails at low and medium wealth levels under a broader set of habit parameters (Gomes and Michaelides (2003) and Polkovnichenko (2007)). In the Internet Appendix, we revisit these results in a simple calibrated model.

Many other characteristics can affect risk-taking, such as real estate, background risk, family composition, borrowing constraints, and other market frictions. We will review their theoretical implications in the next sections as we discuss the empirical results.

B. Empirical Specification

The heterogeneity of household preferences and other latent characteristics represents a major impediment to testing portfolio selection models. For instance, the positive cross-sectional correlation between financial wealth and the risky share can be explained either by: (i) a positive correlation between socioeconomic status and risk tolerance among CRRA investors, or (ii) by DRRA preferences at the individual level. Twin studies, which have been widely used in medicine, psychology, labor economics and many other fields, offer a natural solution to this identification problem. As Table I shows, twins have closer characteristics than two randomly selected households. This proximity has multiple origins. Twins share a common genetic make-up and generally have identical family backgrounds, upbringings, and expected inheritances. Furthermore, they tend to communicate often with each other. For all these reasons, twin siblings have more similar preferences and latent characteristics than two randomly selected investors.

We accordingly consider panel regressions of the risky share on observable characteristics and *yearly twin pair fixed effects*, which control for the common traits of twin siblings in a given year. For every twin pair i, we specify the risky share of twin j's household, $j \in \{1, 2\}$, at date t by:

$$\begin{aligned} \log(w_{i,1,t}) &= \alpha_{i,t} + \eta f_{i,1,t} + \gamma' x_{i,1,t} + \varepsilon_{i,1,t}, \qquad (7) \\ \log(w_{i,2,t}) &= \alpha_{i,t} + \eta f_{i,2,t} + \gamma' x_{i,2,t} + \varepsilon_{i,2,t}, \end{aligned}$$

where the intercept $\alpha_{i,t}$ is a fixed effect specific to twin pair i in year t. By construction, $\alpha_{i,t}$ controls for the common effect of time, such as age or stock market performance, as well as for similarities between twins. The linear coefficients η and γ determine the sensitivity of differences in the log risky share, $\log(w_{i,2,t}) - \log(w_{i,1,t})$, with respect to twin differences in characteristics.

The twin specification (7) contrasts with the yearly fixed effects regressions, $\log(w_{h,t}) = \alpha_t + \eta f_{h,t} + \gamma' x_{h,t} + \varepsilon_{h,t}$, commonly considered in household finance. Yearly fixed effects regressions do not control for latent heterogeneity in the population of investors, and we will often refer to them as the "pooled" or "cross-sectional" approach. A finer level of control is in principle offered by panel specifications with both *individual* fixed effects and *yearly* fixed effects: $\log(w_{h,t}) = \alpha_t + \delta_h + \eta f_{h,t} + \gamma' x_{h,t} + \varepsilon_{h,t}$, which we will refer to as the "dynamic" approach. The linear coefficients η and γ quantify the sensitivity of the risky share to variations in characteristics. Due to inertia in portfolio rebalancing and other endogeneity problems, the estimation of η and γ requires the use of instruments, and the results are sensitive to the choice of instruments (Brunnermeier and Nagel (2008) and CCS (2009*a*)). The twin specification (7) allows us to control for latent traits without requiring instruments or observations over multiple periods. It also permits us to analyze how highly persistent variables such as human capital may impact the risky share, an effect that would be challenging to measure with the dynamic approach.

Since a panel regression with yearly *individual* fixed effects $\alpha_{i,j,t}$ is not identified, the proposed analysis employs the finest level of control for latent heterogeneity available in the data. In Section IV.B, we will nonetheless investigate if the twin regression (7) is contaminated by residual individual fixed effects. In Sections III and IV, the elasticity η will also be allowed to vary across pairs.

C. Impact of Financial Wealth

In Panel A of Table II, we estimate the linear panel (7) on the set of all twins. The financial wealth elasticity of the risky share η is highly significant and estimated at 0.196 in the absence of controls (first set of columns), 0.224 when we include real estate, leverage, human capital, income risk and habit (second set of columns), and 0.223 when we add demographic characteristics (third set). These estimates are slightly lower than the 0.231 coefficient obtained with standard yearly fixed effects (fourth set of columns). In Table III, we reestimate the regressions on the subsample of identical twins. The financial wealth elasticity of the risky share is nearly unchanged and remains strongly significant.

[**Insert Table II about here**]

The richer twin in a pair selects a higher risky share than its poorer sibling, whether or not one controls for a large set of observable characteristics. The regressions therefore document a strong and stable positive link between financial wealth and the risky share. Since we control for the leverage ratio, this relation cannot be attributed to cash-in-advance constraints alone, and provide a strong indication that households exhibit decreasing relative risk aversion. In Section IV, we will provide further evidence that financial wealth has a causal impact on the risky share and its elasticity.

[**Insert Table III about here**]

The empirical estimates of η can be readily interpreted in the context of habit formation models. In the Internet Appendix, we derive from (6) that the financial wealth elasticity of the risky share satisfies:

$$\lambda_h X_{h,t} = HC_{h,t} + \frac{\eta_{h,t}}{1+\eta_{h,t}} F_{h,t}. \tag{8}$$

The cost of maintaining the habit over an infinite horizon, $\lambda_h X_{h,t}$, is financed by human capital $HC_{h,t}$ and a fraction of financial wealth, $F_{h,t}\eta_{h,t}/(1+\eta_{h,t})$. The remaining fraction $F_{h,t}/(1+\eta_{h,t})$ represents the present value of surplus consumption.

We can use equation (8) to impute the habit liability $\lambda_h X_{h,t}$ from the empirical values of the elasticity, financial wealth and human capital. This can prove useful in practice because there is no consensus on the specification of the habit, whereas equation (8) holds for a wide range of internal and external habit models. According to Tables I-III, average human capital is $\$760,000$, the average elasticity η is about 0.20, and average financial wealth $\$45,000$. By (8), the present value of maintaining the habit over an infinite horizon is therefore close to $\$770,000$, whether the habit is external or internal.

Under the external habit model considered by Brunnermeier and Nagel (2008) and reviewed in the Internet Appendix, the coefficient λ_h is the inverse of the discount rate: $\lambda_h = 1/r$. We set r equal to 3%, consistent with the human capital calculation (1). The imputed habit is then $\$770,000 \times 3\% = \$23,000$, which is of the same order of magnitude as the $\$35,000$ population average of the habit proxy. In the Internet Appendix, we impute similarly plausible estimates of $X_{h,t}$ from an internal habit model. Under both specifications, the imputed risky share $w_{h,t} = w^*_{h,t}/(1+\eta_{h,t})$ matches the asset allocation of the average investor. The measured elasticity η thus seems reasonable when habit formation and human capital are both taken into account.

In addition, we note that the calibration results break down when human capital is ignored. If we set $HC_{h,t}$ equal to 0, the habit $X_{h,t}$ imputed from (8) represents only about 1% of average income in all specifications. These results illustrate the importance of taking into account both human capital and habit.

D. *Impact of Other Characteristics*

Besides financial wealth, several characteristics have a significant impact on the allocation of the financial portfolio, as can be seen in the second and third set of columns of Tables II.A and III.A.

The set of explanatory variables available on Swedish individual investors is unusually large and comprehensive. In particular, human capital, as well as the distinction between commercial and residential real estate, are used here for the first time in empirical household finance. In this subsection, we briefly present the empirical results, contrast them with earlier findings, interpret them in the context of portfolio choice theory, and decompose the financial wealth elasticity of the risky share into various channels.

The main results are the following. On the one hand, expected human capital has a positive impact on the risky share, which is significant in the panel of identical twins. On the other hand, the risky share is negatively related to commercial real estate, leverage, income risk, entrepreneurship, unemployment, internal habit, household size, and the gender index. Residential real estate and educational attainment are insignificant.

Our analysis contributes to the literature along several dimensions. First, the twin regressions are consistent with the cross-sectional findings of Heaton and Lucas (2000) on entrepreneurship, Lupton (2002) on internal habit, and Guiso, Jappelli, and Terlizzese (1996) and Palia, Qi and Wu (2009) on background risk and leverage. Second, educational attainment, which is strongly significant in the cross-section, becomes insignificant in the twin regressions. This result is consistent with Guiso and Paiella (2006), who use an experimental measure of individual risk aversion to show that education has no causal impact on the risky share conditional on participation.[10] The twin study is able to pick up this effect in a routine fashion, which confirms the validity of the method. Third, we do not confirm the findings of Massa and Simonov (2006) that investors select stocks that comove with their labor income. The explanation is that Massa and Simonov (2006) measure dependence with the Pearson correlation between labor income and the stock portfolio; by contrast, our findings are based on the beta coefficient between labor income and the risky portfolio return, as portfolio theory suggests (e.g. Campbell and Viceira (2002)).

The results of the twin regressions are mainly in line with the predictions of the portfolio choice literature. Since future income can be viewed, at least partly, as a nontraded bond, households with substantial human capital tilt their financial portfolios toward risky financial assets. Expected human capital is significant in the subsample of identical twins, where the yearly twin pair fixed effects best control for latent heterogeneity. Income risk, which represents a source of background risk, tends to reduce the risky share, as portfolio theory predicts. These results are remarkable because our measures of human capital and income risk are contaminated by measurement error, and twin regressions are even more prone to underestimating the impact of contaminated variables than standard cross-sectional regressions (Griliches (1979)).

Earlier empirical investigations of portfolio choice over the life-cycle emphasize the difficulty of disentangling cohort, time and age effects in household data, and as a result estimation must rely on strong identification assumptions (Ameriks and Zeldes (2004) and Fagereng, Gottlieb and Guiso (2011)). The Swedish dataset allows us to estimate directly the labor income process of every household with an adult twin and then measure how expected human capital drives the risky share. Since twins have the same age, belong to the same cohort, and are observed at the same time, our methodology naturally controls for time, cohort and age effects, along with observable and latent family characteristics. This level of control is, to the best of our knowledge, unprecedented in household finance.

Commercial real estate and private business risk crowd out investment in risky financial assets. The commercial real estate wealth elasticity of the risky share is -0.005, which is of the opposite sign as and about 40 times smaller than the financial elasticity η. These results are consistent with the fact that commercial real estate and private business holdings are sources of background risk, as in the models of Cocco (2005), Flavin and Yamashita (2002), and Yao and Zhang (2005). By contrast, residential real estate represents both a speculative investment and a hedge against future rental costs, which has no significant impact empirically.[11]

Indebted households adopt conservative asset allocations, presumably because they worry that they may be unable to borrow and may be forced to severely cut consumption in the future (Grossman and Vila (1992), Paxson (1990), and Teplá (2000)). The regressions also provide strong support for models of habit formation, subsistence, or committed expenditures, which can all be viewed as forms of "consumption liabilities." In particular, the financial wealth and habit coefficients both confirm Implications 1 and 2.

Large households select conservative portfolios. Since the numbers of adults and children reduce wealth per capita, large households behave like poorer households of smaller size, as in the consumption literature on household equivalence scales (Calvet and Comon (2003), Deaton (1974), Lewbel and Pendakur (2008), and Prais and Houthakker (1955)). Furthermore, large households have high committed expenditures-to-wealth ratios and bear the substantial background risk caused by the random needs of family members. These complementary effects all encourage large households to adopt a prudent asset allocation.

As discussed in Section II.A, several leading portfolio theories imply that the risky share is not a function of financial wealth itself, but is instead driven by the ratio of financial wealth to another variable, such as habit, human capital, or real estate holdings (Flavin and Yamashita (2002)). By contrast, models based on the "spirit of capitalism" imply that financial wealth directly impacts the utility function and the risky share. In the Internet Appendix, we regress the risky share on financial wealth itself and on the ratios of financial wealth to, respectively, human capital, habit and real estate. The financial wealth-to-internal habit ratio has a coefficient of 0.09 ($t-$value = 2.82), the financial wealth-to-external habit ratio a coefficient of -0.04 ($t-$value = -0.44), and standalone financial wealth a coefficient of 0.17 ($t-$value = 1.92), which add up to the 0.22 estimate reported in Table II. The other ratios make no sizeable contribution to the decomposition, perhaps because real estate and human capital are risky and illiquid. Thus, the financial wealth-to-habit ratio and standalone financial wealth are the main contributors to the financial wealth elasticity of the risky share reported in this section.

In contrast to the fragmentary data used in earlier research, the Swedish dataset allows us to simultaneously measure the relation between the risky share and a large number of household characteristics, including most notably human capital. The Swedish dataset permits us to include yearly twin pair fixed effects and thereby control for the common genetic and family traits characteristics of twin siblings. We have documented that while financial wealth and human capital encourage aggressive asset allocations, conservative portfolios are selected by large households with commercial real estate, private businesses, and financial and habit liabilities. We now investigate the explanatory power of the twin regressions.

E. Variance Decomposition

Yearly twin pair fixed effects, financial wealth, and other characteristics explain a fraction $\rho^2 = Var(\alpha_{i,t} + \eta f_{i,j,t} + \gamma' x_{i,j,t})/Var(\log w_{i,j,t})$ of the cross-sectional variation of the log risky share, which is consistently estimated by adjusted R^2. In the sample of all twins, adjusted R^2 is 18.0% when financial wealth is the only characteristic, and 19.1% when all characteristics are included (see Panel A of Table II). The adjusted R^2 coefficient reaches 25.0% on the set of identical twins (Table III). These estimates are high for households finance regressions and dramatically improve on the 11.5% adjusted R^2 of the pooled cross-section.

The predicted variation of the risky share can be decomposed as:

$$\rho^2 = \omega_\alpha^2 + \omega_f^2 + \omega_x^2 + 2\omega_{\alpha,f} + 2\omega_{\alpha,x} + 2\omega_{f,x}, \qquad (9)$$

where $\omega_\alpha^2, \omega_f^2$, and ω_x^2 denote, respectively, the contributions of twin pair fixed effects, financial wealth, and other characteristics, and $\omega_{\alpha,f}$, $\omega_{\alpha,x}$ and $\omega_{f,x}$ are rescaled covariances.[12] We obtain the following results in Panel B of Table II and in Table III.

(i) The share ω_α^2 of the yearly twin pair fixed effects is about 9.5% in the sample of all twins and reaches 16% in the subsample of identical twins. Twin pair fixed effects are quantitatively important and explain the high adjusted R^2 of twin regressions.

(ii) The contribution of observable characteristics, $\omega_f^2 + 2\omega_{f,x} + \omega_x^2$, ranges from 6.9% to $8.95\% - 1.38\% + 1.59\% = 9.16\%$ in the sample of all twins (see Panel B of Table II). Financial wealth is by far the most important characteristic with a contribution ω_f^2 close to 9.0%. By contrast, the share of other observable characteristics ω_x^2 does not exceed 1.6%. Similar results are obtained with identical twins.

(iii) The cross-terms $\omega_{\alpha,f}$, $\omega_{\alpha,x}$ and $\omega_{f,x}$ are small and will not be reported from now on.

Yearly twin pair fixed effects and financial wealth are both major contributors to the cross-sectional variation of the risky share. While genetic and other family fixed effects are important, individual financial circumstances play a major role in explaining the risk-taking behavior of households.

In order to better understand the role of fixed effects, we estimate the twin specification (7) on a "pseudo panel" of randomly matched pairs. As can be seen in the Internet Appendix, random matching produces linear coefficients that are very similar to the ones obtained with the cross-sectional approach. In particular, education variables are strongly significant with randomly matched twins, while we have seen that they are insignificant with actual twins. The adjusted R^2 declines to 13% in the pseudo panel (compared to 19% with actual twin panel in the presence of all characteristics). The contribution of the pseudo yearly twin pair fixed effect ω_α^2 hovers around 2.5% across specifications and is therefore as low as the contribution of standard yearly fixed effects (compared to 9.5% with actual twins). This analysis confirms that yearly twin pair fixed effects pick up major forms of latent heterogeneity in the actual dataset.

F. Communication

Communication between twins may influence the measured relationship between observable characteristics and risk-taking. For instance, we can interpret the insignificant education coefficients in Table II as evidence that educational attainment does not impact the risky share, or alternatively that twins interact frequently enough to overcome schooling differences. Interactions between siblings may also contribute to the pair fixed effects, along with genes and upbringing. To address these issues, we sort twin pairs in a given sample according to: (1) the frequency with which the siblings communicate with each other in person (unmediated communication ranking); or, (2) the frequency with which the siblings interact by telephone, land mail, and e-mail (mediated communication ranking). We classify twins as infrequent communicators if they are in the bottom quartiles of both rankings, and as frequent communicators otherwise. Separate communication classifications are constructed for the subsample of identical twins and for the sample of all twins. We find that frequently communicating identical twins meet in person at least twice a week *and* experience mediated interactions at least five times a week on average during a year.

In Table IV, we estimate the risky share regression separately for frequent and infrequent communicators in the sample of all twins (panel A) and in the subsample of identical twins (panel B). For all groups, the regression coefficients are very similar to the ones reported in Table III. Twins do not simply mimic each other's behavior but respond to their own economic and financial circumstances, whether or not they communicate often with each other. Our findings are related to theoretical models suggesting that informational differences are possible explanations for the positive cross-sectional correlation between risky share and financial wealth; this alternative view, which does not require DRRA preferences, is based on the fact but on the fact that the benefit of acquiring information increases with wealth but the cost of acquiring information does not (Peress (2004)). Table IV shows that financial wealth is unlikely to simply act as a proxy for information differences in risky share regressions, and instead provides further evidence that investors have DRRA.

[Insert Table IV about here]

The adjusted R^2 of the twin regression is twice as high for frequent communicators as for infrequent communicators. This striking result holds both in the set of all twins and in the set of identical twins. In addition, adjusted R^2 reaches 40% for identical twins who communicate frequently with each other. This high value of R^2 is exceptional for a household finance regression and is primarily due to the contribution ω_α^2 of the yearly fixed effects, which explain 32% of the variance of the risky-share.

Another important observation is that the contribution of yearly twin pair fixed effects, ω_α^2, is 4 times higher for frequent communicators as for infrequent communicators, regardless of genetic relationship.[13] By contrast, ω_α^2 is about 1.5 times higher for identical twins as for fraternal twins. Table IV therefore demonstrates that communication and genes both drive yearly twin pair fixed effects.

We conclude that even when identical twins communicate often with each other and yearly twin pair fixed effects explain 32% of the variance of the risky share, the wealthier twin in a pair selects a higher risky share than his poorer sibling. Furthermore, the explanatory power ω_α^2 of the twin fixed effects varies strongly across communication groups and is therefore not purely driven by genes.

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

As discussed in Section II, several leading portfolio choice theories predict that the sensitivity of risk-taking to financial wealth should vary with observable household characteristics. For instance in a habit formation model, the financial wealth elasticity of the risky share increases with habit and decreases with financial wealth (see Implications 3 and 4). To the best of our knowledge, however, the empirical relation between the elasticity of the risky share and household characteristics has not been documented empirically until now, presumably for lack of reliable data and identification techniques.

[Insert Table V about here]

In the first set of columns of Table V, we classify twin pairs annually into quartiles of the average log financial wealth $f_{i,t} = (f_{i,1,t} + f_{i,2,t})/2$, and report the elasticity of the risky share in each quartile. We take financial wealth as the sole characteristic and assume that the elasticity of a given quartile is constant over time. The measured elasticity is 0.29 in the lowest financial wealth quartile, 0.22 in the second quartile, 0.15 in the third quartile, and 0.10 in the top quartile. Consistent with Implication 3, the elasticity decreases sharply with financial wealth. In the second set of columns of Table V, we reestimate the risky share regression when all other characteristics are included as controls. The elasticity increases slightly in each quartile compared to the previous specification, and remains a strongly decreasing function of financial wealth.

[Insert Table VI about here]

Because the elasticity may also depend on habit and other characteristics, we consider the linear specification:

$$\eta_{i,t} = \eta_0 + \eta_1(f_{i,t} - \bar{f}_t) + \psi'(x_{i,t} - \bar{x}_t), \tag{10}$$

where $x_{i,t}$ denotes the average vector of characteristics in pair i, and $\bar{f}_t$ and $\bar{x}_t$ denote the cross-sectional averages of financial wealth and characteristics in year t.[14] The variables $f_{i,t}$ and $x_{i,t}$ are demeaned year by year so that η_0 is the average elasticity in the population. Specification (10) implies:

$$\log(w_{i,j,t}) = \alpha_{i,t} + \left[\eta_0 + \eta_1(f_{i,t} - \bar{f}_t) + \psi'(x_{i,t} - \bar{x}_t)\right] f_{i,j,t} + \gamma' x_{i,j,t} + \varepsilon_{i,j,t}. \tag{11}$$

In regression (1) of Table VI, we estimate (11) when the financial wealth elasticity of the risky share is driven only by financial wealth and internal habit. We focus on the internal habit because our measure of external habit is noisy and less significant in previous tables. The elasticity is again a decreasing function of financial wealth but also an increasing function of habit, thus confirming Implications 3 and 4 of habit formation models.

In regression (2) of Table VI, 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 residential real estate. Family size impacts negatively the risky share itself but impacts positively its elasticity. These results are consistent with the models considered in Section II.A. The asset allocation of households with substantial human capital exhibits low sensitivity to financial wealth. Indeed, the financial wealth of such households represents only a small fraction of their total wealth and therefore has a limited impact on their investment decisions, as implied by equation (6). Consistent with the equivalence scales literature, large households behave like poorer households of smaller size; a complementary explanation is that family size and residential real estate proxy for internal habit, which would explain their positive impact on $\eta_{i,t}$ in regression (2) as well as the positive coefficient of internal habit reported in regression (1).

The financial wealth elasticity of the risky share may also depend on individual preferences. For instance in habit formation models, the coefficient λ_h in (5) is determined by individual preferences as well as interest rates. In the Internet Appendix, we reestimate the twin 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 VI. The coefficient on $\alpha_{i,t}$ is negative and significant: households with a high propensity to take risk tend to have a small financial wealth elasticity of the risky share.

The financial wealth elasticity of the risky share decreases with financial wealth and is heterogeneous across households. The next section examines the robustness of these results to alternative specifications, and Section V derives their implications for the aggregate demand for risky assets.

IV. Robustness Checks

A. Reverse Causality between the Risky Share and Financial Wealth

We have hitherto viewed the positive coefficient of financial wealth in the twin regressions as evidence that households select higher risky shares as they get richer, just as DRRA utility predicts. An alternative interpretation is that the bull market of the nineties enriched aggressive investors substantially more than conservative investors. Causality may therefore run from the risky share to financial wealth in a rising market, and not necessarily from financial wealth to the risky share due to DRRA as has been assumed until now.

In order to differentiate between the two explanations, we use lagged values of the risky share as controls for individual levels of risk aversion. In Table VII, we accordingly report twin regressions of the risky share in year $t \in \{2000, 2001, 2002\}$ on financial wealth in 1999, the risky share in 1999, and the usual characteristics. We also control for household inertia by using as regressors the passive change in the risky share between 1999 and t, as well as the passive change in financial wealth.[15]

[**Insert Table VII about here**]

A household with high financial wealth in 1999 has a high risky share in subsequent years, even though we control for the household's risk tolerance via the 1999 risky share. This result is not mechanically implied by the bull market of the 1990's. Indeed in an economy with CRRA investors, households with high coefficients of risk tolerance would have high risky shares and high financial wealth at the end of a bull market; since the 1999 risky share controls for risk tolerance, the risky share in later years would be unrelated to 1999 financial wealth. The positive relation between risk-taking and lagged financial wealth documented in Table VII therefore provides strong evidence that individual investors exhibit decreasing relative risk aversion.

B. Individual Fixed Effects

Twin regressions may be contaminated by individual fixed effects that are specific to each twin in a pair, such as individual differences in risk aversion. In the Internet Appendix, we address this issue with two alternative strategies.

First, earlier research shows that risk aversion is empirically related to lifestyle variables such as smoking and drinking (Barsky et al. (1997)). In the Internet Appendix, we include variables on the health, physical attributes, and smoking and drinking habits of each twin in the risky share regressions. The coefficients of financial wealth and all the other maintained characteristics are then nearly unchanged. Moreover, we report that the risky share is positively linked to alcohol consumption and negatively linked to depression and high blood pressure.

Second, the dynamic approach explicitly controls for individual fixed effects. It is usually estimated by relating time variations in a household's risky share to time variations in its financial wealth (Brunnermeier and Nagel (2008), Chiappori and Paiella (2011), and CCS (2009*a*)). In order to address portfolio inertia and endogeneity problems, we develop in the Internet Appendix an instrumental variable estimation method in the style of Arellano and Bond (1991).[16] The dynamic approach produces an average elasticity of the risky share that nearly coincides with the twin estimate, and the elasticity is once again a strongly decreasing function of financial wealth. Overall, these findings suggest that the twin regressions are not severely contaminated by individual fixed effects,

C. Other Robustness Checks

We report a number of additional robustness checks in the Internet Appendix. Since it is sometimes suggested that genetic effects matter less with age, we verify that our findings hold in all age groups. The results of the twin regressions remain unchanged when we include marital status as a regressor, when we proxy external habit by the average income in the same age group *and* the same municipality, or when use a finer set of post-high school education variables. Financial theory suggests that households facing liquidity constraints should use a higher discount rate than unconstrained households (e.g., Teplá (2000)); our empirical results are robust to computing human capital (1) with different discount rates for young and old investors, or different discount rates for low-wealth and high-wealth households.

The regression coefficients are even more significant when we control for measurement error in financial wealth; in particular, the internal habit coefficient is larger and more significant than in Table VI. Due to short sales and leverage constraints, the risky share of every household in our sample is contained between zero and one; we report tobit regressions of the risky share on yearly twin pair fixed effects and characteristics that confirm the validity of our results.

The literature on social interactions suggests that investors may imitate the decisions of others (Akerlof and Shiller (2010) and Bikhchandani, Hirshleifer and Welch (1998)). For this reason, we reestimate the twin regressions by adding as controls the average risky share and the average financial wealth in a twin's municipality; the financial wealth elasticity is again estimated at 0.22, and the other results of Table II remain unchanged.

V. Aggregate Implications

We now derive the implications of the micro evidence for aggregate risk-taking. We consider exogenous variations in household wealth and compute their impact on the aggregate demand for risky assets. Security prices are fixed and time indices are henceforth neglected for notational simplicity.

A. Fixed Set of Participants

Let $\mathcal{P}$ denote the set of households that initially hold risky assets. We assume that $\mathcal{P}$ is fixed in this subsection. Prior to the shock, each household h has risky share w_h, financial wealth F_h, and other attributes x_h. An exogenous shock, such as an unexpected tax cut or an increase in welfare transfers, changes the financial wealth of the household to $F_h^* = F_h e^{\Delta f_h}$. As a consequence, the household adjusts its risky share to $w_h e^{\eta_h \Delta f_h}$, where the coefficient η_h is the financial wealth elasticity of the risky share. We consider several scenarios.

Scenario 1. *Every investor has CRRA utility:* $\eta_h = 0$ *for all* h.

Scenario 2. *Investors have a constant, strictly positive, and homogenous elasticity:* $\eta_h = \eta > 0$ *for all* h.

Scenario 3. *The financial wealth elasticity of the risky share is a linear function of financial wealth and other characteristics:* $\eta_h = \eta(f_h, x_h)$ *for all* h.

Scenario 3 is the most plausible given the micro evidence in earlier sections.

The wealth shock modifies the aggregate demand for risky assets from the household sector. Let F denote total financial wealth of participants and F_R the total wealth invested in risky assets prior to the shock. The elasticity

$$\xi = \frac{\Delta \log(F_R)}{\Delta \log(F)} \tag{12}$$

quantifies how the aggregate demand for risky assets responds to the exogenous wealth change. Let $\Delta F_h = F_h^* - F_h$ denote the absolute change in the wealth of household h. When the wealth shocks ΔF_h are small, the increase in aggregate risk-taking is approximately equal to the weighted sum of individual wealth changes:

$$\Delta \log(F_R) \approx F_R^{-1} \sum_{h \in \mathcal{P}} w_h (1 + \eta_h) \Delta F_h, \tag{13}$$

For a given aggregate shock $\Delta \log(F) \approx F^{-1} \sum_{h \in \mathcal{P}} \Delta F_h$, the incremental demand for risky assets (13) and the aggregate elasticity (12) are large if the wealth shocks ΔF_h are concentrated on households with high elasticities or high initial risky shares.

Under scenario 1, the aggregate elasticity ξ equals unity if investors have identical initial asset allocations ($w_h = w$ for all h) or if the wealth shock is homogenous ($\Delta f_h = g$ for all h). The aggregate elasticity can otherwise be smaller or larger than unity.

[**Insert Figure 1 about here**]

In Figure 1, we sort households in twenty financial wealth quantiles, and report for each quantile the aggregate elasticity in response to a 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. The flat line corresponds to the benchmark unit elasticity.

Under heterogeneous CRRA preferences (scenario 1), the aggregate elasticity increases monotonically with the quantile on which the wealth shock is concentrated. ξ is less than 1 in low and medium quantiles and exceeds unity in top quantiles. The explanation is that richer households have higher initial risky shares and a stronger incremental demand for risky assets than poorer households.

If individual elasticities are homogenous and positive (scenario 2), the aggregate elasticity is again a monotonic function of the wealth quantile on which the shock is concentrated. As can be seen from (13), 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.

Under our preferred micro specification (scenario 3), poorer investors have a higher elasticity than average; the aggregate elasticity ξ is therefore higher and closer to unity in bottom quantiles than under scenarios 1 and 2. Conversely, because the elasticity decreases with wealth, ξ is smaller and closer to unity in medium wealth quantiles than under scenario 2. In top quantiles, household elasticities are very close to zero, and the aggregate elasticity ξ coincides almost exactly with the aggregate elasticity obtained with CRRA investors.

The results of scenarios 2 and 3 reported in Figure 1 are based on the micro-level regressions of the risky share and are therefore subject to estimation error. For this reason, we illustrate in dashed lines the 95% confidence interval of aggregate elasticity. The confidence intervals are tight and show that the aggregation results hold with excellent statistical accuracy.

The aggregate elasticity in response to a homogenous wealth shock ($\Delta f_h = g$ for all h) is also important for macro-finance applications. The aggregate elasticity is only 1.09 in 2001 under our preferred heterogeneous elasticity specification, as compared to 1.23 in 2001 under constant positive elasticity. Overall, aggregate risk-taking is less sensitive to the cross-sectional distribution of wealth between investors under the heterogeneous elasticity specification (scenario 3) that under the constant elasticity specifications (scenarios 1 and 2). Since representative-agent models cannot account for distributional effects, this property should help reconcile macro models with the micro evidence.

B. Endogenous Participation

We now recompute the sensitivity of aggregate risk-taking to wealth shocks in the presence of endogenous participation. The analysis begins with the empirical analysis of the participation decision. In Table VIII, we consider a participation logit regression with yearly twin pair fixed effects:

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

where $y_{i,j,t}$ is a participation dummy equal to unity if twin j in pair i holds risky financial assets at date t. Financial wealth, residential real estate, human capital, and internal habit[17] all have a positive impact on participation, while income risk and external habit have negative coefficients. Thus, theories of financial market participation (Haliassos and Bertaut (1995), Heaton and Lucas (1999), Vissing-Jørgensen (2002b), and Calvet, Gonzalez-Eiras and Sodini (2004)) remain empirically valid when one controls for yearly twin pair fixed effects.

[**Insert Table VIII about here**]

In Figure 2, we illustrate the elasticity of aggregate risky wealth with respect to aggregate financial wealth computed over the population of participating and nonparticipating households. The 95% confidence bands are reported in dashed lines. In bottom quantiles, risk-taking is low and the aggregate elasticity is close to zero for all imputation methods. Under the preferred elasticity specification (scenario 3), the aggregate elasticity 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.

[**Insert Figure 2 about here**]

This section illustrates the benefits of considering specifications of the financial wealth elasticity of the risky share that vary with household characteristics. First, this approach is consistent with the micro evidence reported in Sections III and IV. Second, the aggregate elasticity is remarkably stable, whether one considers homogenous or concentrated shocks.

VI. Conclusion

In this paper, we have conducted the first investigation of the micro determinants of household risk-taking that carefully controls for genetic and other family fixed effects. The analysis is based on an administrative panel of more than 23,000 Swedish twins over the 1999-2002 period. The twin data have allowed us to control for latent forms of heterogeneity that are shared by siblings, drive investment decisions, but are either difficult to measure or challenging to explain using the tools of economic theory. The paper solves the identification problem that has long plagued the household finance literature.

We have estimated panel regressions of the risky share on yearly twin pair fixed effects and an unprecedented set of observable characteristics. The explanatory power is unusually high, reaching 40% on the set of identical twins who communicate often with each other. Financial wealth has a strong positive impact on risk-taking. This key result holds across all specifications, whether or not one controls for characteristics and measurement error or follows households dynamically over time. We have estimated the individual labor income process of every household in our sample and found that expected human capital encourages risk-taking. The paper improves on earlier research investigating the link between human capital and risk-taking, in which strong additional identification assumptions are required to disentangle between time, age and cohort effects (Ameriks and Zeldes (2004), Fagereng, Gottlieb and Guiso (2011)). Moreover, internal habit, income risk, leverage and household size negatively impact the risky share, consistent with the predictions of portfolio choice theory. Investment behavior is not simply encoded in DNA; it also responds aggressively to a household's economic circumstances.

We have documented sizeable heterogeneity in the financial wealth elasticity of the risky share across households, which, to the best of our knowledge, is also new to the literature. The elasticity decreases with financial and human wealth, and substantially increases with several proxies of consumption habit and committed expenditures. The empirical properties of the risky share and its financial wealth elasticity are all strikingly consistent with DRRA and habit formation preferences.

Our findings have a number of pricing and macroeconomic implications. Representative-agent models with time-varying risk aversion have had success in matching the time-varying premia of traded securities (see, e.g., Bakshi and Chen (1996), Buraschi and Jiltsov (2007), Campbell and Cochrane (1999), Menzly, Santos, and Veronesi (2004), Verdelhan (2010), or Wachter (2006)) and the joint dynamics of asset returns and the business cycle (Boldrin, Christiano, and Fisher (2001), Jermann (1998)). While the utility specification employed for the representative agent in these models has been questioned (Brunnermeier and Nagel (2008), Chiappori and Paiella (2011)), the present paper provides strong evidence in favor of decreasing relative risk aversion at the *micro* level. In addition, we have investigated the macro implications of our findings. We have shown in Section V that distributional effects, which cannot be captured by representative-agent models, have a weaker impact on aggregate risk-taking if investors have DRRA utilities than if they have CRRA utilities. This finding should help build macro models that approximate well the asset prices generated by a population of heterogeneous DRRA investors.

We have documented that communication and social interactions have a strong influence on the cross-sectional distribution of the risky share. The paper therefore opens the possibility that earlier twin studies, which have neglected interactions between nature and nurture, may have also overestimated the genetic predetermination of financial decisions. Word of mouth and own economic circumstances might be much more important drivers of financial portfolios than DNA.

We have reconciled portfolio micro data with the predictions of habit formation models when human capital is taken into account. In future work, it would be important to better understand the interactions between human capital and habit and their implications for asset prices. Macro-finance extensions, such as the investigation of risk premia across asset classes or the interactions between security, real estate and labor markets, will also be the subject of further research.

Notes

[1]Examples include Buraschi and Jiltsov (2007), Menzly, Santos and Veronesi (2004), Verdelhan (2010), and Wachter (2006).

[2]See Alessie, Hochguertel and van Soest (2002), Banks and Tanner (2002), Bertaut and Starr-McCluer (2002), Campbell (2006), Cohn et al. (1975), Eymann and Börsch-Supan (2002), Friend and Blume (1975), Guiso and Jappelli (2002), Perraudin and Sørensen (2000), and Vissing-Jørgensen (2002a).

[3]Brunnermeier and Nagel (2008) instrument time variations in financial wealth with income growth and inheritance receipts. They find no evidence of a link between wealth and risk-taking in the U.S. Panel Study of Income Dynamics. CCS (2009*a*) apply similar instruments to a panel of Swedish households and confirm Brunnemeier and Nagel's negative results. CCS, however, obtain a positive relation between financial wealth and the risky share when they instrument wealth changes with household portfolio returns. The results of dynamic panel regressions are therefore sensitive to the validity of the instruments.

[4]Sibling data can also be used to control for the genetic similarities and common background of family members, as in the work of Grinblatt, Keloharju and Linnainmaa (2011) linking IQ and stockmarket participation.

[5]The positive impact of human capital on the risky share is the key prediction of the theoretical models of Bodie, Merton and Samuelson (1992), Cocco, Gomes and Maenhout (2005) and Merton (1971). To the best of our knowledge, we provide the first empirical confirmation of this prediction. In addition, portfolio theory suggests that the risky share is negatively related to labor income risk and leverage (Cocco, Gomes and Maenhout (2005), Gomes and Michaelides (2005), Grossman and Vila (1992), Paxson (1990), Teplá (2000), and Viceira (2001)).

[6]The aggregate implications of investor hetorogeneity are investigated in Calvet, Grandmont and Lemaire (2005), Constantinides (1982), Gollier (2001), Hara, Huang and Kuzmics (2007), Jouini and Napp (2007), and Rubinstein (1974).

[7]The genetic relationship 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.

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

[9]See for instance Model 3 in Bakshi and Chen (1996).

[10]Guiso and Paiella (2006) use an experimental question from the Bank of Italy's Survey of Household Income to measure individual risk aversion and show that risk-tolerant investors tend to invest more in education, presumably because they worry less about the possibility of failure. Risk-tolerant individuals have a propensity to choose both high levels of education and high levels of financial risk, but education has no causal impact on the risky share.

[11]In cross-sectional regressions, residential real estate has a positive coefficient. This suggests that residential real estate may act as a cross-sectional proxy for risk tolerance. A complementary view is that investors who were born in a "culture of ownership" may have a stronger propensity to hold risky financial assets and residential real estate than other investors.

[12]Specifically, letting $\sigma_w^2 = Var(\log w_{i,j,t})$, we define $\omega_\alpha^2 = Var(\alpha_{i,t})/\sigma_w^2$, $\omega_f^2 = Var(\eta f_{i,j,t})/\sigma_w^2$, $\omega_x^2 = Var(\gamma' x_{i,j,t})/\sigma_w^2$, $\omega_{\alpha,f} = Cov(\alpha_{i,t}; \eta f_{i,j,t})/\sigma_w^2$, $\omega_{\alpha,x} = Cov(\alpha_{i,t}; \gamma' x_{i,j,t})/\sigma_w^2$, and $\omega_{f,x} = Var(\eta f_{i,j,t}; \gamma' x_{i,j,t})/\sigma_w^2$. Since the unexplained components

$$v_{i,j,t} = \log(w_{i,j,t}) - \eta f_{i,j,t} - \gamma' x_{i,j,t} = \alpha_{i,t} + \varepsilon_{i,j,t}$$

satisfy $Cov(v_{i,1,t}; v_{i,2,t}) = Var(\alpha_{i,t})$, we estimate ω_α^2 by the sample pairwise covariance of the regression residuals divided by the sample variance of the log risky share. We estimate ω_f^2, ω_x^2, $\omega_{f,x}$, $\omega_{\alpha,f}$, $\omega_{\alpha,x}$, and $\omega_{f,x}$ by their sample equivalents.

[13]In the Internet Appendix, we also find that the so-called genetic component strongly varies with communication when we estimate ACE variance decompositions of the risky share of the type considered in earlier work.

[14]We use average pair characteristics to facilitate comparison with Table V. In the Internet Appendix, we verify that the results are very similar when the elasticity is specified as a function of individual characteristics.

[15]We define the passive risky share $w^p_{h,t}$ after an inactivity period of n years as the risky share at the end of year t if the household does not trade between years $t-n$ and t. The passive change is the difference between the passive and the initial log risky share: $\log(w^p_{h,t}) - \log(w_{h,t-n})$. The passive change in financial wealth has a similar definition.

[16]CCS (2009*a*) follow a similar method to estimate an adjustment model of portfolio rebalancing, in which the financial wealth elasticity of the target risky share is assumed to be constant.

[17]The positive coefficient on the internal habit proxy may be due to cash-on-hand effects, because investors with higher realized incomes have higher incentives to participate in risky asset markets (Gomes and Michaelides (2002)).

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Table I
Summary Statistics

The table reports summary statistics of the financial, human capital, habit and demographic characteristics of participating Swedish households. The first set of columns is based on pairs in which both twins participate in risky asset markets, and the second set of columns on a random sample of participating households. For each sample, we report the cross-sectional mean and standard deviation of each characteristic. For the twin sample, we also report the correlation of each characteristic between within twin siblings. 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.

	Twins			Random sample	
	Mean	Standard deviation	Twin correlation	Mean	Standard deviation
Financial characteristics					
Risky share	0.543	0.291	0.185	0.515	0.297
Financial wealth ($)	46,782	72,718	0.312	45,084	74,133
Residential real estate wealth ($)	100,790	94,456	0.322	97,170	96,147
Commercial real estate wealth ($)	18,388	66,043	0.238	14,128	53,071
Leverage ratio	0.693	1.604	0.179	0.844	2.138
Human capital and income risk					
Human capital ($)	760,567	518,625	0.478	758,910	561,847
Permanent income risk	-0.002	0.089	0.029	-0.001	0.116
Transitory income risk	0.060	0.365	0.042	0.069	0.400
Beta of income innovation w.r.t. portfolio return	0.017	0.494	0.041	0.017	0.542
Entrepreneur dummy	0.036	0.186	0.128	0.038	0.191
Unemployment dummy	0.084	0.277	0.109	0.071	0.256
Habit					
Internal habit ($)	36,052	16,901	0.291	35,248	16,629
External habit ($)	25,422	3,210	0.396	25,412	3,172
Demographic characteristics					
High school dummy	0.843	0.364	0.365	0.806	0.395
Post-high school dummy	0.371	0.483	0.470	0.356	0.479
Number of adults	1.728	0.445	0.147	1.733	0.443
Number of children	1.005	1.107	0.403	0.989	1.096
Wealth-weighted gender index	0.542	0.325	0.135	0.547	0.325
Number of observations	55,898	55,898	55,898	85,827	85,827
Number of households	16,788	16,788	16,788	30,000	30,000
Number of twin pairs	8,394	8,394	8,394	N/A	N/A

Table II
Regression of the Log Risky Share on Characteristics

Panel A reports regressions of the log risky share on household characteristics in the presence of yearly twin pair fixed effects (first three sets of columns) or yearly fixed effects (last set of columns). 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. Panel B reports the variance decomposition of the log risky share for each of the four regressions reported in Panel A.

Panel A: Regression Coefficients

	Yearly Twin Pair Fixed Effects						Yearly Fixed	
	(1)		(2)		(3)		(4)	
	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat
Financial characteristics								
Log financial wealth	0.196	24.60	0.224	24.70	0.223	24.60	0.231	38.10
Log residential real estate wealth			0.000	-0.10	0.002	1.03	0.005	2.97
Log commercial real estate wealth			-0.007	-3.16	-0.005	-2.43	-0.008	-6.04
Leverage ratio			-0.006	-2.49	-0.006	-2.46	-0.007	-2.84
Human capital and income risk								
Log human capital			-0.004	-0.31	0.002	0.19	0.020	2.10
Permanent income risk			-0.222	-1.10	-0.276	-1.32	-0.384	-2.31
Transitory income risk			-0.060	-1.58	-0.073	-1.79	-0.120	-2.86
Beta of income innovation w.r.t. portfolio return			0.034	1.39	0.027	1.09	0.032	1.37
Entrepreneur dummy			-0.295	-5.61	-0.257	-4.89	-0.200	-4.93
Unemployment dummy			-0.081	-2.74	-0.075	-2.55	-0.090	-3.89
Habit								
Log internal habit			-0.166	-6.42	-0.089	-2.82	-0.111	-5.30
Log external habit			0.042	0.49	0.038	0.44	-0.059	-1.06
Demographic characteristics								
High school dummy					0.046	1.33	0.116	5.27
Post-high school dummy					0.037	1.50	0.066	4.60
Number of adults					-0.071	-2.38	-0.110	-5.30
Number of children					-0.050	-4.37	-0.037	-5.02
Wealth-weighted gender index					-0.076	-2.49	-0.029	-1.33
Adjusted R^2	17.99%		18.79%		19.10%		11.50%	
Number of observations	55,898		55,898		55,898		55,898	
Number of twin pairs	8,394		8,394		8,394		8,394	

Table II – *Continued*

Panel B: Variance Decomposition

	Yearly Twin Pair			Yearly
	(1)	(2)	(3)	(4)
Adjusted R^2	17.99%	18.79%	19.10%	11.50%
Contribution of the variance of:				
Fixed effect (ω_{α}^2)	9.65%	9.20%	9.13%	1.12%
Log financial wealth (ω_f^2)	6.94%	9.00%	8.95%	9.61%
Other observable characterics (ω_x^2)		1.17%	1.59%	1.89%
Contribution of the covariance of:				
Fixed effect and financial wealth (2 $\omega_{\alpha,f}$)	1.40%	1.49%	0.84%	0.31%
Fixed effect and other characteristics (2 $\omega_{\alpha,x}$)		0.01%	-0.02%	0.11%
Financial wealth and other characteristics (2 $\omega_{f,x}$)		-2.08%	-1.38%	-1.54%

Table III
Identical Twins

This table reports regressions of the log risky share on household characteristics in the presence of yearly twin pair fixed effects (first three sets of columns) or yearly fixed effects (last set of columns). The estimation is based on participating households with an adult identical twin. The education, entrepreneur and unemployment dummies are computed for the twin in the household. All other characteristics are computed at the household level.

	Yearly Twin Pair						Yearly	
	(1)		(2)		(3)		(4)	
	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat
Financial characteristics								
Log financial wealth	0.184	12.60	0.207	12.00	0.207	12.00	0.227	21.70
Log residential real estate wealth			-0.001	-0.31	0.000	0.03	0.005	1.94
Log commercial real estate wealth			-0.005	-1.18	-0.004	-1.03	-0.008	-3.21
Leverage ratio			-0.002	-1.07	-0.003	-1.14	-0.002	-1.08
Human capital and income risk								
Log human capital			0.022	1.64	0.030	2.25	0.039	3.07
Permanent income risk			-0.664	-2.13	-0.770	-2.57	-0.425	-1.75
Transitory income risk			-0.045	-0.94	-0.073	-1.48	-0.097	-1.56
Beta of income innovation w.r.t. portfolio return			0.004	0.12	-0.007	-0.23	-0.020	-0.81
Entrepreneur dummy			-0.141	-1.58	-0.133	-1.49	-0.037	-0.60
Unemployment dummy			-0.023	-0.46	-0.013	-0.27	-0.041	-1.12
Habit								
Log internal habit			-0.155	-3.22	-0.096	-1.72	-0.124	-3.33
Log external habit			0.079	0.54	0.099	0.69	-0.141	-1.46
Demographic characteristics								
High school dummy					0.090	1.40	0.116	2.87
Post-high school dummy					0.041	0.81	0.061	2.39
Number of adults					-0.009	-0.17	-0.059	-1.61
Number of children					-0.082	-4.15	-0.059	-4.73
Wealth-weighted gender index					0.007	0.12	-0.004	-0.09
Adjusted R^2	24.33%		24.62%		25.02%		11.39%	
Number of observations	17,054		17,054		17,054		17,054	
Number of twin pairs	2,545		2,545		2,545		2,545	
Contribution of the variance of:								
Fixed effect (ω_α^2)	15.95%		15.62%		15.55%		1.11%	
Log financial wealth (ω_f^2)	6.47%		8.21%		8.19%		9.87%	
Other observable characterics (ω_x^2)			0.70%		1.43%		1.64%	

Table IV
Communication

The table reports the financial wealth elasticity of the risky share and the variance decomposition estimated on the set of twins who communicate infrequently (left set of columns of each panel) or frequently (right set of each panel) with each other. The results are based on regressions of the log risky share on all household characteristics (used in the third set of columns of Table II) and include either yearly twin pair fixed effects or yearly fixed effects, estimated on all twins (Panel A) or on identical twins (Panel B). The full regression results are reported in the Internet Appendix.

Panel A: All Twins

	Infrequent Communication		Frequent Communication	
Fixed Effect	Yearly Twin Pair	Yearly	Yearly Twin Pair	Yearly
Log financial wealth	0.241	0.244	0.205	0.230
Adjusted R^2	15.32%	12.54%	27.33%	11.77%
Contribution of the variance of:				
Fixed effect (ω_α^2)	4.63%	1.37%	19.73%	1.06%
Log financial wealth (ω_f^2)	9.96%	10.26%	7.46%	9.46%
Other observable characterics (ω_x^2)	2.16%	2.12%	2.50%	2.38%
Number of observations	8,898	8,898	8,878	8,878
Number of twin pairs	1,385	1,385	1,376	1,376

Panel B: Identical Twins

	Infrequent Communication		Frequent Communication	
Fixed Effect	Yearly Twin Pair	Yearly	Yearly Twin Pair	Yearly
Log financial wealth	0.220	0.246	0.240	0.240
Adjusted R^2	15.02%	11.11%	40.24%	13.59%
Contribution of the variance of:				
Fixed effect (ω_α^2)	6.95%	0.87%	32.42%	0.74%
Log financial wealth (ω_f^2)	8.25%	10.30%	11.41%	11.39%
Other observable characterics (ω_x^2)	2.95%	1.64%	4.71%	3.40%
Number of observations	2,822	2,822	2,422	2,422
Number of twin pairs	419	419	370	370

Table V
Elasticity of the Risky Share Across Financial Wealth Quartiles

This table reports yearly twin pair fixed effects 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.

	(1)		(2)	
	Estimate	*t*-stat	Estimate	*t*-stat
Financial wealth quartile				
Lowest	0.289	18.10	0.331	18.90
2	0.224	15.80	0.243	16.80
3	0.150	10.90	0.171	12.30
4	0.101	7.68	0.129	9.07
Log residential real estate wealth			0.001	0.66
Log commercial real estate wealth			-0.004	-1.91
Leverage ratio			-0.003	-1.12
Human capital and income risk				
Log human capital			0.001	0.05
Permanent income risk			-0.242	-1.18
Transitory income risk			-0.050	-1.28
Beta of income innovation w.r.t. portfolio return			0.027	1.08
Entrepreneur dummy			-0.250	-4.76
Unemployment dummy			-0.065	-2.24
Habit				
Log internal habit			-0.044	-1.40
Log external habit			0.038	0.44
Demographic characteristics				
High school dummy			0.041	1.19
Post-high school dummy			0.034	1.39
Number of adults			-0.112	-3.70
Number of children			-0.060	-5.23
Wealth-weighted gender index			-0.070	-2.32
Adjusted R^2	18.56%		19.72%	
Number of observations	55,898		55,898	
Number of twin pairs	8,394		8,394	

Table VI
Financial Wealth Elasticity of the Risky Share

This table reports yearly twin pair fixed effects regressions of the log risky share on financial wealth, other household characteristics, and financial wealth interacted with characteristics. Financial wealth is interacted with itself and internal habit in regression (1), and with all characteristics in regression (2). The education, entrepreneur and unemployment dummies are computed for the twin in the household. All other characteristics are computed at the household level.

	(1)				(2)			
	Direct Effect		Interacted		Direct Effect		Interacted	
	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat
Financial characteristics								
Log financial wealth	0.216	24.70	-0.104	-11.60	0.224	25.50	-0.102	-10.90
Log residential real estate wealth	0.002	0.73			0.002	0.98	0.007	2.91
Log commercial real estate wealth	-0.004	-1.83			-0.004	-1.88	-0.001	-0.77
Leverage ratio	-0.002	-0.65			0.000	0.06	0.004	1.16
Human capital and income risk								
Log human capital	0.003	0.25			-0.001	-0.04	-0.019	-1.64
Permanent income risk	-0.264	-1.28			-0.173	-0.81	-0.065	-0.28
Transitory income risk	-0.052	-1.28			-0.035	-0.79	0.023	0.42
Beta of income innovation w.r.t. portfolio return	0.027	1.06			0.032	1.09	-0.018	-0.69
Entrepreneur dummy	-0.257	-4.91			-0.241	-4.61	-0.039	-0.79
Unemployment dummy	-0.069	-2.35			-0.059	-2.02	0.050	1.53
Habit								
Log internal habit	-0.051	-1.58	0.137	5.79	-0.015	-0.47	0.034	1.17
Log external habit	0.029	0.34			0.026	0.30	-0.040	-0.50
Demographic characteristics								
High school dummy	0.043	1.27			0.039	1.16	0.030	1.06
Post-high school dummy	0.032	1.31			0.027	1.08	-0.013	-0.62
Number of adults	-0.103	-3.36			-0.102	-3.35	0.132	4.09
Number of children	-0.060	-5.24			-0.071	-6.08	0.057	5.48
Wealth-weighted gender index	-0.066	-2.17			-0.055	-1.76	0.054	1.63
Adjusted R^2	20.04%				20.65%			
Number of observations	55,898				55,898			
Number of twin pairs	8,394				8,394			

Table VII
Lagged Financial and Portfolio Characteristics

This table reports yearly twin pair fixed effects regressions of the 2000-2002 log risky shares on: the log risky share in 1999; the passive change in the log risky share since 1999; log financial wealth in 1999; the passive change in log financial wealth since 1999; and the usual characteristics. The estimation is based on households that participate in risky asset markets at the end of two consecutive years.

	(1)		(2)		(3)		(4)	
	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat
Financial wealth quartile in 1999	0.122	15.10			0.122	15.00		
Lowest			0.160	9.55			0.162	9.63
2			0.110	8.05			0.110	8.09
3			0.136	10.00			0.134	9.83
4			0.080	7.17			0.079	7.09
Log risky share in 1999	0.574	32.50	0.570	32.20	0.578	35.90	0.575	35.70
Log passive financial wealth change since 1999	0.119	2.66	0.110	2.46				
Log passive risky share change since 1999	0.190	3.13	0.191	3.16				
Log residential real estate wealth	0.000	0.17	0.000	-0.05	0.001	0.27	0.000	0.04
Log commercial real estate wealth	-0.003	-1.93	-0.003	-1.72	-0.003	-1.69	-0.003	-1.49
Leverage ratio	-0.005	-1.13	-0.004	-0.94	-0.005	-1.13	-0.004	-0.94
Human capital and income risk								
Log human capital	0.015	0.87	0.014	0.82	0.014	0.81	0.013	0.75
Permanent income risk	-0.346	-2.33	-0.328	-2.23	-0.325	-2.20	-0.306	-2.09
Transitory income risk	-0.060	-1.97	-0.050	-1.67	-0.061	-2.00	-0.051	-1.68
Beta of income innovation w.r.t. portfolio return	0.013	0.68	0.014	0.72	0.013	0.66	0.014	0.71
Entrepreneur dummy	-0.094	-1.97	-0.094	-1.97	-0.094	-1.96	-0.094	-1.96
Unemployment dummy	-0.045	-1.82	-0.043	-1.74	-0.047	-1.89	-0.045	-1.80
Habit								
Log internal habit	-0.109	-3.71	-0.095	-3.21	-0.114	-3.89	-0.099	-3.36
Log external habit	-0.025	-0.35	-0.027	-0.38	-0.033	-0.45	-0.035	-0.48
Demographic characteristics								
High school dummy	-0.009	-0.36	-0.010	-0.38	-0.011	-0.42	-0.011	-0.44
Post-high school dummy	0.043	2.16	0.041	2.04	0.042	2.11	0.040	1.99
Number of adults	-0.006	-0.25	-0.017	-0.65	-0.004	-0.15	-0.015	-0.59
Number of children	-0.010	-1.02	-0.012	-1.27	-0.009	-0.97	-0.012	-1.25
Wealth-weighted gender index	-0.051	-2.07	-0.049	-2.01	-0.054	-2.18	-0.052	-2.11
Adjusted R^2	51.06%		51.17%		50.88%		51.00%	
Number of observations	34,684		34,684		34,684		34,684	
Number of twin pairs	6,307		6,307		6,307		6,307	

Table VIII
Participation in Risky Asset Markets

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, include time fixed effects, and are run without and with characteristics (first two sets of columns). The next two sets of columns report the results of logit yearly twin pair fixed effects regressions with or without characteristics. The education, entrepreneur and unemployment dummies are computed for the twin in the household. All other characteristics are computed at the household level.

	Yearly				Yearly Twin Pair			
	(1)		(2)		(3)		(4)	
	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat
Financial characteristics								
Log financial wealth	1.180	73.90	1.119	57.20	1.086	34.40	1.007	28.70
Log residential real estate wealth			0.023	6.71			0.022	3.59
Log commercial real estate wealth			0.020	3.87			0.008	0.75
Leverage ratio			-0.003	-1.76			-0.002	-0.63
Human capital and income risk								
Log human capital			0.245	5.70			0.086	1.63
Permanent income risk			-3.215	-4.41			-1.452	-1.81
Transitory income risk			-0.553	-3.12			-0.233	-1.28
Entrepreneur dummy			-0.050	-0.42			0.033	0.17
Unemployment dummy			-0.043	-0.85			0.032	0.35
Habit								
Log internal habit			-0.020	-0.29			0.268	2.21
Log external habit			-0.368	-2.19			-0.624	-1.77
Demographic characteristics								
High school dummy			0.307	6.56			0.130	1.32
Post-high school dummy			0.152	3.38			0.094	0.97
Number of adults			-0.120	-2.13			0.009	0.09
Number of children			-0.027	-1.15			-0.009	-0.23
Wealth-weighted gender index			-0.104	-2.04			-0.139	-1.47
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	

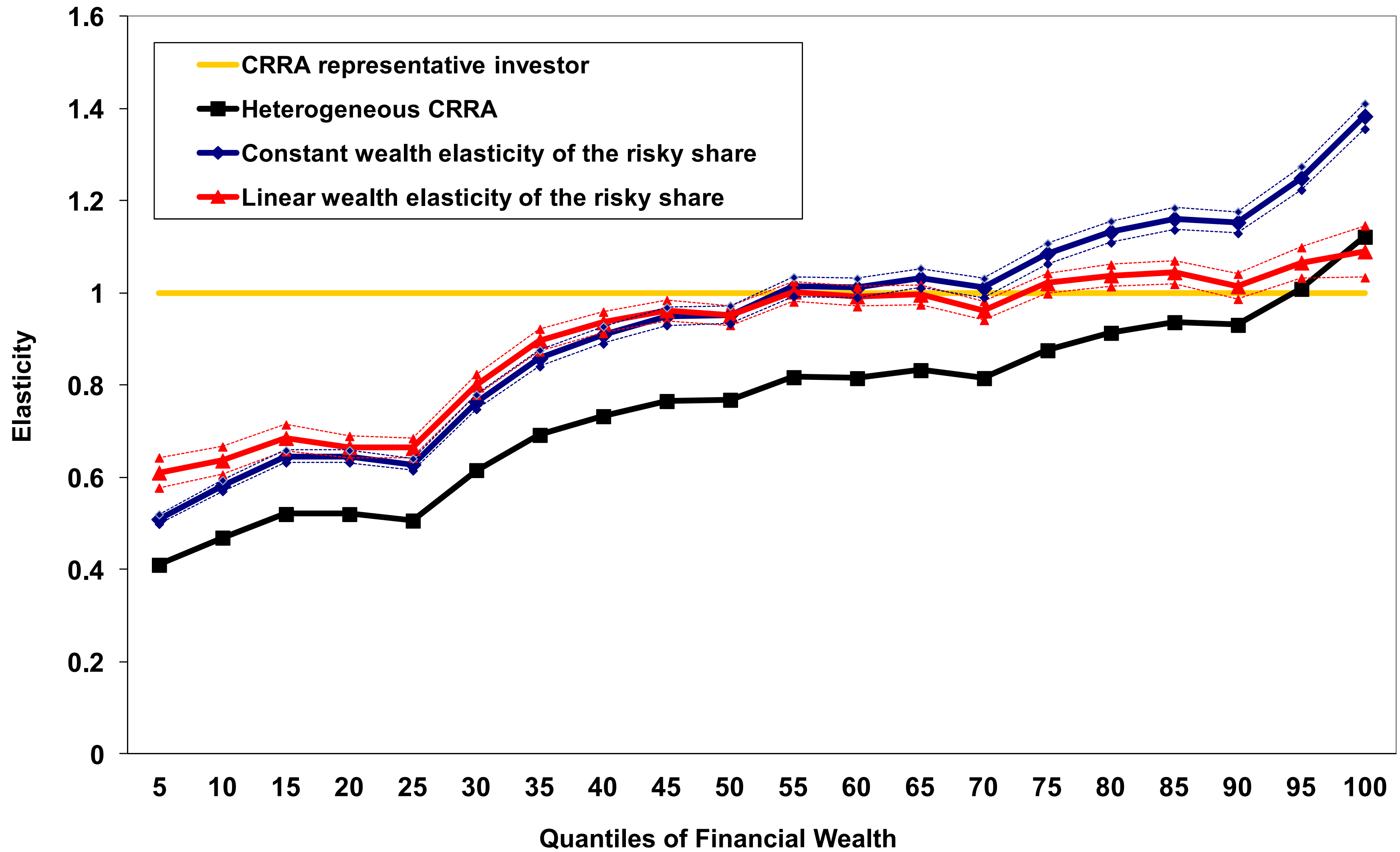

Figure 1. Elasticity of aggregate risky financial wealth computed on the fixed set of 2001 participants. This figure illustrates the elasticity of aggregate risky financial wealth with respect to the aggregate financial wealth of participating households. We consider twenty financial wealth quantiles, 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 the year 2001. The upper and lower bounds of the 95% confidence interval of aggregate elasticity are reported in dashed lines.

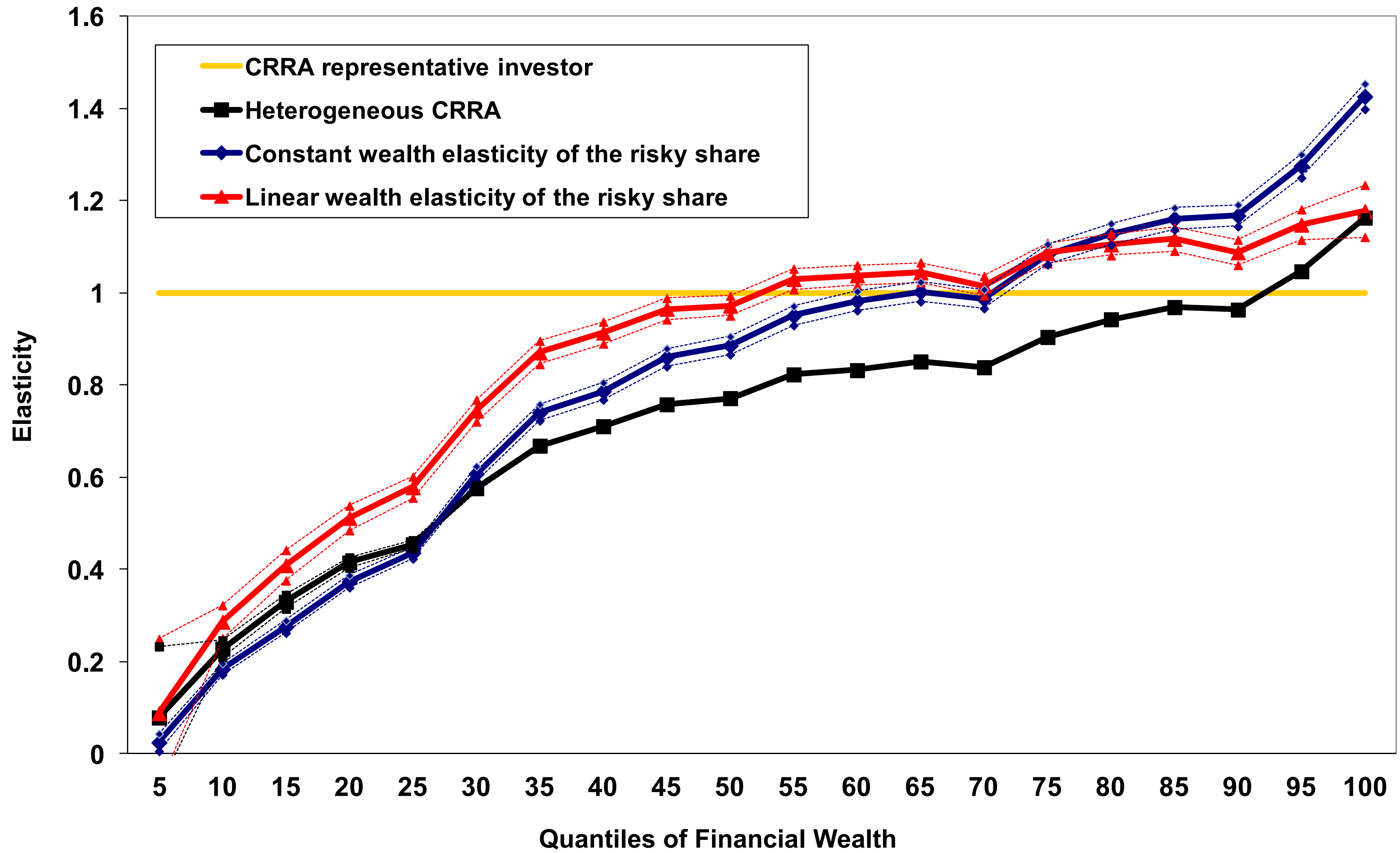

Figure 2. Elasticity of aggregate risky financial wealth with entry and exit. This figure illustrates the elasticity of aggregate risky financial wealth with respect to the aggregate financial wealth of participating and nonparticipating households. We consider twenty financial wealth quantiles, and 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 the year 2001. The upper and lower bounds of the 95% confidence interval of aggregate elasticity are reported in dashed lines.

Internet Appendix for
"Twin Picks: Disentangling the Determinants of Risk-Taking in Household Portfolios"*

LAURENT E. CALVET AND PAOLO SODINI

This Internet Appendix provides a detailed description of the Swedish twin panel, reviews some of the main theoretical determinants of the risky share, and verifies the robustness of the empirical results to alternative assumptions and variables. The appendix is organized as follows. Section I presents the data and estimation methodology. Section II discusses the connection between the risky share and financial wealth in a variety of habit formation models. Section III theoretically analyzes the joint impact of human capital and habit on risk-taking. Section IV compares the empirical results obtained for identical and fraternal twins. Section V reports a battery of robustness checks. Section VI shows that our results are unchanged when we control for measurement error and individual fixed effects. Section VII provides a full treatment of the aggregation procedure.

I. Data and Estimation Methodology

A. The Swedish Dataset

A.1. Swedish Twin Registry

The Swedish Twin Registry, which is administered by the Karolinska Institute in Stockholm, is the largest twin database in the world. It was founded to study the impact of smoking and alcohol consumption on the health of Swedish residents. The registry consists of two surveys: SALT for

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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 60% for the 1959-1990 cohort.

The twin registry provides the genetic relationship (fraternal or identical) of each pair,[1] and the intensity of communication between the twins. We have also obtained for each twin in SALT the following physiological and lifestyle variables: weight, height, blood pressure, self-assessed physical health, mental health, smoking habits, and alcohol and coffee consumption. We refer the reader to Lichtenstein et al. (2006) and Pedersen et al. (2002) for detailed descriptions of the Swedish Twin Registry.

A.2. Swedish Wealth Registry

The twin database allows us to identify twin pairs in the wealth registry compiled by Statistics Sweden which we have used in earlier work (CCS (2007), (2009*a*), (2009*b*)). The information available on every Swedish resident at the end of each year can be grouped into three main categories: demographic characteristics, income, and disaggregated wealth.

– Demographic information includes age, gender, marital status, nationality, birthplace, education, and municipality. The education variables consist of high school and post-high school dummies.

– The income data comprise total yearly disposable income as well as disaggregated income variables. 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 wealth data include the worldwide assets owned by the resident on December 31 of each year, including bank accounts, mutual funds, stocks and real estate. Holdings are provided for each property, account or security. The database also records debt outstanding at year end and contributions made during the year to private pension savings.

[1] The genetic relationship 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.

This administrative dataset is available because Sweden levied both a wealth tax and an income tax during the sample period. In order to collect this tax, the Swedish tax authority and Statistics Sweden had a parliamentary mandate to collected disaggregated records of income and assets, using statements from employers and financial institutions that were verified by taxpayers.

We focus on the set of households for which all characteristics are available. As we mention in Section I.A of the paper, we filter out households that own less than 3,000 Swedish kronor ($339) in financial wealth, or have a yearly disposable income lower than 1,000 kronor ($113), or are headed by an adult younger than 25. These rules imply the elimination of 79 twin pairs in 1999, 70 pairs in 2000, 59 pairs in 2001, and 63 pairs in 2002. We then extract from the Swedish Wealth Registry a random subsample of 30,000 households satisfying the above criteria.

B. *Measuring Labor Income and Human Capital*

We adopt the specification of labor income used in Cocco, Gomes and Maenhout (2005). The log of household h's real income in year t is given by

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

where a_h is a household fixed effect, $x_{h,t}$ is a vector of characteristics, $\nu_{h,t}$ is an idiosyncratic random 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.

All income measures are deflated to 1993 prices using the consumer price index published by Statistics Sweden. The vector of characteristics $x_{h,t}$ include household size, marital status, age, and unemployment and business dummies. The age and unemployment and business dummies refer to the household head, who is defined as the household member with the highest income in 2002.

We classify households by the head's age and education level. Since the vast majority of

Swedish residents retire at 65, we distinguish between two age groups: less than 65, or at least 65. We also consider three levels of educational attainment: (1) basic or missing education; (2) high school education; and (3) post-high school education. For each of the six groups, we estimate the income process on the 1993-2002 panel of nonfinancial disposable income, which is defined as disposable income minus after-tax interest and dividends.

B.1. Estimation

We estimate the coefficients a_h and b by regressing log income on characteristics and a household fixed effect. In order to measure $\sigma^2_{\xi,h}$ and $\sigma^2_{\varepsilon,h}$, we define the income growth innovation $u_{h,t}$ as the difference between income growth, $\log(L_{h,t}/L_{h,t-1})$, and the fitted value, $b'(x_{h,t} - x_{h,t-1})$. The sample variance of the cumulative residual,

$$v_{d,h} = Var(u_{h,t-d+1} + ... + u_{h,t}),$$

is an estimate of $d\sigma^2_{\xi,h} + 2\sigma^2_{\varepsilon,h}$. As in Carroll and Samwick (1997), we estimate $\sigma^2_{\xi,h}$ and $\sigma^2_{\varepsilon,h}$ by running the OLS regression of $(v_{1,h}; ...; v_{n,h})'$ on

$$\begin{pmatrix} 2 & 2 \\ \vdots & \vdots \\ n & 2 \end{pmatrix}.$$

We use $n = 5$ throughout our analysis.

B.2. Permanent Income

Let $\mu_{\nu,h,t} = \mathbb{E}_t(\nu_{h,t})$ and $\sigma^2_{\nu,h,t} = Var_t(\nu_{h,t})$, respectively, denote the permanent component's mean and variance conditional on current and past income. The conditional moments satisfy the recursion:

$$\mu_{\nu,h,t} = \mu_{\nu,h,t-1} + \frac{\sigma^2_{\nu,h,t-1} + \sigma^2_{\xi,h}}{\sigma^2_{\nu,h,t-1} + \sigma^2_{\xi,h} + \sigma^2_{\varepsilon,h}}(\ell_{h,t} - \mu_{\nu,h,t-1}), \tag{IA.1}$$

$$\sigma^2_{\nu,h,t} = \sigma^2_{\varepsilon,h}\frac{\sigma^2_{\nu,h,t-1} + \sigma^2_{\xi,h}}{\sigma^2_{\nu,h,t-1} + \sigma^2_{\xi,h} + \sigma^2_{\varepsilon,h}}, \tag{IA.2}$$

where $\ell_{h,t} = \log(L_{h,t}) - a_h - b'x_{h,t}$ denotes the difference between log income and its fitted value.[2] For all t, we set $\sigma^2_{\nu,h,t}$ equal to the steady state[3]

$$\sigma^2_{\nu,h} = \frac{1}{2}\left(\sqrt{\sigma^4_{\xi,h} + 4\sigma^2_{\varepsilon,h}\sigma^2_{\xi,h}} - \sigma^2_{\xi,h}\right).$$

We assume that permanent income coincides with actual income at date 0 ($\mu_{\nu,h,0} = 0$), and iterate forward the relation: $\mu_{\nu,h,t} = \mu_{\nu,h,t-1} + (\ell_{h,t} - \mu_{\nu,h,t-1})\sigma^2_{\nu,h}/\sigma^2_{\varepsilon,h}$.

B.3. Expected Human Capital

We choose components of $x_{h,t}$ that are constant over time. The only exception is age, which is fully predictable. Under these simplifying assumptions, $x_{h,t+n}$ is known with certainty at date t. Hence

$$\begin{aligned}
\mathbb{E}_t(L_{h,t+n}) &= e^{a_h + b'x_{h,t+n}}\mathbb{E}_t\left(e^{\nu_{h,t+n}+\varepsilon_{h,t+n}}\right) \\
&= e^{a_h + b'x_{h,t+n} + \mathbb{E}_t(\nu_{h,t+n}) + 0.5\sigma^2_{\varepsilon,h} + 0.5Var_t(\nu_{h,t+n})}.
\end{aligned}$$

The relation $\nu_{h,t+n} = \nu_{h,t} + \xi_{h,t+1} + ... + \xi_{h,t+n}$ implies that $Var_t(\nu_{h,t+n}) = Var_t(\nu_{h,t}) + n\sigma^2_{\xi,h}$, and therefore

$$\mathbb{E}_t(L_{h,t+n}) = e^{a_h + b'x_{h,t+n} + \mu_{\nu,h,t} + 0.5(\sigma^2_{\varepsilon,h} + \sigma^2_{\nu,h} + n\sigma^2_{\xi,h})}$$

for all $n \geq 1$. Expected human capital is given by

$$HC_{h,t} = \sum_{n=1}^{T_h} \pi_{h,t,t+n} \frac{e^{a_h + b'x_{h,t+n} + \mu_{\nu,h,t} + 0.5(\sigma^2_{\varepsilon,h} + \sigma^2_{\nu,h} + n\sigma^2_{\xi,h})}}{(1+r)^n}, \tag{IA.3}$$

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

[2] Assume that $\mathbb{E}_{t-1}(\nu_{h,t-1})$ and $Var_{t-1}(\nu_{h,t-1})$ are known. As of date $t-1$, the permanent component $\nu_{h,t} = \nu_{h,t-1} + \xi_{h,t}$ has conditional mean $\mathbb{E}_{t-1}(\nu_{h,t}) = \mu_{\nu,h,t-1}$ and variance $Var_{t-1}(\nu_{h,t}) = Var_{t-1}(\nu_{h,t-1}) + \sigma^2_{\xi,h} = \sigma^2_{\nu,h} + \sigma^2_{\xi,h}$. The observed innovation $\ell_{h,t} = \nu_{h,t} + \varepsilon_{h,t}$ and the permanent component $\nu_{h,t}$ are jointly normal, which implies that (IA.1) holds and that:

$$Var_t(\nu_{h,t}) = Var_{t-1}(\nu_{h,t})\left\{1 - [Corr_{t-1}(\nu_{h,t};\ell_{h,t})]^2\right\}.$$

Since $Var_{t-1}(\nu_{h,t}) = \sigma^2_{\nu,h,t-1} + \sigma^2_{\xi,h}$, and $[Corr_{t-1}(\nu_{h,t};\ell_{h,t})]^2 = (\sigma^2_{\nu,h,t-1} + \sigma^2_{\xi,h})/(\sigma^2_{\nu,h,t-1} + \sigma^2_{\xi,h} + \sigma^2_{\varepsilon,h})$, we conclude that (IA.2) holds as well.

[3] We set $\sigma^2_{\nu,h}$ equal to zero if the argument of the square root, $\sigma^4_{\xi,h} + 4\sigma^2_{\varepsilon,h}\sigma^2_{\xi,h}$, has a negative estimate.

probability is estimated using the life table provided by Statistics Sweden.

C. Bank Account Imputation

In the Swedish Wealth Registry, the balance of a bank account is frequently unreported when the account yields less than 100 Swedish kronor (or $11) during the year. As in CCS (2007, 2009*a*, 2009*b*), we impute the balance of every household for which no bank account data are available.

The imputation rule is obtained from the subsample of about 250,000 individuals for which we observe the bank account balance even though the earned interest is less than 100 kronor. Specifically, we regress the balance onto age and squared age of household head, household size, real estate wealth, level and squared level of household disposable income, and financial wealth other than bank accounts. The coefficient of determination is modest ($R^2 = 1.2\%$) but the regression coefficients are highly significant.

We use the regression coefficients to impute the account balances of individual household members and then aggregate up the imputed amounts to infer the household bank account balance. This imputation method is used throughout the main text and appendix.

II. Portfolio Selection in the Presence of Habit

The equation

$$w_{h,t} = w_{h,t}^{*}\left(1 - \frac{\lambda_h X_{h,t}}{F_{h,t}}\right) \tag{IA.4}$$

holds in a variety of habit formation contexts, such as:

1. two-period settings with a fixed subsistence level, as in ch. 6 of Campbell and Viceira (2002);
2. external habit models with an infinite horizon and a constant $X_{h,t}$, as in Brunnermeier and Nagel (2008);
3. the internal habit formation model of Constantinides (1990), in which habit is a weighted average of past consumption.

The proof of (IA.4) is provided below for each specification. For notational simplicity, we neglect the household index h in this section.

A. *Static Case*

We consider an investor living two periods. At date $t = 0$, the investor is endowed with financial wealth F, which she can invest either in a riskless asset with net return R_f or in a risky asset with random return R_m. The investor consumes at date $t = 1$. The utility over final consumption is $u(c - X)$, where

$$u(c) = c^{1-\gamma}/(1-\gamma)$$

and X is a known subsistence or habit level.

At date $t = 0$, the investor solves the static portfolio optimization problem

$$\max_w \mathbb{E}\left[u(C - X)\right]$$

subject to the budget constraint $C = F[1 + R_f + w(R_m - R_f)]$. Surplus consumption can be rewritten as

$$\begin{aligned} C - X &= \left(F - \frac{X}{1+R_f}\right)(1 + R_f) + wF(R_m - R_f) \\ &= (F - \lambda X)\left[1 + R_f + w^*(R_m - R_f)\right], \end{aligned}$$

where $\lambda = 1/(1 + R_f)$ and $w^* = w(1 - \lambda X/F)^{-1}$. Since u is a power function, terminal utility satisfies

$$u(C - X) = (F - \lambda X)^{1-\gamma}\, u\left[1 + R_f + w^*(R_m - R_f)\right].$$

The risky share w maximizes $\mathbb{E}\left[u(C - X)\right]$ if and only if $w^* = w(1 - \lambda X/F)^{-1}$ maximizes $\mathbb{E}\left\{u\left[1 + R_f + w^*(R_m - R_f)\right]\right\}$. Thus, w^* is the optimal risky share of the CRRA investor. We conclude that $w = w^*(1 - \lambda X/F)$.

B. *External Habit*

A similar logic applies to the external habit formation model considered by Brunnermeier and Nagel (2008). Assume that the agent consumes and trades assets every period $t = 0, ..., \infty$. Her utility is $\mathbb{E}_0\left[\sum_{t=0}^{\infty}\delta^t u(C_t - X)\right]$, where C_t denotes period$-t$ consumption, X a fixed external habit or subsistence level, and δ a subjective discount rate $(0 < \delta < 1)$. Every period t, the agent can trade a riskless asset with net return R_f or a stock with random return $R_{m,t}$.

The agent solves the consumption-portfolio problem

$$\max_{\{C_t, w_t, F_t\}} \mathbb{E}_0\left[\sum_{t=0}^{\infty}\delta^t u(C_t - X)\right] \tag{IA.5}$$

subject to the sequential budget constraints

$$F_{t+1} = F_t[1 + R_f + w_t(R_{m,t+1} - R_f)] - C_{t+1}.$$

We consider the change of variables: $C_t^* = C_t - X$ and $F_t^* = F_t - X/R_f$ for all t. The budget constraint can then be rewritten as:

$$\begin{aligned} F_{t+1}^* &= (F_t^* + X/R_f)[1 + R_f + w_t(R_{m,t+1} - R_f)] - (C_{t+1}^* + X) - X/R_f \\ &= F_t^*(1 + R_f) + (F_t^* + X/R_f)w_t(R_{m,t+1} - R_f) - C_{t+1}^* + X(1 + R_f)/R_f - X - X/R_f. \end{aligned}$$

Let $w_t^* = (F_t^* + X/R_f)w_t/F_t^*$. Since $X(1 + R_f)/R_f - X - X/R_f = 0$, the renormalized variables satisfy the usual budget constraint

$$F_{t+1}^* = F_t^*\left[1 + R_f + w_t^*(R_{m,t+1} - R_f)\right] - C_{t+1}^*. \tag{IA.6}$$

The plan $\{(C_t, w_t, F_t)\}_{t=0}^{\infty}$ solves (IA.5) if and only $\{(C_t^*, w_t^*, F_t^*)\}_{t=0}^{\infty}$ solves

$$\max_{\{C_t^*, w_t^*, F_t^*\}} \mathbb{E}_0\left[\sum_{t=0}^{\infty}\delta^t u(C_t^*)\right].$$

subject to the sequential budget constraints (IA.6). Hence w_t^* coincides with the optimal risky share of a CRRA agent. We conclude that $w_t = w_t^* F_t^*/(F_t^* + X/R_f) = w_t^*(1 - \lambda X/F_t)$.

C. *Internal Habit*

We now turn to the internal habit formation model of Constantinides (1990). Time is continuous and the representative agent has utility

$$\mathbb{E}_0\left[\int_0^{+\infty} e^{-\delta t} u(C_t - X_t)dt\right].$$

Internal habit is defined as a function of lagged consumption:

$$X_t = e^{-at} X_0 + b\int_0^t e^{-a(t-s)} C_s ds. \tag{IA.7}$$

The parameter a quantifies persistence, and b the sensitivity of the habit to consumption. The investor can continuously trade a riskless asset with constant instantaneous rate r_f and a stock whose price P_t follows a geometric Brownian motion.

The agent solves:

$$\max_{\{C_t, w_t, F_t\}} \mathbb{E}_0\left[\int_0^{+\infty} e^{-\delta t} u(C_t - X_t)dt\right] \tag{IA.8}$$

subject to the budget constraint

$$dF_t = F_t\left[r_f dt + w_t\left(\frac{dP_t}{P_t} - r_f dt\right)\right] - C_t dt.$$

The habit (IA.7) follows the diffusion

$$dX_t = (bC_t - aX_t)dt.$$

We let

$$\lambda = \frac{1}{r_f + a - b}$$

and consider the change of variables

$$C_t^* = \frac{r_f + a}{r_f + a - b}(C_t - X_t), \tag{IA.9}$$

$$w_t^* = w_t F_t / (F_t - \lambda X_t), \tag{IA.10}$$

$$F_t^* = F_t - \lambda X_t. \tag{IA.11}$$

With the new variables, the law of motion of internal habit becomes

$$\begin{aligned} dX_t &= \left[b\left(\frac{r_f+a-b}{r_f+a}C_t^* + X_t\right) - aX_t\right]dt \\ &= \left[b\frac{r_f+a-b}{r_f+a}C_t^* + (b-a)X_t\right]dt. \end{aligned}$$

Renormalized financial wealth F_t^* satisfies:

$$\begin{aligned} dF_t^* &= (F_t^* + \lambda X_t)r_f dt + F_t^* w_t^* \left(\frac{dP_t}{P_t} - r_f dt\right) - \left(\frac{r_f+a-b}{r_f+a}C_t^* + X_t\right)dt - \lambda dX_t \\ &= r_f F_t^* dt + F_t^* w_t^* \left(\frac{dP_t}{P_t} - r_f dt\right) - \left(\frac{r_f+a-b}{r_f+a}C_t^* + X_t\right)dt + \frac{r_f}{r_f+a-b}X_t dt \\ &\quad - \left(\frac{b}{r_f+a}C_t^* + \frac{b-a}{r_f+a-b}X_t\right)dt \end{aligned}$$

and therefore

$$dF_t^* = F_t^*\left[r_f dt + w_t^*\left(\frac{dP_t}{P_t} - r_f dt\right)\right] - C_t^* dt. \tag{IA.12}$$

The plan $\{(C_t, w_t, F_t)\}_{t=0}^{\infty}$ maximizes (IA.8) if and only if $\{(C_t^*, w_t^*, F_t^*)\}_{t=0}^{\infty}$ defined by (IA.9)$-$(IA.11) maximizes $\mathbb{E}_0\left[\int_0^{+\infty} e^{-\delta t}u(C_t^*)dt\right]$ under the usual budget constraint (IA.12). We conclude that (C_t^*, w_t^*, F_t^*) is the optimal solution of a CRRA agent. Hence, $w_t = w_t^*(1 - \lambda X_t/F_t)$.

III. Portfolio Selection in the Presence of Human Capital and Habit

In this section, we discuss the joint impact of human capital and habit on the asset allocation of individual investors. We begin by assuming that human capital is riskless, and then show by calibration how the results are modified in the presence of income risk.

A. Asset Allocation in the Absence of Income Risk

A.1. External Habit

We consider a variant of the external habit formation model in Brunnermeier and Nagel (2008), in which liquid wealth includes both physical and human capital. As in Section II.B of this

Internet Appendix, the agent has utility

$$\mathbb{E}_0\left[\sum_{t=0}^{\infty}\delta^t\frac{(C_t-X)^{1-\gamma}}{1-\gamma}\right],$$

where C_t denotes period$-t$ consumption and X a fixed external habit. Every period t, the agent can trade a riskless asset with net return R_f and a stock with random return $R_{m,t}$. The agent receives an exogenous stream of labor income L_t, which is assumed to be tradable and riskless. We denote by $HC_t = \sum_{n=1}^{\infty} L_{t+n}(1+R_f)^{-n}$ the market value of future income. The agent's budget constraint is now:

$$F_{t+1} = L_{t+1} + F_t[1 + R_f + w_t(R_{m,t+1} - R_f)] - C_{t+1}. \tag{IA.13}$$

In the absence of habit ($X = 0$), the agent has CRRA utility. If the market return $R_{m,t+1}$ is lognormal, the optimal share of *total* liquid wealth allocated to risky assets is $w_t^* \approx S_m/(\gamma\sigma_m)$, where S_m denotes the stock's Sharpe ratio and σ_m the volatility of the stock's log return.

In the presence of habit, the agent's utility maximization problem has a solution if the household's overall resources exceed the cost of maintaining the habit over an infinite horizon:

$$F_t + HC_t > \lambda X, \tag{IA.14}$$

where $\lambda = 1/R_f$. This condition is a direct implication of the sequential budget constraint (IA.13). We will refer to λX as the *habit liability.* If condition (IA.14) holds, the investor allocates a fraction $w_t^*[1 - \lambda X/(F_t + HC_t)]$ of *total wealth* to risky assets.[4] The corresponding fraction of *financial wealth* is:

$$w_t = w_t^*\left(1 - \frac{\lambda X}{F_t + HC_t}\right)\frac{F_t + HC_t}{F_t},$$

or equivalently

$$w_t = w_t^*\left(1 - \frac{\lambda X - HC_t}{F_t}\right). \tag{IA.15}$$

[4] The variables $C_t^* = C_t - X$, $F_t^* = F_t + HC_t - X/R_f$ and $w_t^* = w_t F_t/F_t^*$ satisfy the usual sequential budget constraint $F_{t+1}^* = F_t^*[1 + R_f + w_{t+1}^*(R_{m,t+1} - R_f)] - C_{t+1}^*$. As in Section II.B of this Internet Appendix, we conclude that $\{(C_t^*, w_t^*, F_t^*)\}_{t=0}^{\infty}$ coincides with the optimal consumption-investment plan of a CRRA investor.

The financial wealth elasticity of the risky share is therefore:

$$\eta_t = \frac{d\log(w_t)}{d\log(F_t)} = \frac{(\lambda X - HC_t)/F_t}{1-(\lambda X - HC_t)/F_t}, \tag{IA.16}$$

which is positive if the habit liability exceeds human capital: $\lambda X > HC_t$.

We infer from (IA.16) that the habit liability λX satisfies

$$\lambda X = HC_t + \frac{\eta_t}{1+\eta_t} F_t, \tag{IA.17}$$

and from (IA.15) that the risky share is

$$w_t = \frac{w_t^*}{1+\eta_t}. \tag{IA.18}$$

Equations (IA.17) and (IA.18) can be used to impute the habit liability and the risky share from the elasticity η_t, financial wealth F_t and human capital HC_t.

In the Swedish dataset, η_t is about 0.223, average financial wealth F_t about $\$45,000$, and average human capital HC_t about \$760,000 when the discount rate R_f is set equal to 3%. The imputed cost of maintaining the habit over an infinite horizon is

$$\begin{aligned} \lambda X &= \$760,000 + \frac{0.223}{1.223}\$45,000 \\ &= \$768,200. \end{aligned}$$

Since the interest rate is $R_f = 3\%$, the yearly habit is

$$X = 3\% \times 768,205 = \$23,000,$$

when human capital is taken into account. This estimate seems reasonable since it is close average consumption and income in Sweden. By contrast, when human capital is not taken account, λX is $\$8,200$ and the yearly habit is only \$250 per year; habit then only has a negligible effect on the asset allocation. Human capital is therefore essential in order to reconcile our micro estimates with representative-agent habit formation models in which the habit-to-consumption ratio is close to unity (e.g. Campbell and Cochrane (1999)).

The model is also consistent with the measured risky share. Assume for instance that the curvature is $\gamma = 3$, the stock's Sharpe ratio is $S_m = 0.4$, and that the standard deviation of the stocks's log return is $\sigma_m = 0.2$. The risky share w_t^* of the corresponding CRRA investor is then equal to 2/3. With habit, risky share is $w_t = 0.667/1.223 = 0.572$, which is consistent with Table I. Overall, the measured financial wealth elasticity of the risky share implies reasonable levels of external habit and the risky share when human capital is taken into account.

A.2. Internal Habit

Human capital can similarly be incorporated into the internal habit model of Constantinides (1990). The notation is the same as in Section II.C of this Internet Appendix. If consumption grows deterministically at rate g (so that $C_t = C_0 e^{gt}$), the internal habit satisfies

$$X_t = e^{-at} X_0 + \frac{bC_t}{a+g}[1 - e^{-(a+g)t}].$$

The habit-to-consumption ratio is therefore

$$X_t/C_t = b/(a+g) \qquad \text{(IA.19)}$$

in a steady state.

The investor can continuously trade a riskless asset with constant instantaneous rate r_f and a stock whose price P_t follows a geometric Brownian motion. We assume that liquid wealth includes both financial and riskless human capital. Analogous to the external habit formation case, the risky share is

$$w_t = w_t^* \left(1 - \frac{\lambda X_t}{F_t + HC_t}\right) \frac{F_t + HC_t}{F_t}, \qquad \text{(IA.20)}$$

where $\lambda = 1/(r_f + a - b)$. The financial wealth elasticity of the risky share is given by

$$\eta_t = \frac{d\log(w_t)}{d\log(F_t)} = \frac{(\lambda X_t - HC_t)/F_t}{1 - (\lambda X_t - HC_t)/F_t}.$$

Imputed habit is therefore

$$X_t = (r_f + a - b)\left(HC_t + \frac{\eta_t}{1+\eta_t} F_t\right), \qquad \text{(IA.21)}$$

and the imputed risky share is again $w_t = w_t^*/(1+\eta_t)$.

In the aggregate habit formation literature, the parameters a and b are generally close to each other and contained between 0.1 and 0.6 (see, for instance, Table I in Constantinides (1990)). Assume, for instance, that $a = 0.35$, $b = 0.34$, and that aggregate consumption grows at rate $g = 2\%$. The benchmark internal habit (IA.19) in the Swedish dataset is

$$X_t = \frac{b}{a+g} C_t = \frac{0.34}{0.35+0.02} \$32,400 = \$29,800.$$

We set the log interest rate $r_f = \log(1+R_f)$ equal to $\log(1+3\%) = 2.96\%$. The imputed habit (IA.21) is therefore

$$\begin{aligned} X_t &= (0.0296 + 0.35 - 0.34) \left(\$760,000 + \frac{0.223}{1.223} \$45,000 \right) \\ &= \$30,400, \end{aligned}$$

which is close to the benchmark. The imputed risky share is unchanged at 0.572.

The financial wealth elasticity of the risky share measured on micro data implies reasonable levels of the (external or internal) habit and the risky share when human capital is taken into account. These results have been obtained under the assumption that income is deterministic. We now investigate how these results are modified when labor income is stochastic.

B. *Asset Allocation in the Presence of Income Risk*

The relation between financial wealth and the risky share is generally ambiguous in the presence of both habit and labor income. Equations (IA.15) and (IA.20) show that habit channel dominates if habit is sufficiently high. When income is risky, the habit channel also dominates through a complementary mechanism (Polkovnichenko (2007)). Habit imposes a binding upper bound on the risky share, which is determined by the worst realization of human capital and asset returns. As financial wealth goes up, the constraint becomes progressively looser and the risky share increases. In this subsection, we develop this logic in a two-period portfolio selection model that includes both human capital and habit. Our static model is a simplified version of Polkovnichenko's dynamic analysis.

The investor has financial wealth F at date $t = 0$ and receives a stochastic labor income L at $t = 1$. We denote by $L_{\min}$ the minimal value of L. As in Section II.A of this Internet Appendix, consumption takes place at date $t = 1$. The investor has expected utility

$$\mathbb{E}\left[\frac{(C-X)^{1-\gamma}}{1-\gamma}\right], \tag{IA.22}$$

where C denotes terminal consumption at date $t = 1$ and X is a habit or subsistence level. At date $t = 0$, the agent invests her financial wealth F in a riskless asset with net return R_f and a stock with random net return R_m. We denote by $R_{\min}$ the lowest possible return on the stock. We assume limited liability and no arbitrage, which implies that $-1 \leq R_{\min} < R_f$. We also assume that labor income and the stock return are independent.

Let w denote the share of the agent's financial wealth invested in the stock. Short sales and borrowing are ruled out, so that $w \in [0, 1]$. The investor selects the value of w that maximizes (IA.22) under the budget constraint $C = L + F[1 + R_f + w(R_m - R_f)]$. The optimal risky share must be such that $C \geq X$ almost surely, or equivalently:

$$L_{\min} + F[1 + R_f + w(R_{\min} - R_f)] \geq X. \tag{IA.23}$$

To emphasize the connection with the dynamic models in previous subsections, we let $\lambda = 1/(1 + R_f)$ and $HC_{\min} = \lambda L_{\min}$. The feasibility constraint (IA.23) can be rewritten as $w \leq \omega(F; X, HC_{\min})$, where

$$\omega(F; X, HC_{\min}) = \frac{1}{\lambda(R_f - R_{\min})}\left[1 - \frac{\lambda X - HC_{\min}}{F}\right].$$

If the habit liability exceeds the minimum level of human capital: $\lambda X > HC_{\min}$, the function $\omega(F; X, HC_{\min})$ increases from 0 to $1/\lambda(R_f - R_{\min}) \geq 1$ as financial wealth varies from $\lambda X - HC_{\min}$ to $+\infty$.

Intuition suggests that if $HC_{\min}$ is low, the optimal risky share coincides with $\omega(F; X, HC_{\min})$ on a range of financial wealth levels, and then converges to the CRRA solution w^* as $F \to \infty$. If instead $HC_{\min}$ is high compared to the habit, the effect of human capital dominates and the risky share is a decreasing function of financial wealth. We verify these intuitions in a set of simulations. The choice of parameters is guided by the following considerations. We set $\gamma = 5$ and normalize the habit to unity $X = 1$. We assume that labor income L has a mean $\bar{L}$ equal to 1.5 and a standard deviation σ_L equal to 0.2. The mean corresponds to a habit-to-average income ratio $\bar{L}/X$ equal to 2/3, which is in line with the literature; for instance, Polkovnichenko

(2007) chooses a habit-to-average consumption ratio of 0.6. The worst possible level of income, $L_{\min}$, ranges between 0.6 and 1.1, so that $L_{\min}/\bar{L}$ ranges between 0.40 and 0.73. To complete the specification, we assume that labor income is a Bernoulli random variable that can take the low value $L_{\min}$ with probability $1-p$ and the high value $L_{\max}$ with probability p. The quantities $L_{\max}$ and p are implicitly defined by the conditions $\sigma_L = \sqrt{(L_{\max}-\bar{L})(\bar{L}-L_{\min})}$ and $\bar{L} = pL_{\max} + (1-p)L_{\min}$.[5] The net interest rate R_f is set equal to 3%. We also assume that the stock return is lognormal: $\log(1+R_m) \sim \mathcal{N}(\mu_m, \sigma_m^2)$, where $\mu_m = 0.08$ and $\sigma_m = 0.20$.

Figure IA.1 illustrates the theoretical relation between the risky share and financial wealth. For low to moderate values of $L_{\min}$, the risky share strongly increases in financial wealth and then stabilizes, as the habit formation model predicts. The risky share is hump-shaped for intermediate values of $L_{\min}$: the feasibility constraint ceases to be binding and the impact of human capital dominates at medium wealth levels. For $L_{\min} = 1.1$, the risky share decreases with financial wealth, as the human capital model predicts.

In Figure IA.2, we illustrate how the financial wealth elasticity of the risky share varies with financial wealth itself. We observe that the elasticity decreases with financial wealth under most specifications. For $L_{\min} = 1.1$, the elasticity falls down to -0.6 and then increases to zero as financial wealth varies from 0 to $+\infty$.

Overall, the theoretical models presented in this section imply that in the presence of human capital and habit, the relation between the risky share and financial wealth is positive under a wide range of conditions. The main requirement is that the lowest possible realization of human capital be lower than the habit liability, which seems very reasonable for most individual investors. Under this condition, the risky share increases with financial wealth on a broad (and possibly unbounded) range of financial wealth levels, consistent with the empirical evidence.

[5]That is, $L_{\max} = \bar{L} - \sigma_L^2/(\bar{L}-L_{\min})$ and $p = (\bar{L}-L_{\min})/(L_{\max}-L_{\min})$.

IV. Comparison of Identical and Fraternal Twins

A. *Summary Statistics and ACE Decomposition*

In the first six columns of Table IA.I, we report the mean, standard deviation, and twin correlation of observable characteristics computed over the subsamples of identical and fraternal twins. As one would expect, the pairwise correlations of all characteristics are substantially higher for identical twins than for fraternal twins. Standard deviations are correspondingly lower in the subsample of identical twins.

In the last two columns of Table IA.I, we report the results of an ACE decomposition, a linear model of genetic effects that has been widely used in medicine and is now starting to be used in household finance (Barnea, Cronqvist and Siegel (2010) and Cesarini et al. (2009), (2010)). In ACE, the characteristic $x_{i,j}$ of twin j in pair i is the sum of a genetic component $a_{i,j}$, a common component c_i, and an idiosyncratic component $\varepsilon_{i,j}$:

$$x_{i,j} = a_{i,j} + c_i + \varepsilon_{i,j}.$$

The genetic, common, and idiosyncratic components are assumed to be uncorrelated. Thus, ACE does not take into account interactions between genetic and environmental variables, which have been shown to be empirically important (Ridley (2003)). ACE also assumes that the pairwise correlation of the genetic component, $Corr(a_{i,1}; a_{i,2})$, equals 1 for identical twins and 1/2 for fraternal twins. In the simplest specifications, the genetic component has the same unconditional variance in the group of identical twins as in the group of fraternal twins. Similarly, the variance of the common component, σ_c^2, and the variance of the idiosyncratic component, σ_ε^2, are assumed to be the same in both groups.

The pairwise correlation of the characteristics, $Corr(x_{i,1}; x_{i,2})$, is:

$$\begin{aligned}
\rho^{MZ} &= \frac{\sigma_c^2 + \sigma_a^2}{\sigma_c^2 + \sigma_a^2 + \sigma_\varepsilon^2} \quad \text{for monozygotic twins, and} \\
\rho^{DZ} &= \frac{\sigma_c^2 + \sigma_a^2/2}{\sigma_c^2 + \sigma_a^2 + \sigma_\varepsilon^2} \quad \text{for dizygotic twins.}
\end{aligned}$$

The differences

$$2(\rho^{MZ} - \rho^{DZ}) = \frac{\sigma_a^2}{\sigma_c^2 + \sigma_a^2 + \sigma_\varepsilon^2}, \quad \text{and} \quad 2\rho^{DZ} - \rho^{MZ} = \frac{\sigma_c^2}{\sigma_c^2 + \sigma_a^2 + \sigma_\varepsilon^2}$$

quantify the contributions of the genetic and common components to the cross-sectional variance of the characteristic according to ACE.

The genetic component seems empirically important for most characteristics, including the risky share, financial wealth, education, and income risk. The estimated contribution of the common component is negative for seven characteristics, for which $\rho^{DZ} \leq \rho^{MZ}/2$. This observation suggests that the simple ACE decomposition cannot be applied to these variables.

In Table IA.II, we sort twins by communication frequency and report the ACE decomposition of the risky share in each group. We consider both the risky share itself ("No controls") and the residual of a regression of the risky share on characteristics ("With controls"), both in levels (Panel A) and in logs (Panel B). We observe that in all cases, the genetic component is substantially larger among frequent communicators than among infrequent communicators. This finding suggests that the so-called genetic component of an ACE decomposition is unlikely to be purely driven by genes.

B. Regression with Heterogeneous Elasticity

In Table IA.III, we separately estimate on identical twins and on fraternal twins the panel regressions with wealth-dependent elasticity reported in Table V of the main text. The elasticity strongly decreases with financial wealth in both twin subsamples.

V. Robustness Checks

A. Yearly Estimates of Twin Pair Fixed Effects Regressions

Table IA.IV reports year-by-year estimates of the twin pair fixed effects regression. The estimates of financial wealth elasticity of the risky share tend to decline over time from 0.28 in 1999 to 0.23 in 2001 and 0.12 in 2002. The relation between risk-taking and financial wealth weakened as the bear market took hold. The financial wealth elasticity of the risky share is nonetheless significantly positive in all years.

B. Normalized Wealth Ratios

Economic theory suggests that the risky share is a function of:

- the financial wealth-to-human capital ratio (Merton (1971));
- the financial wealth-to-habit liability ratio (Constantinides (1990) and Campbell and Cochrane (1999));
- the financial wealth-to-real estate ratio (Flavin and Yamashita (2002)).

By contrast, models based on the "spirit of capitalism" imply that financial wealth may directly impact individual utility and the risky share. The twin dataset allows us measure the relative importance of each channel for the financial wealth elasticity risky share.

We estimate regressions of the log risk share on renormalized wealth ratios and other characteristics estimated on the set of all twins (Table IA.V) and on the set of identical twins (Table IA.VI). The coefficients on the financial wealth-to-commercial real estate ratio, the financial wealth-to-human capital ratio and the financial wealth to habit ratio have the signs predicted by theory. Commercial real estate and internal habit are significant in the sample of all twins and lose significance in the subsample of identical twins, consistent with the smaller size of the identical twin subsample. Perhaps more strikingly, the financial wealth-to-human capital ratio is insignificant in the full sample but is significant in the subsample of identical twins, for which our procedure best controls for latent heterogeneity. Financial wealth as a standalone variable has a positive coefficient that is significant at the 10% level in the full sample. This finding suggests that some durable goods and consumption commitments may be missing from the analysis, or that models based the capitalistic spirit are indeed correct in assuming that financial wealth has a direct impact on the risky share independently of other assets held by the household. The financial wealth coefficient may also be related to different levels of financial literacy or different access to investment opportunities across households.

The table provides a decomposition of the financial wealth elasticity of the risky share reported in the main text. The coefficient on standalone financial wealth is 0.17, the coefficient on the financial wealth-to-internal habit ratio is 0.09, and the coefficient on the financial wealth to external habit ratio is -0.04, which add up to the 0.22 estimate reported in the main text. Internal habit is a sizeable contributor, but it cannot fully explain the financial wealth elasticity of the risky share reported in the main text.

C. Human Capital

Financial theory suggests that households facing liquidity constraints should use a higher discount rate than unconstrained households (e.g., Cvitanić and Karatzas (1992) and Teplá (2000)). For this reason, we recompute human capital (IA.3) with the discount rate $r = 5\%$ when the twin in the household is less than 35 years old, and $r = 3\%$ otherwise. We report the corresponding risky share regressions in Table IA.VII (all twins) and IA.VIII (identical twins). The results are very similar to the regression coefficients reported in Tables II and III of the main text.

Low financial wealth is another proxy for leverage constraints. We therefore recompute human capital by using a discount rate of 5% for households in the bottom half of the financial wealth distribution, and a discount rate of 3% for households in the top half. The corresponding results are reported in Tables IA.IX (all twins) and IA.X (identical twins). The results are once again similar to the ones reported in the main text.

D. External Habit

In the main text, a household's external habit is proxied by the three-year average income in the household's municipality. Another and perhaps finer proxy for the external habit is the average income of households in the same municipality *and* the same age group. In Table IA.XI, we report the risky share regressions based on this alternative proxy. The external habit coefficient remains insignificant.

E. Education

The risky share regressions reported in the main text include a high school dummy and a dummy for post-high school education. In Table IA.XII, we decompose the post-high school dummy as the sum of three dummy variables corresponding to: (1) incomplete undergraduate training, (2) an undergraduate degree but no post-graduate education, and (3) some post-graduate education. The three dummies are mutually exclusive, and the second dummy refers to all forms of undergraduate education, including university, college and vocational training. All the education variables are insignificant.

F. Marital Status

Until now, we have grouped individuals into households if they live together, regardless of their marital status. In Table IA.XIII, we reestimate the regression when marital status in included as a control. Our results are unchanged and the marriage dummy is insignificant.

G. Age

It is sometimes suggested that genetic effects matter less with age. In Table IA.XIV, we reestimate the twin regression on four age groups. The financial wealth elasticity of the risky share remains significantly positive and close to 0.2 in all groups. The effects of other characteristics are generally robust, albeit with less significance than in Table II due to the smaller size of each age group. Leverage, income risk, internal habit and family size have a negative impact on the risky share. The beta of income growth relative to the risky portfolio return, β_h, is significant and positively related to risk-taking for investors between 35 and 45, and is insignificant in the other three age groups.

In Table IA.XV, we estimate a parametric specification that includes age and age squared as explanatory variables of elasticity. The two age coefficients are now insignificant, which suggests that the variations reported in Table IA.XIV are insignificant and that the financial wealth elasticity of the risky share is approximately constant with age. Overall, Tables IA.XIV and IA.XV show that our main findings hold consistently in all age groups.

H. Communication Between Twins

Tables IA.XVI and IA.XVII report yearly twin pair fixed effects regressions computed on the subsamples of frequent and infrequent communicators. Table IA.XVI considers all twins, while Table IA.XVII focuses on identical twins. The first and third set of columns of each table assume a constant financial wealth elasticity of the risky share and are therefore the complete version of the regressions reported in Table IV of the main text. The second and fourth set of columns of each table allows the elasticity to vary across financial wealth quartiles. The coefficients on all characteristics are fully consistent with the empirical regularities documented in the main text and in the rest of this Internet Appendix.

I. Local Interactions

A household's asset household may be driven not only by its own preferences and characteristics, but also by social interactions with their neighbors, friends and coworkers. Table IA.XVIII reports the cross-sectional variance of the risky share within and between Swedish municipalities. The variance of the risky share (in logs or in levels) within Swedish municipalities is about 30 times larger than the variance between municipalities. This analysis does not control for heterogeneity in observable characteristics. We therefore recompute the variance decomposition for the residual of the yearly twin pair fixed effects regression reported in the third set of columns of Table II. The variance of the residual within municipalities is now 80 times larger than its variance across municipalities. Thus, local interactions do not appear to be the main drivers of risk-taking.

In Table IA.XIX, we reestimate the twin regressions by including as controls the average log risky share and the average log financial wealth of households in the same municipality. The average financial wealth elasticity is again estimated at 0.22, and the impact of other characteristics remains largely unchanged. The municipality log risky share has a positive and significant coefficient of about 0.35. This result should be taken with caution, however, since the econometric analysis of social interactions is fraught with difficulties (e.g. Manski, 2000). While we leave the full investigation of social interactions in risk-taking for further research, we conclude that social interactions within municipalities do not alter the relation between risk-taking and individual characteristics.

J. *Alternative Elasticity Specifications*

J.1. *Elasticity as a Function of Individual Characteristics*

In the main text, we have specified the risky share as

$$\log(w_{i,j,t}) = \alpha_{i,t} + \eta_{i,t} f_{i,j,t} + \gamma' x_{i,j,t} + \varepsilon_{i,j,t},$$

where the financial wealth elasticity of the risky share $\eta_{i,t}$ is a function of the average characteristics of the pair:

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

We have adopted this specification because it is the linear analogue of the bin regressions in Table V. In Table IA.XX, we reestimate the panel when the elasticity is specified as a function of the *individual* characteristics of each twin. Our results are robust to this alternative specification.

J.2. *Impact of Twin Pair Fixed Effects*

We now investigate if there is a relation between the elasticity $\eta_{i,t}$ and the overall propensity to take risk, as measured by the fixed effect $\alpha_{i,t}$. For instance, if one interprets $\alpha_{i,t}$ as a measure of risk tolerance, one might ask if there is a relation between risk tolerance and the financial wealth elasticity of the risky share. In Table IA.XXI, we reestimate a twin regression in which the twin pair fixed effect $\alpha_{i,t}$ (obtained from the regression reported in the third set of columns of Table II) is used as an explanatory variable of the elasticity:

$$\eta_{i,t} = \eta_0 + \eta_1 f_{i,t} + \eta_2 \alpha_{i,t} + \psi' x_{i,t}.$$

The impact of $\alpha_{i,t}$ is negative and significant. Individual investors with a high propensity to take risk tend to also have a low financial wealth elasticity of the risky share.

K. *Randomly Matched Pairs*

In Table IA.XXII, we reestimate the twin regressions on a group of randomly matched pairs. The coefficients reported in Panel A are similar to the yearly fixed effects coefficients reported in the last set of columns of the panel (and in the last columns of Table II, Panel A). In particular, educational attainment is strongly significant with randomly matched pairs, in contrast to the insignificant coefficients obtained with actual twins.

The adjusted R^2 and the fixed effect share ω_α^2 are substantially lower with randomly matched pairs than with actual twins. We obtain $R^2 = 11.4\%$ (compared to $R^2 = 18.0\%$ with actual twin pairs) when financial wealth is the only characteristic, and 12.8% (compared to 19.1% with actual pairs) when all characteristics are included. In the variance decomposition reported in Panel B, the contribution of the fixed effect ω_α^2 hovers around 2.6% across specifications, as compared to the $9.1\% - 9.7\%$ values obtained with actual twins. These findings confirm that twin pair fixed effects are quantitatively important and modify the measured impact of education on risk-taking.

L. *Tobit Regression*

Short sale constraints preclude most households from holding financial portfolios with a negative share of risky assets, and debt is by definition excluded from gross financial wealth. For these reasons, the risky share of every household in our sample is contained between zero and one: $w_{h,t} \in [0, 1]$ for all h, t. This restriction is taken explicitly into account in the estimation methods used in main text. We now consider a tobit model of the risky share:

$$w_{h,t} = \begin{cases} 0 & \text{if} \quad w_{h,t}^* < 0, \\ w_{h,t}^* & \text{if} \quad 0 \leq w_{h,t}^* \leq 1, \\ 1 & \text{if} \quad w_{h,t}^* > 1. \end{cases}$$

where the latent variable $w_{h,t}^*$ is a linear function of yearly fixed effects and household characteristics:

$$w_{h,t}^* = \alpha_t + \zeta f_{h,t} + \gamma' x_{h,t} + \varepsilon_{h,t}.$$

The ζ coefficient quantifies the impact of financial wealth on the probability of participation in risky asset market markets *and* the level of the risky share conditional on entry. The vector γ plays a similar role for other household characteristics.

In Table IA.XXIII, we estimate the tobit model on the set of participating and non-participating households using standard (maximum likelihood) estimation. Regression (1) shows that the average financial wealth coefficient ζ is positive and strongly significant. Regression (2) allows the coefficient ζ to vary with wealth. We report that ζ is nearly invariant across financial wealth quantiles. The impact of characteristics other than financial wealth is analogous to earlier cross-sectional findings. Risky investing is positively correlated with residential real estate, human capital, and education, and negatively related to commercial real estate, leverage, income risk, entrepreneurship, unemployment, habit and family size.

Since $\zeta_{h,t} = dw_{h,t}/df_{h,t}$ and $\eta_{h,t} = d\log(w_{h,t})/df_{h,t}$, the relation between the financial wealth coefficient measured in Table IA.XXIII and the financial wealth elasticity of the risky share considered in the main text is:

$$\eta_{h,t} = \zeta_{h,t}/w_{h,t}. \tag{IA.24}$$

In the last set of columns of each regression, we report the elasticity $\eta_{h,t}$ implied by (IA.24). As one expects, the implied elasticity is higher than the one reported in the main text, since it captures the impact of financial wealth on both the probability of participation and the asset allocation conditional on entry.

In Table IA.XXIV, we estimate a tobit specification with yearly twin pair fixed effects. That is, we consider the latent variable

$$w^*_{i,j,t} = \alpha_{i,t} + \zeta f_{i,j,t} + \gamma' x_{i,j,t} + \varepsilon_{i,j,t},$$

and, as previously, define the risky share as $w_{i,j,t} = 0$ if $w^*_{i,j,t} < 0$, $w_{i,j,t} = w^*_{i,j,t}$ if $w^*_{i,j,t} \in [0,1]$, and $w_{i,j,t} = 1$ if $w^*_{h,t} > 1$. Since there are 42,766 yearly twin pair fixed effects in our sample, the standard (maximum likelihood) estimation method is unfeasible. For this reason, we employ the estimation methodology of Alan, Honoré, Hu and Leth-Petersen (2011), a two-sided extension of Honoré (1992)'s one-sided tobit estimator. The financial wealth coefficient ζ is once again strongly significant and nearly invariant across wealth quantiles. The other coefficients are mainly in line with our earlier results.

The financial wealth coefficient ζ of the tobit model can be conveniently interpreted in the context of habit formation models. The risky share $w_{h,t} = w^*_{h,t}\,(1 - \lambda_{h,t} X_{h,t}/F_{h,t})$ implies that

$$\zeta_{h,t} = w^*_{h,t} \frac{\lambda_h X_{h,t}}{F_{h,t}}.$$

The invariance of $\zeta_{h,t}$ across wealth quantiles suggests that the habit is proportional to financial wealth, which seems intuitively plausible and is also consistent with the theoretical models of Constantinides (1990) and others. Overall, the tobit analysis confirms the validity of the main results reported in the main text and the appendix.

M. Bank Account Imputation

As is explained in Section I.C of this Internet Appendix, all the results reported so far are based on the imputation of unreported bank account balances from household characteristics. We check the robustness of our results by using another approach introduced in the Appendix of CCS (2007), which takes advantage of the comprehensive nature of the data. We estimate the aggregate value of missing bank balances by taking the difference between: (a) the aggregate household deposits reported to the Swedish Central Bank, and (b) the aggregate bank balances in our dataset. The implied average balance is assigned to each missing observation. In Table IA.XXV, we report regression (2) of Table VI using the constant imputation method. All our results are robust to this alternative specification of bank account balances. We conclude that the bank imputation method is not a cause for concern.

N. Individual Regressions

In the main text and in all previous sections of the Internet Appendix, we have grouped Swedish residents by living units and investigated the relation between household risk-taking and household variables such as financial wealth, real estate and consumption habit. We now investigate if the main results of the paper hold when finances are studied at the individual level using only individual data, excluding any information about other adults. Twins that participate in risky asset markets at the household level but not at the individual level are now excluded from the sample, which results in a smaller sample size than in the rest of the paper.

In Table IA.XXVI, we regress an individual's risky share on own financial, habit and demographic characteristics. The gender dummy variable is equal to unity for a man. The financial wealth elasticity of the risky share is positive and strongly significant in all specifications. The risky share is negatively related to commercial real estate, leverage, entrepreneurship, unemployment, habit and the number of children, consistent with the results of our household regressions.

In Table IA.XXVII, we allow the elasticity to vary across financial wealth quantiles. The financial wealth elasticity of the risky share strongly decreases with financial wealth, consistent with Table V of the main text. In Table IA.XXVIII, we estimate the linear elasticity specifications considered in Table VI. The elasticity decreases with financial wealth and increases with internal habit and the number of children, which confirms the robustness of the regularities documented in the main text.

Tables IA.XXVI–XXIX show that individual regressions are generally consistent with household-level regressions. Significance tends to be slightly weaker for individuals, which we attribute to the smaller size of the participating twin subsample; a complementary explanation is that measurement error is likely more acute for individual variables than for household variables. Perhaps more importantly, all adjusted R^2 coefficients are lower for individual regressions. These various findings confirm that it is preferable to study finances at the household level rather than at the individual level, just as financial theory implies.

VI. Controlling for Measurement Error and Individual Fixed Effects

A. Measurement Error

Financial wealth and the risky share are observed with measurement error. For instance, households experience high-frequency variations in their cash balances at the end of the year, which are partly unrelated to the asset allocation of the financial portfolio. For this reason, we consider the instrumental variable estimation of the twin specification

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

We begin with a few 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. Similarly, *passive financial wealth* is the financial wealth the household has if it does not trade, save or dissave during the year. Formally the log of 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 $\phi(F, w, r, r_f) = \log\{[w(1+r) + (1-w)(1+r_f)]F\}$.

In Table IA.XXIX, we instrument log financial wealth with log passive financial wealth. In the first regression, the average elasticity η is estimated to be 0.28, which is slightly higher than the 0.22 value reported in earlier tables. The second regression reestimates the elasticity η in every financial wealth quartile. Consistent with Section III of the main text, the measured elasticity strongly decreases with financial wealth, and the impact of other characteristics is qualitatively unchanged. Internal habit now has a strongly significant negative coefficient.

Table VI of the main text reports within estimates of:

$$\log(w_{i,j,t}) = \alpha_{i,t} + (\eta_0 + \eta_1 f_{i,t} + \psi' x_{i,t}) f_{i,j,t} + \gamma' x_{i,j,t} + \varepsilon_{i,j,t}. \qquad \text{(IA.25)}$$

In Table IA.XXX, we control for measurement error in financial wealth by conducting the instrumental variable estimation of (IA.25). For each twin, we use as instruments its passive financial wealth, passive financial wealth interacted with demeaned passive financial wealth, and passive financial wealth interacted with demeaned characteristics. The elasticity is again a decreasing function of financial wealth and an increasing function of internal habit. In contrast to Table VI, internal habit remains significant once other characteristics are controlled for. The results of Sections II and III are documented even more strongly when we control for measurement error.

B. Individual Fixed Effects

Twin regressions may be contaminated by individual fixed effects that are specific to each twin in the pair, such as individual differences in risk aversion. We now propose two robustness checks.

B.1. Health and Lifestyle

Barsky et al. (1997) show that risk aversion is empirically related to lifestyle variables such as smoking and drinking. In Table IA.XXXI, 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 II and III are generally robust to the inclusion of this new set of controls.

Health and lifestyle variables are mainly insignificant at the 5% level, which is partly due to the smaller number of observations. Alcohol drinking is positively and significantly related to the risky share $w_{h,t}$ and its elasticity $\eta_{h,t}$, while depression and high blood pressure have a negative relation. Coffee, tobacco, regular physical exercise, height, and weight are insignificant. Overall, Table IA.XXXI confirms the robustness of our elasticity estimates, and shows that risk-taking is linked positively to alcohol consumption and negatively to depression and high blood pressure.

In a recent working paper, Korniotis and Kumar (2012) document that tall individuals select more aggressive asset allocations and obese individuals less aggressive asset allocations than the average investor. These regularities are documented in multiple cross-sectional surveys conducted in several European countries and the United States. Korniotis and Kumar conjecture that height and obesity act as cross-sectional proxies for family background, quality of upbringing, genes, beauty, and physical and mental health, which in turn affect investment horizons and attitudes toward risk (Cesarini et al. (2010) and Rosen and Wu (2003)). The Swedish twin dataset allows us to control for yearly fixed effects as well as for physical and mental health. Since twins generally have similar family background, upbringing, physical beauty and genes, all these features are picked up by the yearly twin pair fixed effects. Height and obesity are insignificant in Table IA.XXXI, which indicates that these physical attributes have no causal impact on the risky share. Our findings confirm Korniotis and Kumar (2012)'s conjecture that obesity and height do not matter *per se* but instead act as cross-sectional proxies for important latent characteristics that actually drive investment decisions.

B.2. Dynamic Panel Estimation

We now relate time variations in a household's risky share to time variations in its financial wealth (Brunnermeier and Nagel (2008), Chiappori and Paiella (2011), and CCS (2009*a*)). This method controls for individual fixed effects and naturally applies to any household, not just a household with a twin. We assume that the risky share satisfies $\log(w_{h,t}) = \alpha_h + \delta_{0,t} + +\eta f_{h,t} + \varepsilon_{h,t}$, where α_h is a household fixed effect and $\delta_{0,t}$ is a yearly fixed effect. We eliminate the household fixed effect by taking the first time-difference:

$$\Delta_t \log(w_{h,t}) = \delta_t + \eta\Delta_t(f_{h,t}) + \Delta_t(\varepsilon_{h,t}). \tag{IA.26}$$

As discussed in CCS (2009*a*), the estimation of (IA.26) must take into account two related issues. First, households display inertia in portfolio rebalancing. When a household saves in the form of cash during the year, its risky share tends to fall mechanically. For this reason, we need to include variables that capture passive risky share variations. Second, since the error $\varepsilon_{h,t-1}$ has an impact on the following period's financial wealth $f_{h,t}$, the regressor $\Delta_t(f_{h,t})$ and the error term $\Delta_t(\varepsilon_{h,t})$ in (IA.26) are correlated. A natural solution is to instrument changes in financial wealth.

In the first set of columns of Table IA.XXXII, we estimate the specification

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

with the following two instruments: (a) the change in financial wealth in the absence of period $t-1$ rebalancing, $\phi(F_{h,t-1}, w^p_{h,t-1}, r_{h,t}, r_{f,t}) - f_{h,t-1}$;[6] and (b) the period $t-1$ log passive risky share, $\log(w^p_{h,t-1})$.[7] The elasticity η is estimated at 0.22, which is consistent with the twin regressions of Section II. The change in the log passive share has a significantly positive coefficient, confirming that there is inertia in portfolio rebalancing. In the second set of columns, we report that η strongly decreases with financial wealth. In the third and fourth set of columns, we reestimate these specifications in the presence of all controls, which are computed at the end of year $t-1$ 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 regressions are strongly complementary. On one hand, the dynamic method controls for household fixed effects but requires valid instruments, which is a source of concern and can hamper applicability to a large set of explanatory variables. Twin regressions, on the other hand, can be estimated by standard panel methods, 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] The instrument coincides with the passive log return on the portfolio of cash and risky financial assets, $\log[w^p_{h,t-1}(1+r_{h,t}) + (1-w^p_{h,t-1})(1+r_f)]$.

[7] CCS (2009*a*) follows a similar method to estimate an adjustment model of portfolio rebalancing, in which the financial wealth elasticity of the target risky share is assumed to be constant.

VII. Aggregate Implications

A. *Fixed Participation Methodology*

We now present the full methodology used to compute the aggregate estimates reported in Section V of the main text. The analysis is based on a fixed year t, and time indices are henceforth neglected. We focus for now on the set of households $\mathcal{P}$ that initially take financial risk, and we do not consider exit from and exit to risky asset markets.

At the end of a given year, each household h is characterized by its risky share w_h, financial wealth F_h, and other observable attributes x_h.

We consider an exogenous change in the cross-sectional distribution of financial wealth. After the shock, each household h has financial wealth $F_h^* = F_h e^{\Delta f_h}$ and selects the new risky share

$$w_h^* = w_h e^{\eta_h \Delta f_h},$$

where η_h denotes the household's financial wealth elasticity of the risky share. We consider three scenarios for η_h.

- **Scenario 1.** Every investor has CRRA utility: $\eta_h = 0$ for all h.
- **Scenario 2.** Investors have a homogenous and strictly positive elasticity: $\eta_h = \eta > 0$ for all h.
- **Scenario 3.** The financial wealth elasticity of the risky share is a linear function of financial wealth and characteristics: $\eta_h = \eta_0 + \eta_1(f_h - \bar{f}) + \psi'(x_h - \bar{x})$ for all h, where $\bar{f}$ and $\bar{x}$ respectively denote the cross-sectional mean of financial wealth and other characteristics in the year of interest. We write the elasticity more compactly as

  $$\eta_h = \theta'(z_h - \bar{z}),$$

  where $\theta = (\eta_0, \eta_1, \psi')'$, $z_h = (1, f_h, x_h')'$, and $\bar{z} = (0, \bar{f}, \bar{x}')'$.

The choice of the parameters used for scenarios 2 and 3 will be discussed below.

Under these assumptions, we can easily compute the aggregate holdings of participants before and after the shock. Aggregate financial wealth is initially $F = \sum_{h\in\mathcal{P}} F_h$, out of which $F_R = \sum_{h\in\mathcal{P}} w_h F_h$ is invested in risky assets. After the shock, aggregate wealth becomes $F^* = \sum_{h\in\mathcal{P}} F_h e^{\Delta f_h}$, and aggregate risky wealth $F_R^* = \sum_{h\in\mathcal{P}} w_h^* F_h^* = \sum_{h\in\mathcal{P}} w_h F_h e^{(1+\eta_h)\Delta f_h}$. The elasticity of aggregate risky wealth is therefore

$$\xi = \log\left[\frac{\sum_{h\in\mathcal{P}} w_h F_h e^{(1+\eta_h)\Delta f_h}}{\sum_{h\in\mathcal{P}} w_h F_h}\right] \Big/ \log\left[\frac{\sum_{h\in\mathcal{P}} F_h e^{\Delta f_h}}{\sum_{h\in\mathcal{P}} F_h}\right]. \tag{IA.27}$$

Since asset prices are fixed, ξ is the elasticity of the aggregate demand for risky assets in response to exogenous changes in household wealth. 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 $(\eta_h)_{h\in\mathcal{P}}$.

B. *Endogenous Participation Methodology*

Let $\mathcal{N}$ denote the set of households that do not initially participate. Every household $h \in \mathcal{P}\cup\mathcal{N}$ is specified by its risky share w_h, financial wealth F_h, and other observable characteristics x_h. The initial aggregate financial wealth is $F = \sum_{h\in\mathcal{P}\cup\mathcal{N}} F_h$, out of which $F_R = \sum_{h\in\mathcal{P}} w_h F_h$ is invested in risky assets.

The key additional ingredient is the probability $\Lambda(\phi' z_h)$ that a household participates in risky asset markets, where $\Lambda(u) = 1/(1+e^{-u})$ denotes the logistic function.

We then consider a shock to the cross-sectional distribution of financial wealth. After the shock, every household holds $F_h^* = F_h e^{\Delta f_h}$. If $\Delta f_h \leq 0$, the probability that a household in $\mathcal{N}$ enters after the shock is 0; if instead $\Delta f_h > 0$, the household enters with probability

$$p_h^*(\phi) = \frac{\Lambda(\phi' z_h^*) - \Lambda(\phi' z_h)}{1 - \Lambda(\phi' z_h)}$$

and selects the imputed risky share $w_h^* = e^{\chi' z_h^*}$, where $z_h^* = (1, f_h + \Delta f_h, x_h')'$. Conversely, a household in $\mathcal{P}$ maintains its participation in risky asset markets with probability:

$$p_h^*(\phi) = \min[1; \Lambda(\phi' z_h^*)/\Lambda(\phi' z_h)]$$

and then selects the risky share $w_h^* = w_h e^{\eta_h \Delta f_h}$.

Under these assumptions, aggregate financial wealth is $F^* = \sum_{h \in \mathcal{P} \cup \mathcal{N}} F_h^*$, and risky financial wealth $F_R^* = \sum_{h \in \mathcal{P} \cup \mathcal{N}} p_h^*(\phi) w_h^* F_h^*$. The aggregate elasticity

$$\xi = \frac{\log(F_R^*/F_R)}{\log(F^*/F)}$$

is then readily available.

C. Choice of Parameters

The parameters η, θ, ϕ and χ are obtained from regressions estimated on subsamples of Swedish residents in the year of interest.

- We estimate either the constant elasticity specification $\log(w_{i,j}) = \alpha_{i,j} + \eta f_{i,j} + \gamma' x_{i,j} + \varepsilon_{i,j}$, or the heterogeneous elasticity specification $\log(w_{i,j}) = \alpha_{i,j} + [\eta_0 + \eta_1(f_{i,j} - \bar{f}) + \psi'(x_{i,j} - \bar{x})] f_{i,j} + \gamma' x_{i,j} + \varepsilon_{i,j}$, on the set of participating twins in the year of interest. The results reported in the main text are based on 2001 yearly estimates. In this Internet Appendix, we will also conduct robustness checks based on other years.
- The logit participation regression $\mathbb{E}(y_h|z_h) = \Lambda(\phi' z_h)$ is estimated on a random sample of households. The logit estimator $\hat{\phi}$ is asymptotically normal with estimated variance-covariance matrix $\hat{V}_\phi$.
- We run the cross-sectional regression of the log risky share on financial wealth and other characteristics, $\mathbb{E}[\log(w_h)|z_h] = \chi' z_h$, on an independent subsample of participating households observed in the year of interest. The estimator $\hat{\chi}$ is normal with estimated variance-covariance matrix $\hat{V}_\chi$.

The resulting estimators $\hat{\theta}, \hat{\phi}$ and $\hat{\chi}$ are mutually independent because they are estimated on independent samples. For the same reason, the estimators $\hat{\eta}, \hat{\phi}$ and $\hat{\chi}$ are mutually independent, which simplifies the construction of confidence intervals in the next subsection.

D. Confidence Bands

We now derive the confidence intervals of the aggregate elasticity estimates obtained under scenario 3. Analogous and simpler results hold for scenario 2. Under fixed participation, the aggregate elasticity estimator is:

$$\hat{\xi} = X(\hat{\theta}) = \left[\log\left(\frac{F^*}{F}\right)\right]^{-1} \log\left[\frac{\sum_h w_h F_h^* e^{\Delta f_h \hat{\theta}\,'(z_h - \bar{z})}}{F_R}\right].$$

By the delta method, the variance of $\hat{\xi}$ is consistently estimated by

$$\hat{\sigma}_\xi^2 = \frac{\partial X}{\partial \theta'}(\hat{\theta})\,\hat{V}_\theta\,\frac{\partial X}{\partial \theta}(\hat{\theta}),$$

where

$$\frac{\partial X}{\partial \theta}(\hat{\theta}) = \left[F_R^* \log\left(\frac{F^*}{F}\right)\right]^{-1} \sum_{h \in \mathcal{P}} w_h^*\, F_h^*\, \Delta f_h\,(z_h - \bar{z}).$$

The confidence interval is therefore $[\hat{\xi} - 1.96\,\hat{\sigma}_\xi; \hat{\xi} + 1.96\,\hat{\sigma}_\xi]$.

We turn to the endogenous participation case and consider a positive shock to the cross-sectional distribution of financial wealth. Let $\hat{\omega} = (\hat{\theta}\,', \hat{\phi}\,', \hat{\chi}\,')'$. The aggregate elasticity is

$$\hat{\xi} = Z(\hat{\omega}) = \frac{1}{\log\left(\frac{F^*}{F}\right)} \log\left[\frac{\sum_{h\in\mathcal{P}} w_h F_h^* e^{\Delta f_h \hat{\theta}\,'(z_h - \bar{z})} + \sum_{h\in\mathcal{N}} p_h(\hat{\phi}) F_h^* e^{\hat{\chi}' z_h}}{F_R}\right].$$

The delta method implies the following property.

Proposition 1 *The variance of $\hat{\xi}$ is consistently estimated by*

$$\hat{\sigma}_\xi^2 = \frac{\partial Z}{\partial \theta'}(\hat{\omega})\hat{V}_\theta \frac{\partial Z}{\partial \theta}(\hat{\omega}) + \frac{\partial Z}{\partial \phi'}(\hat{\omega})\hat{V}_\phi \frac{\partial Z}{\partial \phi}(\hat{\omega}) + \frac{\partial Z}{\partial \chi'}(\hat{\omega})\hat{V}_\chi \frac{\partial Z}{\partial \chi}(\hat{\omega}), \tag{IA.28}$$

where

$$\frac{\partial Z}{\partial \theta} = \frac{1}{F_R^* \log\left(\frac{F^*}{F}\right)} \sum_{h\in\mathcal{P}} w_h^*\, F_h^*\, \Delta f_h\,(z_h - \bar{z}), \tag{IA.29}$$

$$\frac{\partial Z}{\partial \phi} = \frac{1}{F_R^* \log\left(\frac{F^*}{F}\right)} \sum_{h\in\mathcal{N}} [1 - p_h(\hat{\phi})] w_h^* F_h^* [\Lambda(\hat{\phi}\,' z_h^*) z_h^* - \Lambda(\hat{\phi}\,' z_h) z_h], \tag{IA.30}$$

$$\frac{\partial Z}{\partial \chi} = \frac{1}{F_R^* \log\left(\frac{F^*}{F}\right)} \sum_{h\in\mathcal{N}} p_h(\hat{\phi})\, w_h^*\, F_h^*\ z_h^*. \tag{IA.31}$$

Proof. We differentiate Z and obtain (IA.29), (IA.31), and

$$\frac{\partial Z}{\partial \phi} = \frac{1}{F_R^* \log\left(\frac{F^*}{F}\right)} \sum_{h \in \mathcal{N}} w_h^* \, F_h^* \, \frac{\partial p_h}{\partial \phi}(\hat{\phi}).$$

Since

$$p_h(\hat{\phi}) = \frac{\Lambda(\hat{\phi}' z_h^*) - 1}{1 - \Lambda(\hat{\phi}' z_h)} + 1, \tag{IA.32}$$

and $\Lambda'(u) = \Lambda(u)[1 - \Lambda(u)]$ for all u, we infer that

$$\frac{\partial p_h}{\partial \phi}(\hat{\phi}) = \frac{1 - \Lambda(\hat{\phi}' z_h^*)}{1 - \Lambda(\hat{\phi}' z_{h,t})} [\Lambda(\hat{\phi}' z_h^*) z_h^* - \Lambda(\hat{\phi}' z_h) z_h].$$

We conclude from (IA.32) that (IA.30) holds.

Since the regressions are estimated independently from each other, the variance-covariance matrix of $\hat{\omega} = (\hat{\theta}', \hat{\phi}', \hat{\chi}')'$ is block diagonal with diagonal elements $\hat{V}_\theta$, $\hat{V}_\phi$ and $\hat{V}_\chi$. We conclude that (IA.28) holds. ■

E. Yearly Estimates

In Figures 1 and 2 of the main text, we have considered twenty financial wealth quantiles and computed the aggregate elasticity ξ corresponding to an exogenous wealth shock that affects only households in a quantile. Figures 1 and 2 are based on the 2001 estimates. We now verify the robustness of our results in other years.

In Figure IA.3, we illustrate ξ for each quantile and each year in our sample when the set of participants is fixed. The curves are qualitatively similar in all years. The preferred linear elasticity specification generally implies a higher aggregate elasticity ξ than the heterogeneous CRRA specification. The few exceptions are due to negative values of the linear elasticity $\eta_h(f_h, x_h)$ for households with large financial wealth, which suggests that the specification of η_h could be improved.

In Figure IA.4, we report yearly estimates of the aggregate elasticity when participation changes are taken into account. The results are qualitatively similar to Figure 2 in the main text.

All elasticities have been so far calculated using yearly estimates of η (constant elasticity case) and η_0, η_1, and ψ (linear elasticity). We next illustrate the aggregate elasticity when η, η_0, η_1, and ψ are assumed to be constant over time. In Figures IA.5, we illustrate the aggregation results for the estimates reported in the third column of Table II. In Figure IA.6, we use instead the estimates in the last column of Table VI. The results are nearly identical to the ones reported in Figures IA.3 and IA4, which shows that our results are strongly robust to the choice of estimation method.

F. Homogenous Wealth Shock

In Table IA.XXXIII, we report the aggregate elasticity to a homogenous wealth shock $\Delta(f_h) = g$ for each year and scenario.

In the heterogeneous CRRA case (scenario 1), the aggregate elasticity equals unity when the set of participants is fixed. When participation is endogenous, the entry of new participants in response to a positive wealth shock implies that $F_R^* > e^g F_R$, and therefore $\xi > 1$. Table IA.XXXIII shows that deviations of ξ from unity are modest and do not exceed a few percentage points.

When the elasticity η is a constant common to all households in all years (scenario 2), aggregate risky wealth is $F_R^* = e^{g(1+\eta)} F_R$, and the aggregate elasticity satisfies

$$\xi = 1 + \eta.$$

The aggregate elasticity is slightly higher in the presence of participation effects. Once again, the deviations of ξ from unity are most pronounced under this scenario.

The heterogeneous elasticity specification (scenario 3), which is the most consistent with the micro evidence, provides aggregate elasticity estimates that remain close to unity, whether one considers a homogenous shock or concentrated shocks that affect only specific quantiles.

G. Impact of Negative Wealth Shocks

Entry and exit imply that the aggregate elasticity is in principle sensitive to the sign of the financial wealth shock. Figure 2 of the main text illustrates the impact of a 10% increase in the wealth of all households in a particular quantile. In Figure IA.7, we report the equivalent curve for a -10% wealth shock. Figures 2 and IA.7 are nearly identical. The explanation is that participation turnover is limited and only has a modest impact on the aggregate elasticity.

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Table IA.I
Summary Statistics and ACE Decomposition

	Identical Twins			Fraternal Twins			ACE Decomposition	
	Mean	Standard deviation	Twin correlation	Mean	Standard deviation	Twin correlation	Genetic component	Common component
Financial characteristics								
Risky share	0.541	0.289	0.266	0.543	0.291	0.149	23.41%	3.23%
Financial wealth ($)	44,730	69,070	0.418	47,611	73,877	0.269	29.89%	11.92%
Residential real estate wealth ($)	103,058	97,935	0.424	99,787	92,841	0.272	30.45%	11.97%
Commercial real estate wealth ($)	15,360	59,361	0.327	19,661	68,399	0.208	23.89%	8.81%
Leverage ratio	0.770	1.756	0.251	0.658	1.522	0.140	22.14%	2.96%
Human capital and income risk								
Log human capital	811,926	534,178	0.543	737,697	508,616	0.445	19.72%	34.63%
Permanent income risk	-0.001	0.063	0.118	-0.002	0.098	0.013	21.00%	-9.23%
Transitory income risk	0.051	0.250	0.137	0.063	0.405	0.027	22.07%	-8.38%
Beta of income innovation w.r.t. portfolio return	0.030	0.396	0.113	0.012	0.532	0.024	17.83%	-6.56%
Entrepreneur dummy	0.031	0.172	0.347	0.038	0.192	0.050	59.39%	-24.67%
Unemployment dummy	0.089	0.284	0.190	0.081	0.274	0.071	23.77%	-4.76%
Habit								
Internal habit ($)	36,408	16,919	0.418	35,903	16,925	0.235	36.57%	5.21%
External habit ($)	25,606	3,416	0.461	25,343	3,121	0.362	19.65%	26.40%
Demographic characteristics								
High school dummy	0.398	0.489	0.649	0.360	0.480	0.387	52.38%	12.52%
Post-high school dummy	0.871	0.335	0.511	0.830	0.375	0.312	39.71%	11.38%
Number of adults	1.727	0.445	0.280	1.729	0.445	0.089	38.16%	-10.21%
Number of children	1.032	1.086	0.468	0.993	1.116	0.375	18.50%	28.28%
Wealth-weighted gender index	0.530	0.323	0.378	0.548	0.325	0.029	69.71%	-31.92%
Number of observations	17,054			38,844				
Number of twin pairs	2,545			5,849				

Table IA.II
ACE Decomposition and Communication

Panel A: Risky Share				
	No Controls		With Controls	
	Genetic Component	Common Component	Genetic Component	Common Component
Frequent communicators	28.19%	8.98%	31.52%	-4.22%
Infrequent communicators	8.53%	6.42%	12.21%	-4.31%

Panel B: Log Risky Share				
	No Controls		With Controls	
	Genetic Component	Common Component	Genetic Component	Common Component
Frequent communicators	36.26%	-1.23%	39.72%	-10.47%
Infrequent communicators	2.08%	6.21%	1.62%	2.21%

Table IA.III
Identical vs. Fraternal Twins
Yearly twin pair fixed effects

	Identical Twins		Fraternal Twins	
	Estimate	*t*-stat	Estimate	*t*-stat
Financial wealth quartile				
Lowest	0.253	7.29	0.353	17.40
2	0.227	8.50	0.243	14.30
3	0.192	6.94	0.167	10.10
4	0.141	5.05	0.121	7.39
Log residential real estate wealth	0.000	-0.10	0.002	0.81
Log commercial real estate wealth	-0.003	-0.89	-0.005	-1.67
Leverage ratio	-0.002	-0.76	-0.004	-1.00
Human capital and income risk				
Log human capital	0.030	2.26	-0.006	-0.40
Permanent income risk	-0.754	-2.55	-0.167	-0.69
Transitory income risk	-0.050	-1.06	-0.047	-0.99
Beta of income innovation w.r.t. portfolio return	-0.011	-0.34	0.036	1.19
Entrepreneur dummy	-0.135	-1.53	-0.275	-4.43
Unemployment dummy	-0.012	-0.24	-0.087	-2.42
Habit				
Log internal habit	-0.066	-1.13	-0.040	-1.07
Log external habit	0.099	0.68	0.002	0.02
Demographic characteristics				
High school dummy	0.085	1.33	0.027	0.67
Post-high school dummy	0.039	0.78	0.033	1.16
Number of adults	-0.032	-0.60	-0.144	-3.98
Number of children	-0.085	-4.27	-0.051	-3.64
Wealth-weighted gender index	0.011	0.18	-0.093	-2.66
Adjusted R^2	25.15%		17.73%	
Number of observations	17,054		38,844	
Number of twin pairs	2,545		5,849	

Table IA.IV
Yearly Twin Regressions
Twin pair fixed effects

	1999		2000		2001		2002	
	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat
Financial characteristics								
Log financial wealth	0.280	25.90	0.248	24.10	0.226	18.70	0.117	8.01
Log residential real estate wealth	0.002	0.58	0.004	1.41	0.003	0.95	0.000	0.03
Log commercial real estate wealth	-0.007	-2.43	-0.005	-2.07	-0.005	-1.66	-0.004	-1.26
Leverage ratio	-0.004	-1.07	-0.004	-1.63	-0.009	-1.93	-0.010	-1.89
Human capital and income risk								
Log human capital	-0.019	-0.73	0.006	0.40	0.001	0.08	0.018	1.31
Permanent income risk	-0.007	-0.02	-0.348	-1.40	-0.228	-0.91	-0.449	-1.51
Transitory income risk	-0.054	-0.99	-0.103	-1.90	-0.044	-1.12	-0.091	-1.39
Beta of income innovation w.r.t. portfolio return	0.040	0.90	0.022	0.56	-0.003	-0.14	0.084	2.84
Entrepreneur dummy	-0.281	-4.24	-0.274	-4.73	-0.299	-4.40	-0.173	-2.18
Unemployment dummy	-0.099	-2.28	-0.020	-0.54	-0.071	-1.71	-0.125	-2.41
Habit								
Log internal habit	-0.139	-3.17	-0.074	-2.06	-0.102	-2.57	-0.041	-0.85
Log external habit	0.052	0.49	-0.015	-0.17	0.146	1.35	-0.032	-0.23
Demographic characteristics								
High school dummy	0.063	1.59	0.042	1.13	0.046	1.10	0.033	0.67
Post-high school dummy	0.033	1.04	0.002	0.08	0.066	2.11	0.053	1.50
Dummy for unavailable education data	0.867	1.67	0.340	1.21	0.517	2.79	0.986	1.50
Number of adults	-0.075	-1.95	-0.091	-2.62	-0.051	-1.33	-0.051	-1.12
Number of children	-0.055	-3.86	-0.064	-4.75	-0.047	-3.29	-0.033	-1.89
Wealth-weighted gender index	-0.037	-1.00	-0.076	-2.16	-0.105	-2.68	-0.087	-1.95
Adjusted R^2	22.15%		20.27%		17.25%		13.44%	
Number of observations	13,718		14,702		14,164		13,314	
Number of twin pairs	6,859		7,351		7,082		6,657	

Table IA.V

Regression of the Log Risky Share on Characteristics (All twins)

Normalized real estate, human capital and habit

	Yearly Twin Pair Fixed Effects						Yearly Fixed	
	(1)		(2)		(3)		(4)	
	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat
Financial characteristics								
Log financial wealth	0.196	24.60	0.088	1.02	0.171	1.92	0.078	1.40
Log of financial wealth/residential real estate			0.000	0.10	-0.002	-1.03	-0.005	-2.97
Log of financial wealth/commercial real estate			0.007	3.16	0.005	2.43	0.008	6.04
Leverage ratio			-0.006	-2.49	-0.006	-2.46	-0.007	-2.84
Human capital and income risk								
Log of financial wealth/human capital			0.004	0.31	-0.002	-0.19	-0.020	-2.10
Permanent income risk			-0.222	-1.10	-0.276	-1.32	-0.384	-2.31
Transitory income risk			-0.060	-1.58	-0.073	-1.79	-0.120	-2.86
Beta of income innovation w.r.t. portfolio return			0.034	1.39	0.027	1.09	0.032	1.37
Entrepreneur dummy			-0.295	-5.61	-0.257	-4.89	-0.200	-4.93
Unemployment dummy			-0.081	-2.74	-0.075	-2.55	-0.090	-3.89
Habit								
Log of financial wealth/internal habit			0.166	6.42	0.089	2.82	0.111	5.30
Log of financial wealth/external habit			-0.042	-0.49	-0.038	-0.44	0.059	1.06
Demographic characteristics								
High school dummy					0.046	1.33	0.116	5.27
Post-high school dummy					0.037	1.50	0.066	4.60
Number of adults					-0.071	-2.38	-0.110	-5.30
Number of children					-0.050	-4.37	-0.037	-5.02
Wealth-weighted gender index					-0.076	-2.49	-0.029	-1.33
Adjusted R^2	17.99%		18.79%		19.10%		11.50%	
Number of observations	55,898		55,898		55,898		55,898	
Number of twin pairs	8,394		8,394		8,394		8,394	

Table IA.VI

Regression of the Log Risky Share on Characteristics (Identical Twins)

Normalized real estate, human capital and habit

	Yearly Twin Pair Fixed Effects						Yearly Fixed	
	(1)		(2)		(3)		(4)	
	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat
Financial characteristics								
Log financial wealth	0.184	12.60	0.147	1.01	0.236	1.59	-0.001	-0.02
Log of financial wealth/residential real estate			0.001	0.31	0.000	-0.03	-0.005	-1.94
Log of financial wealth/commercial real estate			0.005	1.18	0.004	1.03	0.008	3.21
Leverage ratio			-0.002	-1.07	-0.003	-1.14	-0.002	-1.08
Human capital and income risk								
Log of financial wealth/human capital			-0.022	-1.64	-0.030	-2.25	-0.039	-3.07
Permanent income risk			-0.664	-2.13	-0.770	-2.57	-0.425	-1.75
Transitory income risk			-0.045	-0.94	-0.073	-1.48	-0.097	-1.56
Beta of income innovation w.r.t. portfolio return			0.004	0.12	-0.007	-0.23	-0.020	-0.81
Entrepreneur dummy			-0.141	-1.58	-0.133	-1.49	-0.037	-0.60
Unemployment dummy			-0.023	-0.46	-0.013	-0.27	-0.041	-1.12
Habit								
Log of financial wealth/internal habit			0.155	3.22	0.096	1.72	0.124	3.33
Log of financial wealth/external habit			-0.079	-0.54	-0.099	-0.69	0.141	1.46
Demographic characteristics								
High school dummy					0.090	1.40	0.116	2.87
Post-high school dummy					0.041	0.81	0.061	2.39
Number of adults					-0.009	-0.17	-0.059	-1.61
Number of children					-0.082	-4.15	-0.059	-4.73
Wealth-weighted gender index					0.007	0.12	-0.004	-0.09
Adjusted R^2	24.33%		24.62%		25.02%		11.39%	
Number of observations	17,054		17,054		17,054		17,054	
Number of twin pairs	2,545		2,545		2,545		2,545	

Table IA.VII
Regression of the Log Risky Share on Characteristics (All Twins)
Human capital of the young computed with a high discount rate

	(1)		(2)	
	Estimate	*t*-stat	Estimate	*t*-stat
Log financial wealth	0.223	24.60		
Financial wealth quartile				
Lowest			0.331	18.90
2			0.243	16.80
3			0.171	12.30
4			0.129	9.07
Log residential real estate wealth	0.002	1.03	0.001	0.66
Log commercial real estate wealth	-0.005	-2.43	-0.004	-1.91
Leverage ratio	-0.006	-2.46	-0.003	-1.12
Human capital and income risk				
Log human capital (r =5% if age < 35yrs, 3% if age ≥ 35)	0.002	0.18	0.001	0.05
Permanent income risk	-0.276	-1.31	-0.241	-1.17
Transitory income risk	-0.073	-1.78	-0.050	-1.26
Beta of income innovation w.r.t. portfolio return	0.027	1.09	0.027	1.08
Entrepreneur dummy	-0.257	-4.89	-0.250	-4.76
Unemployment dummy	-0.075	-2.55	-0.065	-2.24
Habit				
Log internal habit	-0.089	-2.82	-0.044	-1.40
Log external habit	0.038	0.44	0.038	0.44
Demographic characteristics				
High school dummy	0.046	1.33	0.041	1.19
Post-high school dummy	0.037	1.50	0.034	1.39
Number of adults	-0.071	-2.38	-0.112	-3.70
Number of children	-0.050	-4.37	-0.060	-5.23
Wealth-weighted gender index	-0.076	-2.49	-0.070	-2.32
Adjusted R^2	19.10%		19.72%	
Number of observations	55,898		55,898	
Number of twin pairs	8,394		8,394	

Table IA.VIII

Regression of the Log Risky Share on Characteristics (Identical Twins)

Human capital of the young computed with a high discount rate

	(1)		(2)	
	Estimate	*t*-stat	Estimate	*t*-stat
Log financial wealth	0.207	12.00		
Financial wealth quartile				
Lowest			0.253	7.29
2			0.227	8.50
3			0.191	6.94
4			0.141	5.05
Log residential real estate wealth	0.000	0.03	0.000	-0.10
Log commercial real estate wealth	-0.004	-1.03	-0.003	-0.89
Leverage ratio	-0.003	-1.14	-0.002	-0.76
Human capital and income risk				
Log human capital (r =5% if age < 35yrs, 3% if age ≥ 35)	0.030	2.17	0.029	2.17
Permanent income risk	-0.759	-2.50	-0.742	-2.48
Transitory income risk	-0.072	-1.45	-0.049	-1.03
Beta of income innovation w.r.t. portfolio return	-0.007	-0.23	-0.011	-0.34
Entrepreneur dummy	-0.133	-1.49	-0.135	-1.53
Unemployment dummy	-0.013	-0.27	-0.012	-0.24
Habit				
Log internal habit	-0.096	-1.72	-0.066	-1.13
Log external habit	0.100	0.69	0.099	0.68
Demographic characteristics				
High school dummy	0.090	1.40	0.085	1.33
Post-high school dummy	0.041	0.81	0.039	0.78
Number of adults	-0.009	-0.16	-0.032	-0.59
Number of children	-0.082	-4.15	-0.085	-4.27
Wealth-weighted gender index	0.007	0.11	0.011	0.18
Adjusted R^2	25.02%		25.15%	
Number of observations	17,054		17,054	
Number of twin pairs	2,545		2,545	

Table IA.IX

Regression of the Log Risky Share on Characteristics (All Twins)

Human capital of low wealth-households computed with a high discount rate

	(1)		(2)	
	Estimate	t-stat	Estimate	t-stat
Log financial wealth	0.223	24.60		
Financial wealth quartile				
Lowest			0.331	18.90
2			0.244	16.80
3			0.171	12.20
4			0.129	9.07
Log residential real estate wealth	0.002	1.03	0.001	0.66
Log commercial real estate wealth	-0.005	-2.43	-0.004	-1.92
Leverage ratio	-0.006	-2.46	-0.003	-1.12
Human capital and income risk				
Log human capital (r =5% if financial wealth < median, 3% otherwise)	-0.001	-0.08	-0.002	-0.18
Permanent income risk	-0.241	-1.16	-0.211	-1.03
Transitory income risk	-0.067	-1.67	-0.045	-1.15
Beta of income innovation w.r.t. portfolio return	0.027	1.09	0.027	1.08
Entrepreneur dummy	-0.257	-4.89	-0.250	-4.76
Unemployment dummy	-0.075	-2.55	-0.066	-2.24
Habit				
Log internal habit	-0.087	-2.75	-0.042	-1.34
Log external habit	0.038	0.44	0.038	0.44
Demographic characteristics				
High school dummy	0.045	1.32	0.041	1.18
Post-high school dummy	0.037	1.51	0.034	1.39
Number of adults	-0.071	-2.36	-0.111	-3.69
Number of children	-0.050	-4.36	-0.060	-5.22
Wealth-weighted gender index	-0.076	-2.49	-0.070	-2.32
Adjusted R^2	19.10%		19.72%	
Number of observations	55,898		55,898	
Number of twin pairs	8,394		8,394	

Table IA.X

Regression of the Log Risky Share on Characteristics (Identical Twins)

Human capital of low wealth-households computed with a high discount rate

	(1)		(2)	
	Estimate	*t*-stat	Estimate	*t*-stat
Log financial wealth	0.205	11.90		
Financial wealth quartile				
Lowest			0.252	7.27
2			0.225	8.41
3			0.190	6.86
4			0.141	5.03
Log residential real estate wealth	0.000	0.03	0.000	-0.10
Log commercial real estate wealth	-0.004	-1.03	-0.003	-0.89
Leverage ratio	-0.003	-1.14	-0.002	-0.76
Human capital and income risk				
Log human capital (r =5% if financial wealth < median, 3% otherwise)	0.027	1.97	0.026	1.93
Permanent income risk	-0.717	-2.34	-0.693	-2.28
Transitory income risk	-0.066	-1.34	-0.042	-0.88
Beta of income innovation w.r.t. portfolio return	-0.007	-0.23	-0.011	-0.33
Entrepreneur dummy	-0.133	-1.49	-0.136	-1.53
Unemployment dummy	-0.013	-0.27	-0.012	-0.24
Habit				
Log internal habit	-0.094	-1.68	-0.064	-1.10
Log external habit	0.100	0.69	0.100	0.69
Demographic characteristics				
High school dummy	0.089	1.39	0.085	1.32
Post-high school dummy	0.041	0.81	0.040	0.78
Number of adults	-0.008	-0.15	-0.031	-0.58
Number of children	-0.082	-4.15	-0.085	-4.26
Wealth-weighted gender index	0.007	0.11	0.011	0.17
Adjusted R^2	25.02%		25.14%	
Number of observations	17,054		17,054	
Number of twin pairs	2,545		2,545	

Table IA.XI

Regression of the Log Risky Share on Characteristics

External habit computed on age-municipality groups

	(1)		(2)	
	Estimate	*t*-stat	Estimate	*t*-stat
Log financial wealth	0.223	24.60		
Financial wealth quartile				
Lowest			0.331	18.90
2			0.243	16.80
3			0.171	12.30
4			0.129	9.07
Log residential real estate wealth	0.002	1.02	0.001	0.67
Log commercial real estate wealth	-0.005	-2.42	-0.004	-1.91
Leverage ratio	-0.006	-2.46	-0.003	-1.12
Human capital and income risk				
Log human capital	0.002	0.19	0.001	0.06
Permanent income risk	-0.277	-1.32	-0.242	-1.19
Transitory income risk	-0.073	-1.79	-0.050	-1.27
Beta of income innovation w.r.t. portfolio return	0.027	1.10	0.027	1.08
Entrepreneur dummy	-0.257	-4.89	-0.250	-4.76
Unemployment dummy	-0.075	-2.55	-0.066	-2.25
Habit				
Log internal habit	-0.089	-2.84	-0.045	-1.42
Log external habit (age and municipality groups)	0.041	0.59	0.034	0.50
Demographic characteristics				
High school dummy	0.046	1.33	0.041	1.19
Post-high school dummy	0.037	1.50	0.034	1.39
Number of adults	-0.071	-2.37	-0.111	-3.70
Number of children	-0.050	-4.38	-0.060	-5.23
Wealth-weighted gender index	-0.076	-2.49	-0.070	-2.32
Adjusted R^2	19.10%		19.72%	
Number of observations	55,898		55,898	
Number of twin pairs	8,394		8,394	

Table IA.XII
Regression of the Log Risky Share on Characteristics
Higher education variables

	(1)		(2)	
	Estimate	*t*-stat	Estimate	*t*-stat
Log financial wealth	0.223	24.60		
Financial wealth quartile				
Lowest			0.331	18.90
2			0.243	16.80
3			0.171	12.20
4			0.129	9.07
Log residential real estate wealth	0.002	1.02	0.001	0.66
Log commercial real estate wealth	-0.005	-2.40	-0.004	-1.89
Leverage ratio	-0.006	-2.49	-0.003	-1.15
Human capital and income risk				
Log human capital	0.002	0.21	0.001	0.08
Permanent income risk	-0.277	-1.33	-0.243	-1.19
Transitory income risk	-0.074	-1.82	-0.051	-1.30
Beta of income innovation w.r.t. portfolio return	0.027	1.10	0.027	1.09
Entrepreneur dummy	-0.258	-4.90	-0.251	-4.77
Unemployment dummy	-0.075	-2.54	-0.065	-2.23
Habit				
Log internal habit	-0.092	-2.94	-0.048	-1.53
Log external habit	0.038	0.43	0.037	0.43
Demographic characteristics				
High school dummy	0.046	1.34	0.042	1.21
Undergraduate dropout dummy	0.024	0.93	0.021	0.80
3-yr undergraduate (college or vocational) degree dummy	0.047	1.52	0.050	1.62
Post-graduate education dummy	0.050	0.60	0.041	0.50
Number of adults	-0.069	-2.30	-0.109	-3.62
Number of children	-0.050	-4.38	-0.060	-5.24
Wealth-weighted gender index	-0.077	-2.52	-0.071	-2.34
Adjusted R^2	19.11%		19.73%	
Number of observations	55,898		55,898	
Number of twin pairs	8,394		8,394	

Table IA.XIII
Regression of the Log Risky Share on Characteristics
Marriage status

	(1)		(2)	
	Estimate	*t*-stat	Estimate	*t*-stat
Log financial wealth	0.205	11.90		
Financial wealth quartile				
Lowest			0.331	18.90
2			0.243	16.80
3			0.172	12.30
4			0.129	9.09
Log residential real estate wealth	0.000	0.03	0.001	0.64
Log commercial real estate wealth	-0.004	-1.03	-0.004	-1.92
Leverage ratio	-0.003	-1.14	-0.003	-1.14
Human capital and income risk				
Log human capital	0.027	1.97	0.001	0.05
Permanent income risk	-0.717	-2.34	-0.241	-1.18
Transitory income risk	-0.066	-1.34	-0.050	-1.29
Beta of income innovation w.r.t. portfolio return	-0.007	-0.23	0.027	1.08
Entrepreneur dummy	-0.133	-1.49	-0.250	-4.77
Unemployment dummy	-0.013	-0.27	-0.065	-2.22
Habit				
Log internal habit	-0.094	-1.68	-0.046	-1.45
Log external habit	0.100	0.69	0.035	0.41
Demographic characteristics				
High school dummy	0.089	1.39	0.041	1.19
Post-high school dummy	0.041	0.81	0.034	1.40
Number of adults	-0.008	-0.15	-0.134	-3.50
Number of children	-0.082	-4.15	-0.060	-5.19
Marriage dummy	0.031	0.99	0.029	0.92
Wealth-weighted gender index	0.007	0.11	-0.070	-2.32
Adjusted R^2	19.11%		19.72%	
Number of observations	17,054		55,898	
Number of twin pairs	8,394		8,394	

Table IA.XIV
Age
Yearly twin pair fixed effects

	Less than 35		35-45		45-55		Older than 55	
	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat
Financial characteristics								
Log financial wealth	0.223	8.76	0.255	13.70	0.220	14.80	0.194	11.30
Log residential real estate wealth	-0.002	-0.38	0.001	0.23	0.001	0.35	0.010	1.98
Log commercial real estate wealth	-0.007	-1.00	-0.004	-1.05	-0.004	-1.09	-0.007	-1.59
Leverage ratio	-0.007	-1.40	-0.002	-0.48	-0.012	-2.25	-0.001	-0.55
Human capital and income risk								
Log human capital	0.024	1.81	0.025	1.30	-0.044	-1.39	0.004	0.09
Permanent income risk	-0.439	-1.29	-0.535	-1.52	0.212	0.50	-0.309	-0.61
Transitory income risk	-0.081	-1.27	-0.111	-1.76	0.005	0.05	-0.061	-0.53
Beta of income innovation w.r.t. portfolio return	0.090	0.84	0.090	2.45	-0.021	-0.55	0.006	0.30
Entrepreneur dummy	-0.377	-2.25	-0.233	-2.61	-0.268	-2.82	-0.243	-2.57
Unemployment dummy	-0.059	-0.99	-0.004	-0.07	-0.126	-2.25	-0.104	-1.66
Habit								
Log internal habit	-0.003	-0.04	-0.148	-2.40	-0.065	-1.16	-0.061	-0.87
Log external habit	0.050	0.20	-0.151	-0.89	0.076	0.55	0.202	1.09
Demographic characteristics								
High school dummy	0.172	1.02	0.096	1.25	0.021	0.38	0.015	0.24
Post-high school dummy	0.028	0.49	-0.010	-0.22	0.033	0.76	0.109	1.95
Number of adults	-0.168	-2.12	0.065	1.03	-0.054	-1.07	-0.145	-2.47
Number of children	-0.074	-2.13	-0.086	-4.09	-0.020	-1.14	-0.103	-2.89
Wealth-weighted gender index	0.064	0.88	-0.186	-2.89	-0.058	-1.12	-0.106	-1.73
Adjusted R^2	25.89%		21.89%		16.23%		15.99%	
Number of observations	8,382		14,374		20,134		13,008	
Number of twin pairs	1,368		2,057		2,888		2,081	

Table IA.XV
Relation Between Elasticity and Age
Age squared interacted with financial wealth – Yearly twin pair fixed effects

	Direct Effect		Interacted	
	Estimate	*t*-stat	Estimate	*t*-stat
Financial characteristics				
Log financial wealth	0.222	25.20	-0.105	-11.20
Log residential real estate wealth	0.002	0.84	0.007	2.65
Log commercial real estate wealth	-0.004	-1.97	-0.002	-0.96
Leverage ratio	0.000	0.01	0.004	1.20
Human capital and income risk				
Log human capital	-0.003	-0.25	0.018	1.30
Permanent income risk	-0.118	-0.56	-0.353	-1.48
Transitory income risk	-0.019	-0.43	-0.037	-0.65
Beta of income innovation w.r.t. portfolio return	0.031	1.06	-0.018	-0.69
Entrepreneur dummy	-0.240	-4.58	-0.040	-0.80
Unemployment dummy	-0.059	-2.02	0.052	1.59
Habit				
Log internal habit	-0.008	-0.26	0.003	0.10
Log external habit	0.027	0.32	-0.036	-0.45
Demographic characteristics				
High school dummy	0.038	1.13	0.049	1.69
Post-high school dummy	0.026	1.05	-0.011	-0.51
Age			-0.004	-0.47
Age squared			0.000	1.02
Number of adults	-0.102	-3.35	0.120	3.71
Number of children	-0.070	-6.00	0.071	6.22
Wealth-weighted gender index	-0.054	-1.72	0.061	1.85
Adjusted R^2	20.71%			
Number of observations	55,898			
Number of twin pairs	8,394			

Table IA.XVI
Communication (All Twins)
Yearly twin pair fixed effects

	Infrequent Communication				Frequent Communication			
	(1)		(2)		(3)		(4)	
	Estimate	*t*- stat	Estimate	*t*- stat	Estimate	*t*- stat	Estimate	*t*- stat
Log financial wealth	0.241	11.00			0.205	8.18		
Financial wealth quartile								
Lowest			0.253	7.29			0.353	17.40
2			0.227	8.50			0.243	14.30
3			0.192	6.94			0.167	10.10
4			0.141	5.05			0.121	7.39
Log residential real estate wealth	0.006	1.09	0.000	-0.10	-0.002	-0.42	0.002	0.81
Log commercial real estate wealth	-0.005	-0.73	-0.003	-0.89	-0.001	-0.09	-0.005	-1.67
Leverage ratio	-0.004	-0.73	-0.002	-0.76	-0.005	-1.50	-0.004	-1.00
Human capital and income risk								
Log human capital	0.027	1.10	0.030	2.26	-0.033	-1.39	-0.006	-0.40
Permanent income risk	-0.558	-1.36	-0.754	-2.55	0.738	1.33	-0.167	-0.69
Transitory income risk	-0.095	-0.94	-0.050	-1.06	0.178	1.36	-0.047	-0.99
Beta of income innovation w.r.t. portfolio return	0.029	0.47	-0.011	-0.34	-0.010	-0.63	0.036	1.19
Entrepreneur dummy	-0.322	-2.33	-0.135	-1.53	-0.291	-2.18	-0.275	-4.43
Unemployment dummy	-0.188	-2.20	-0.012	-0.24	-0.017	-0.25	-0.087	-2.42
Habit								
Log internal habit	-0.104	-1.42	-0.066	-1.13	-0.112	-1.45	-0.040	-1.07
Log external habit	0.077	0.38	0.099	0.68	0.732	2.55	0.002	0.02
Demographic characteristics								
High school dummy	0.028	0.31	0.085	1.33	0.040	0.48	0.027	0.67
Post-high school dummy	0.071	1.17	0.039	0.78	0.104	1.47	0.033	1.16
Number of adults	-0.181	-2.22	-0.032	-0.60	0.114	1.49	-0.144	-3.98
Number of children	-0.029	-1.05	-0.085	-4.27	-0.075	-2.63	-0.051	-3.64
Wealth-weighted gender index	-0.093	-1.23	0.011	0.18	-0.087	-1.05	-0.093	-2.66
Adjusted R^2	15.32%		16.73%		27.33%		27.67%	
Number of observations	8,898		17,054		8,878		38,844	
Number of twin pairs	1,385		1,385		1,376		1,376	

Table IA.XVII
Communication (Identical Twins)
Yearly twin pair fixed effects

	Infrequent Communication				Frequent Communication			
	(1)		(2)		(3)		(4)	
	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat
Log financial wealth	0.220	5.45			0.240	5.47		
Financial wealth quartile								
Lowest			0.258	4.34			0.427	4.24
2			0.217	4.23			0.273	3.81
3			0.210	2.67			0.165	2.26
4			0.164	2.08			0.185	3.39
Log residential real estate wealth	0.018	1.86	0.017	1.71	-0.013	-1.48	-0.016	-1.72
Log commercial real estate wealth	0.007	0.68	0.007	0.68	-0.010	-1.14	-0.009	-1.02
Leverage ratio	0.002	0.62	0.003	0.95	-0.007	-2.19	-0.006	-2.11
Human capital and income risk								
Log human capital	0.183	1.29	0.174	1.22	-0.089	-1.29	-0.082	-1.19
Permanent income risk	-1.294	-1.39	-1.172	-1.23	2.956	2.39	2.825	2.30
Transitory income risk	-0.385	-2.46	-0.327	-1.89	0.829	3.49	0.825	3.53
Beta of income innovation w.r.t. portfolio return	-0.092	-1.38	-0.099	-1.49	-0.259	-2.09	-0.259	-2.08
Entrepreneur dummy	-0.132	-0.66	-0.153	-0.77	0.068	0.25	0.063	0.22
Unemployment dummy	0.009	0.08	0.017	0.14	0.201	1.87	0.208	1.95
Habit								
Log internal habit	-0.061	-0.30	-0.042	-0.20	0.037	0.24	0.029	0.20
Log external habit	-0.365	-1.35	-0.360	-1.33	0.088	0.17	0.012	0.02
Demographic characteristics								
High school dummy	0.325	1.72	0.318	1.64	-0.025	-0.15	-0.014	-0.09
Post-high school dummy	-0.045	-0.29	-0.041	-0.27	-0.001	0.00	-0.010	-0.08
Number of adults	-0.048	-0.30	-0.057	-0.36	0.133	1.03	0.081	0.60
Number of children	-0.094	-2.10	-0.099	-2.12	-0.105	-2.02	-0.109	-2.10
Wealth-weighted gender index	-0.156	-1.00	-0.153	-0.99	-0.119	-0.79	-0.088	-0.58
Adjusted R^2	14.95%		15.02%		40.24%		40.83%	
Number of observations	2,822		2,822		2,422		2,422	
Number of twin pairs	419		419		370		370	

Table IA.XVIII
Variance Decomposition Within and Across Municipalities

	Risky share	Log risky share	Residual
Variance between municipalities	0.25%	2.93%	0.52%
Variance within municipalities	7.93%	98.64%	41.25%
Total variance	8.18%	101.57%	41.78%

Table IA.XIX
Impact of Average Wealth and Risky share in Municipality
Yearly twin pair fixed effects

	(1)		(2)	
	Estimate	*t*-stat	Estimate	*t*-stat
Log financial wealth	0.222	24.60		
Financial wealth quartile				
Lowest			0.330	18.90
2			0.242	16.70
3			0.172	12.30
4			0.128	9.03
Log residential real estate wealth	0.002	1.08	0.002	0.71
Log commercial real estate wealth	-0.005	-2.28	-0.004	-1.80
Leverage ratio	-0.006	-2.49	-0.003	-1.15
Human capital and income risk				
Log human capital	0.002	0.19	0.001	0.06
Permanent income risk	-0.271	-1.31	-0.237	-1.17
Transitory income risk	-0.072	-1.78	-0.049	-1.26
Beta of income innovation w.r.t. portfolio return	0.028	1.13	0.028	1.11
Entrepreneur dummy	-0.256	-4.87	-0.249	-4.74
Unemployment dummy	-0.074	-2.52	-0.065	-2.22
Habit				
Log internal habit	-0.088	-2.81	-0.044	-1.38
Log external habit	-0.215	-1.54	-0.227	-1.63
Demographic characteristics				
High school dummy	0.046	1.33	0.041	1.20
Post-high school dummy	0.035	1.42	0.032	1.32
Number of adults	-0.071	-2.37	-0.112	-3.71
Number of children	-0.050	-4.31	-0.060	-5.17
Wealth-weighted gender index	-0.077	-2.51	-0.071	-2.34
Local interactions				
Average log risky share in municipality	0.356	3.46	0.342	3.36
Average log financial wealth in municipality	0.116	1.95	0.123	2.09
Adjusted R^2	19.19%		19.80%	
Number of observations	55,898		55,898	
Number of twin pairs	8,394		8,394	

Table IA.XX

Financial Wealth Elasticity of the Risky Share

Interacted individual characteristics

	(1)				(2)			
	Direct Effect		Interacted		Direct Effect		Interacted	
	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat
Financial characteristics								
Log financial wealth	0.217	24.80	-0.065	-13.50	0.236	25.30	-0.071	-14.20
Log residential real estate wealth	0.002	1.09			0.005	1.99	0.004	2.82
Log commercial real estate wealth	-0.004	-1.95			-0.005	-2.15	0.000	-0.06
Leverage ratio	-0.001	-0.52			0.011	1.03	0.006	1.66
Human capital and income risk								
Log human capital	0.000	0.00			-0.015	-1.16	-0.013	-1.87
Permanent income risk	-0.249	-1.22			-0.065	-0.31	-0.061	-0.57
Transitory income risk	-0.058	-1.44			-0.023	-0.52	0.014	0.61
Beta of income innovation w.r.t. portfolio return	0.027	1.07			0.027	1.07	-0.005	-0.48
Entrepreneur dummy	-0.266	-5.09			-0.255	-4.83	-0.009	-0.27
Unemployment dummy	-0.072	-2.48			-0.058	-2.00	0.034	1.77
Habit								
Log internal habit	-0.088	-2.68	0.126	8.88	-0.016	-0.47	0.047	2.83
Log external habit	0.017	0.20			-0.022	-0.24	0.011	0.21
Demographic characteristics								
High school dummy	0.044	1.29			0.033	0.99	0.007	0.33
Post-high school dummy	0.033	1.36			0.024	0.99	-0.013	-0.92
Number of adults	-0.083	-2.70			-0.092	-3.04	0.110	6.02
Number of children	-0.056	-4.94			-0.066	-5.84	0.064	8.88
Wealth-weighted gender index	-0.061	-2.02			-0.061	-2.02	0.019	1.00
Adjusted R^2	20.34%				21.55%			
Number of observations	55,898				55,898			
Number of twin pairs	8,394				8,394			

Table IA.XXI
Impact of the Pair Fixed Effect on the Financial Wealth Elasticity of the Risky Share

	Direct Effect		Interacted	
	Estimate	*t*-stat	Estimate	*t*-stat
Financial characteristics				
Log financial wealth	0.219	27.20	-0.092	-10.30
Log residential real estate wealth	0.003	1.19	0.007	2.94
Log commercial real estate wealth	-0.005	-2.10	-0.002	-0.90
Leverage ratio	0.000	-0.11	0.003	1.23
Yearly twin pair fixed effect			-0.116	-5.24
Human capital and income risk				
Log human capital	-0.001	-0.09	-0.016	-1.32
Permanent income risk	-0.151	-0.70	-0.113	-0.49
Transitory income risk	-0.033	-0.71	-0.002	-0.03
Beta of income innovation w.r.t. portfolio return	0.031	1.07	-0.014	-0.54
Entrepreneur dummy	-0.250	-4.79	-0.035	-0.70
Unemployment dummy	-0.060	-2.09	0.046	1.46
Habit				
Log internal habit	-0.020	-0.62	0.018	0.63
Log external habit	0.016	0.19	-0.042	-0.54
Demographic characteristics				
High school dummy	0.038	1.13	0.036	1.28
Post-high school dummy	0.027	1.10	-0.011	-0.51
Number of adults	-0.088	-2.93	0.130	4.05
Number of children	-0.065	-5.62	0.056	5.52
Wealth-weighted gender index	-0.051	-1.65	0.067	2.01
Adjusted R^2	21.47%			
Number of observations	55,898			
Number of twin pairs	8,394			

Table IA.XXII
Randomly Matched Pairs

Panel A: Regression Coefficients								
	Yearly Twin Pair Fixed Effects						Yearly Fixed	
	(1)		(2)		(3)		(4)	
	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat
Financial characteristics								
Log financial wealth	0.198	28.00	0.223	26.90	0.216	25.80	0.231	38.80
Log residential real estate wealth			0.003	1.18	0.005	2.28	0.005	2.99
Log commercial real estate wealth			-0.010	-5.08	-0.008	-4.37	-0.008	-6.20
Leverage ratio			-0.006	-2.08	-0.007	-2.40	-0.007	-2.85
Human capital and income risk								
Log human capital			0.014	1.28	0.022	1.87	0.020	2.13
Permanent income risk			-0.277	-1.69	-0.369	-2.12	-0.384	-2.32
Transitory income risk			-0.091	-2.70	-0.117	-3.15	-0.120	-2.87
Beta of income innovation w.r.t. portfolio return			0.036	1.48	0.026	1.08	0.032	1.37
Entrepreneur dummy			-0.179	-3.26	-0.136	-2.49	-0.200	-4.96
Unemployment dummy			-0.105	-3.42	-0.084	-2.74	-0.090	-3.91
Habit								
Log internal habit			-0.170	-7.01	-0.122	-4.38	-0.111	-5.38
Log external habit			-0.031	-0.37	-0.066	-0.80	-0.059	-1.08
Demographic characteristics								
High school dummy					0.122	4.57	0.116	5.56
Post-high school dummy					0.064	3.25	0.066	4.64
Number of adults					-0.078	-2.79	-0.110	-5.33
Number of children					-0.035	-3.57	-0.037	-5.16
Wealth-weighted gender index					-0.003	-0.10	-0.029	-1.36
Adjusted R^2	11.39%		12.27%		12.82%		11.50%	
Number of observations	55,898		55,898		55,898		55,898	
Number of twin pairs	8,394		8,394		8,394		8,394	

Table IA.XXII – *Continued*

Panel B: Variance Decomposition				
	Yearly Twin Pair			Yearly
	(1)	(2)	(3)	(4)
Adjusted R^2	11.39%	12.27%	12.82%	11.50%
Contribution of the variance of:				
Fixed effect (ω_α^2)	3.04%	2.58%	2.56%	1.12%
Log financial wealth (ω_f^2)	7.03%	8.98%	8.38%	9.61%
Other observable characterics (ω_x^2)		1.03%	1.54%	1.89%
Contribution of the covariance of:				
Fixed effect and financial wealth ($2\ \omega_{\alpha,f}$)	1.33%	1.44%	1.37%	0.31%
Fixed effect and other characteristics ($2\ \omega_{\alpha,x}$)		0.25%	0.30%	0.11%
Financial wealth and other characteristics ($2\ \omega_{f,x}$)		-2.01%	-1.33%	-1.54%

Table IA.XXIII
Tobit Regression of the Risky Share on Characteristics
Yearly fixed effects

	(1)			(2)		
	Estimate	t-stat	Implied η	Estimate	t-stat	Implied η
Log financial wealth	0.161	98.30	0.386			
Financial wealth quartile						
Lowest				0.188	46.10	1.453
2				0.199	55.10	0.505
3				0.192	58.40	0.372
4				0.182	60.60	0.286
Log residential real estate wealth	0.003	7.03		0.003	6.00	
Log commercial real estate wealth	-0.003	-6.79		-0.002	-4.97	
Leverage ratio	-0.003	-5.98		-0.002	-3.88	
Human capital and income risk						
Log human capital	0.023	6.14		0.021	5.95	
Permanent income risk	-0.345	-4.71		-0.310	-4.57	
Transitory income risk	-0.088	-4.18		-0.076	-3.98	
Entrepreneur dummy	-0.067	-5.78		-0.063	-5.49	
Unemployment dummy	-0.025	-4.08		-0.019	-3.17	
Habit						
Log internal habit	-0.062	-9.28		-0.049	-7.33	
Log external habit	-0.032	-1.88		-0.025	-1.48	
Demographic characteristics						
High school dummy	0.052	8.84		0.050	8.59	
Post-high school dummy	0.031	6.70		0.032	6.89	
Dummy for unavailable education data	0.046	0.67		0.036	0.53	
Number of adults	-0.021	-3.34		-0.041	-6.50	
Number of children	-0.009	-3.96		-0.017	-8.19	
Wealth-weighted gender index	-0.014	-2.11		-0.013	-1.93	
Pseudo R^2	37.40%			40.30%		
Number of observations	85,532			85,532		
Number of twin pairs	11,721			11,721		

Table IA.XXIV

Tobit Regression of the Risky Share on Characteristics

Yearly twin pair fixed effects

	(1)			(2)		
	Estimate	t-stat	Implied η	Estimate	t-stat	Implied η
Log financial wealth	0.162	90.50	0.387			
Financial wealth quartile						
Lowest				0.175	36.20	1.357
2				0.186	43.90	0.473
3				0.180	46.50	0.350
4				0.173	48.50	0.273
Log residential real estate wealth	0.001	1.72		0.000	1.08	
Log commercial real estate wealth	-0.004	-8.91		-0.004	-7.75	
Leverage ratio	-0.007	-9.02		-0.004	-4.88	
Human capital and income risk						
Log human capital	0.011	3.61		0.010	3.36	
Permanent income risk	-0.257	-4.93		-0.243	-4.68	
Transitory income risk	-0.061	-4.48		-0.055	-4.01	
Entrepreneur dummy	-0.077	-6.37		-0.071	-5.96	
Unemployment dummy	-0.012	-1.90		-0.010	-1.66	
Habit						
Log internal habit	-0.044	-6.30		-0.036	-5.21	
Log external habit	0.002	0.09		0.006	0.33	
Demographic characteristics						
High school dummy	0.017	2.82		0.016	2.60	
Post-high school dummy	0.033	6.31		0.031	6.07	
Dummy for unavailable education data	0.144	1.95		0.112	1.69	
Number of adults	-0.032	-5.03		-0.047	-7.38	
Number of children	-0.026	-11.60		-0.033	-14.50	
Wealth-weighted gender index	-0.017	-2.72		-0.018	-2.88	
Number of observations	85,532			85,532		
Number of twin pairs	11,721			11,721		

Table IA.XXV
Impact of Constant Bank Imputation
Yearly twin pair fixed effects

	Direct Effect		Interacted	
	Estimate	*t*-stat	Estimate	*t*-stat
Financial characteristics				
Log financial wealth	0.330	38.90	-0.263	-25.90
Log residential real estate wealth	0.002	1.16	0.003	1.19
Log commercial real estate wealth	0.001	0.73	-0.002	-1.13
Leverage ratio	-0.005	-1.21	0.003	0.51
Human capital and income risk				
Log human capital	-0.004	-0.40	-0.020	-1.70
Permanent income risk	-0.021	-0.11	-0.030	-0.13
Transitory income risk	0.005	0.13	0.064	1.23
Beta of income innovation w.r.t. portfolio return	0.033	1.11	-0.033	-1.19
Entrepreneur dummy	-0.147	-3.37	-0.005	-0.11
Unemployment dummy	-0.081	-3.08	0.057	1.87
Habit				
Log internal habit	0.075	2.52	0.109	3.85
Log external habit	0.061	0.80	-0.030	-0.40
Demographic characteristics				
High school dummy	0.033	1.06	0.028	1.00
Post-high school dummy	0.028	1.27	-0.032	-1.59
Number of adults	0.007	0.26	0.092	3.00
Number of children	0.050	4.90	0.050	5.18
Wealth-weighted gender index	-0.013	-0.45	0.077	2.43
Adjusted R^2	34.58%			
Number of observations	55,898			
Number of twin pairs	8,394			

Table IA.XXVI
Regression of the Individual Log Risky Share on Individual Characteristics

Panel A: Regression Coefficients

	Yearly Twin Pair Fixed Effects						Yearly Fixed	
	(1)		(2)		(3)		(4)	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Financial characteristics								
Log financial wealth	0.139	14.87	0.148	15.14	0.145	14.92	0.158	25.79
Log residential real estate wealth			-0.003	-1.63	-0.002	-1.02	0.002	1.16
Log commercial real estate wealth			-0.011	-2.99	-0.009	-2.48	-0.012	-5.81
Leverage ratio			-0.005	-2.79	-0.005	-2.72	-0.006	-3.49
Human capital and income risk								
Log human capital			-0.005	-0.40	-0.004	-0.28	-0.001	-0.13
Permanent income risk			-0.092	-0.52	-0.103	-0.58	-0.112	-1.00
Transitory income risk			-0.031	-0.68	-0.026	-0.58	-0.055	-1.88
Beta of income innovation w.r.t. portfolio return			0.023	1.56	0.022	1.48	0.031	2.06
Entrepreneur dummy			-0.242	-3.54	-0.203	-3.01	-0.204	-4.19
Unemployment dummy			-0.098	-2.86	-0.099	-2.91	-0.093	-3.40
Habit								
Log internal habit			-0.107	-3.14	-0.066	-1.83	-0.094	-4.09
Log external habit			0.067	0.56	0.044	0.37	-0.115	-1.65
Demographic characteristics								
High school dummy					0.072	1.89	0.082	3.35
Post-high school dummy					0.007	0.23	0.052	2.98
Number of children					-0.015	-1.27	-0.004	-0.55
Gender					-0.119	-4.16	-0.078	-4.50
Adjusted R^2	16.72%		17.38%		17.66%		7.79%	
Number of observations	38,468		38,468		38,468		38,468	
Number of twin pairs	5,957		5,957		5,957		5,957	

Table IA.XXVI – *Continued*

Panel B: Variance Decomposition				
	Yearly Twin Pair			Yearly
	(1)	(2)	(3)	(4)
Adjusted R^2	16.72%	17.38%	17.66%	7.79%
Contribution of the variance of:				
Fixed effect (ω_α^2)	11.70%	11.40%	11.48%	1.07%
Log financial wealth (ω_f^2)	4.12%	4.66%	4.47%	5.32%
Other observable characterics (ω_x^2)		0.96%	1.36%	1.45%
Contribution of the covariance of:				
Fixed effect and financial wealth ($2\ \omega_{\alpha,f}$)	0.92%	1.13%	1.02%	0.27%
Fixed effect and other characteristics ($2\ \omega_{\alpha,x}$)		-0.06%	-0.25%	0.18%
Financial wealth and other characteristics ($2\ \omega_{f,x}$)		-0.71%	-0.42%	-0.50%

Table IA.XXVII
Individual Elasticity of the Risky Share Across Financial Wealth Quantiles

	(1)		(2)	
	Estimate	*t*-stat	Estimate	*t*-stat
Financial wealth quartile				
Lowest	0.353	18.11	0.350	17.64
2	0.114	7.65	0.115	7.67
3	0.064	4.02	0.073	4.53
4	0.054	2.90	0.069	3.67
Log residential real estate wealth			-0.002	-1.12
Log commercial real estate wealth			-0.008	-2.13
Leverage ratio			-0.002	-1.02
Human capital and income risk				
Log human capital			-0.008	-0.62
Permanent income risk			-0.020	-0.12
Transitory income risk			0.002	0.05
Beta of income innovation w.r.t. portfolio return			0.023	1.53
Entrepreneur dummy			-0.190	-2.78
Unemployment dummy			-0.083	-2.48
Habit				
Log internal habit			-0.029	-0.82
Log external habit			0.065	0.56
Demographic characteristics				
High school dummy			0.066	1.74
Post-high school dummy			0.005	0.18
Dummy for unavailable education data			0.538	1.64
Number of children			-0.020	-1.74
Gender			-0.118	-4.21
Adjusted R^2	18.38%		19.12%	
Number of observations	38,468		38,468	
Number of twin pairs	5,957		5,957	

Table IA.XXVIII
Individual Financial Wealth Elasticity of the Risky Share

	(1)				(2)			
	Direct Effect		Interacted		Direct Effect		Interacted	
	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat
Financial characteristics								
Log financial wealth	0.135	14.20	-0.109	-10.70	0.136	14.24	-0.105	-9.51
Log residential real estate wealth	-0.003	-1.24			-0.002	-1.15	0.002	0.73
Log commercial real estate wealth	-0.007	-2.01			-0.008	-2.09	0.001	0.36
Leverage ratio	-0.002	-1.25			0.000	-0.04	0.003	1.20
Human capital and income risk								
Log human capital	-0.010	-0.76			-0.007	-0.50	-0.012	-0.83
Permanent income risk	0.042	0.24			0.020	0.12	0.102	0.66
Transitory income risk	0.022	0.50			0.017	0.40	0.041	1.05
Beta of income innovation w.r.t. portfolio return	0.022	1.50			0.021	1.39	-0.031	-1.36
Entrepreneur dummy	-0.192	-2.82			-0.183	-2.72	-0.091	-1.27
Unemployment dummy	-0.088	-2.63			-0.085	-2.53	0.025	0.62
Habit								
Log internal habit	-0.008	-0.22	0.044	1.88	-0.009	-0.24	0.047	1.54
Log external habit	0.054	0.46			0.071	0.61	-0.310	-3.00
Demographic characteristics								
High school dummy	0.064	1.70			0.064	1.70	0.044	1.23
Post-high school dummy	0.002	0.07			-0.001	-0.03	-0.005	-0.18
Number of children	-0.018	-1.56			-0.018	-1.56	0.021	1.82
Gender	-0.123	-4.37			-0.122	-4.34	0.019	0.77
Adjusted R^2	18.90%				19.07%			
Number of observations	38,468				38,468			
Number of twin pairs	5,957				5,957			

Table IA.XXIX
Instrumental Variable Estimation of the Constant and Piecewise-Constant Elasticity Specifications

Yearly twin pair fixed effects

	(1)		(2)	
	Estimate	*t*-stat	Estimate	*t*-stat
Log financial wealth	0.280	37.30		
Financial wealth quartile				
Lowest			0.474	23.90
2			0.295	16.40
3			0.223	12.50
4			0.153	9.23
Log residential real estate wealth	0.002	1.27	0.001	0.69
Log commercial real estate wealth	-0.007	-4.33	-0.006	-3.47
Leverage ratio	-0.003	-1.11	0.005	1.93
Human capital and income risk				
Log human capital	0.009	0.91	0.006	0.64
Permanent income risk	-0.333	-2.37	-0.290	-2.07
Transitory income risk	-0.087	-2.96	-0.056	-1.90
Beta of income innovation w.r.t. portfolio return	0.015	1.15	0.016	1.20
Entrepreneur dummy	-0.261	-6.87	-0.252	-6.63
Unemployment dummy	-0.067	-2.61	-0.054	-2.10
Habit				
Log internal habit	-0.164	-6.97	-0.108	-4.49
Log external habit	0.044	0.70	0.041	0.65
Demographic characteristics				
High school dummy	0.036	1.56	0.030	1.30
Post-high school dummy	0.029	1.53	0.024	1.28
Number of adults	-0.057	-2.53	-0.115	-5.08
Number of children	-0.046	-5.40	-0.062	-7.16
Wealth-weighted gender index	-0.094	-4.23	-0.083	-3.74
Adjusted R^2	25.40%		25.71%	
Number of observations	40,424		40,424	
Number of twin pairs	7,940		7,940	

Table IA.XXX

Instrumental Variable Estimation of the Linear Elasticity Specification

Yearly twin pair fixed effects

	(1)				(2)			
	Direct Effect		Interacted		Direct Effect		Interacted	
	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat
Financial characteristics								
Log financial wealth	0.282	37.70	-0.084	-10.60	0.293	36.80	-0.079	-9.56
Log residential real estate wealth	0.002	1.12			0.003	1.89	0.007	3.29
Log commercial real estate wealth	-0.006	-3.77			-0.006	-3.78	-0.002	-1.07
Leverage ratio	0.002	0.95			0.015	3.08	0.012	3.56
Human capital and income risk								
Log human capital	0.010	1.02			0.010	1.03	-0.006	-0.49
Permanent income risk	-0.327	-2.34			-0.296	-2.00	-0.043	-0.27
Transitory income risk	-0.075	-2.55			-0.075	-2.40	0.038	0.92
Beta of income innovation w.r.t. portfolio return	0.014	1.07			0.018	1.29	-0.017	-1.02
Entrepreneur dummy	-0.263	-6.95			-0.256	-6.71	-0.007	-0.15
Unemployment dummy	-0.062	-2.45			-0.052	-2.03	0.074	2.27
Habit								
Log internal habit	-0.144	-5.93	0.122	6.93	-0.128	-5.13	0.050	1.97
Log external habit	0.037	0.58			0.030	0.48	-0.027	-0.40
Demographic characteristics								
High school dummy	0.034	1.50			0.033	1.46	0.064	2.75
Post-high school dummy	0.024	1.29			0.020	1.05	-0.038	-2.06
Number of adults	-0.077	-3.35			-0.078	-3.37	0.053	1.91
Number of children	-0.053	-6.22			-0.063	-7.32	0.046	4.73
Wealth-weighted gender index	-0.086	-3.86			-0.075	-3.30	0.064	2.30
Adjusted R^2	26.07%				26.52%			
Number of observations	40,424				40,424			
Number of twin pairs	7,940				7,940			

Table IA.XXXI
Health and Lifestyle Variables
Yearly twin pair fixed effects

	(1)		(2)	
	Estimate	*t*-stat	Estimate	*t*-stat
Log financial wealth	0.222	20.90		
Financial wealth quartile				
Lowest			0.319	15.60
2			0.217	13.40
3			0.180	9.65
4			0.125	7.31
Log residential real estate wealth	0.004	1.39	0.003	0.95
Log commercial real estate wealth	-0.005	-1.98	-0.004	-1.59
Leverage ratio	-0.006	-1.91	-0.004	-1.12
Human capital and income risk				
Log human capital	-0.038	-1.86	-0.039	-1.92
Permanent income risk	0.186	0.79	0.205	0.85
Transitory income risk	0.008	0.19	0.032	0.70
Beta of income innovation w.r.t. portfolio return	-0.005	-0.23	-0.006	-0.31
Entrepreneur dummy	-0.260	-4.11	-0.254	-4.00
Unemployment dummy	-0.111	-2.73	-0.106	-2.62
Habit				
Log internal habit	-0.086	-2.21	-0.040	-1.00
Log external habit	0.080	0.78	0.072	0.70
Demographic characteristics				
High school dummy	0.042	1.08	0.036	0.95
Post-high school dummy	0.032	1.01	0.028	0.91
Number of adults	-0.066	-1.81	-0.106	-2.87
Number of children	-0.043	-3.07	-0.050	-3.59
Wealth-weighted gender index	-0.108	-2.77	-0.099	-2.55

Table IA.XXXI–*Continued*

Lifestyle				
Regular smoker	-0.009	-0.34	-0.015	-0.57
Alcohol drinker	0.067	2.12	0.060	1.90
Coffee drinker	0.060	1.28	0.062	1.32
Exercise level	-0.008	-0.44	-0.009	-0.51
Physical attributes				
Height	-0.001	-0.55	-0.001	-0.71
Overweight	-0.031	-1.12	-0.037	-1.36
Obese	-0.049	-0.95	-0.043	-0.84
Mental health				
Eating disorder (EDNOS)	0.005	0.15	0.010	0.34
Anxiety (GAD)	0.088	0.99	0.080	0.90
Depression symptoms	-0.096	-2.32	-0.093	-2.29
Major depression	0.028	0.96	0.026	0.91
Health conditions				
Indifferent or bad self-assessed health	-0.029	-0.85	-0.026	-0.76
Deterioration of self-assessed health over past 5 years	-0.005	-0.17	-0.004	-0.14
Recurrent headaches and migraines	0.001	0.05	-0.001	-0.04
High blood pressure	-0.068	-1.96	-0.071	-2.08
Adjusted R^2	17.75%		18.35%	
Number of observations	36,258		36,258	
Number of twin pairs	5,354		5,354	

Table IA.XXXII
Dynamic Panel

This table reports the instrumental variable 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. Characteristics are taken at the beginning of the period and are the same as in the third set of columns of Table II in the main text.

	No Controls				With Controls			
	(1)		(2)		(3)		(4)	
	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat
Log financial wealth	0.225	4.91			0.232	4.90		
Financial wealth quartile								
Lowest			0.454	2.81			0.456	2.74
2			0.420	3.16			0.408	3.09
3			0.333	3.35			0.340	3.39
4			0.037	0.74			0.028	0.52
Change in log passive share	0.097	3.21	0.088	2.82	0.097	3.24	0.088	2.82
Number of observations	38,467		38,467		38,467		38,467	

Table IA.XXXIII
Elasticity of Aggregate Risky Financial Wealth
Homogenous wealth shock

Panel A: Yearly Estimates of the Elasticity Specification

	Fixed Set of Participants				With Entry and Exit			
	1999	2000	2001	2002	1999	2000	2001	2002
CRRA representative investor	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Heterogeneous CRRA	1.000	1.000	1.000	1.000	1.025	1.020	1.023	1.030
Constant financial wealth elasticity of the risky share	1.280	1.248	1.226	1.117	1.282	1.249	1.228	1.123
Linear financial wealth elasticity of the risky share	1.084	1.059	1.087	0.965	1.110	1.079	1.111	0.996

Panel B: Panel Estimates of the Elasticity Specification

	Fixed Set of Participants				With Entry and Exit			
	1999	2000	2001	2002	1999	2000	2001	2002
CRRA representative investor	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Heterogeneous CRRA	1.000	1.000	1.000	1.000	1.023	1.016	1.024	1.042
Constant financial wealth elasticity of the risky share	1.223	1.223	1.223	1.223	1.225	1.224	1.225	1.227
Linear financial wealth elasticity of the risky share	1.034	1.037	1.059	1.073	1.057	1.054	1.084	1.116

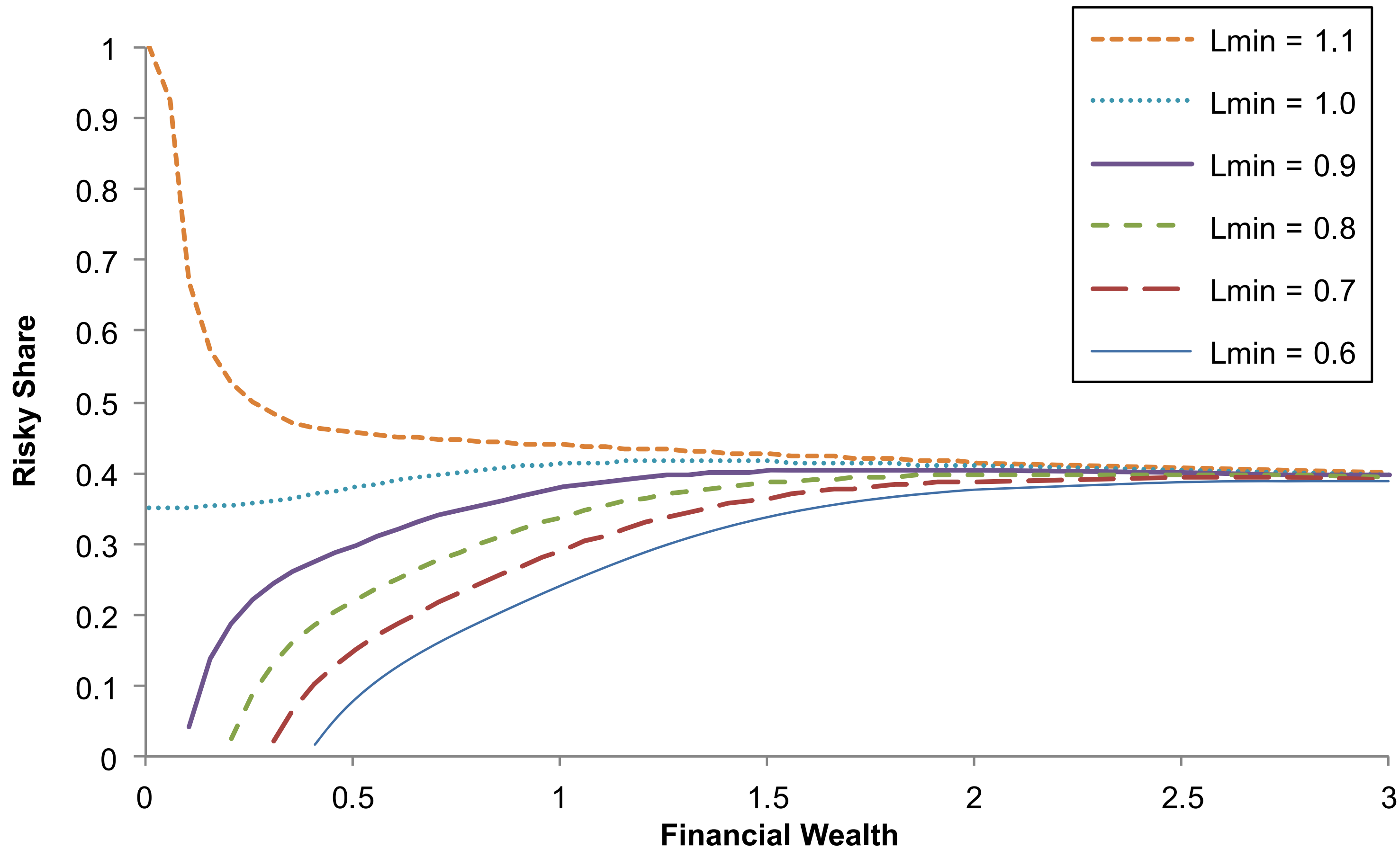

Figure IA.1. Theoretical link between financial wealth and the risky share. The figure illustrates how the risky share varies with financial wealth in the calibrated portfolio model with human capital and habit developed in section **III** of this Internet Appendix.

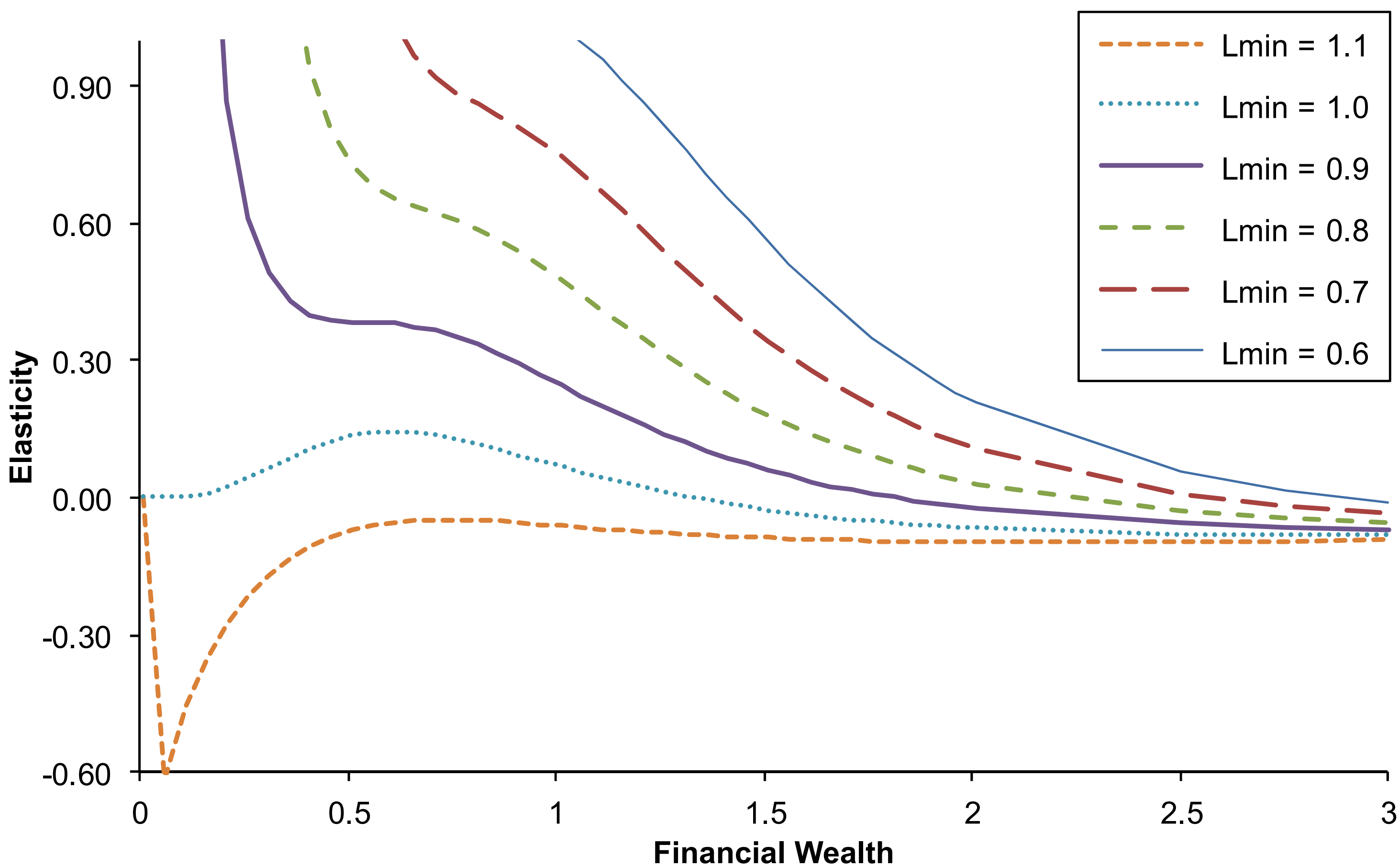

Figure IA.2. Theoretical link between financial wealth and the financial wealth elasticity of the risky share. The figure illustrates how the financial wealth elasticity of the risky share varies with financial wealth itself in the calibrated portfolio model with human capital and habit developed in section III of this Internet Appendix.

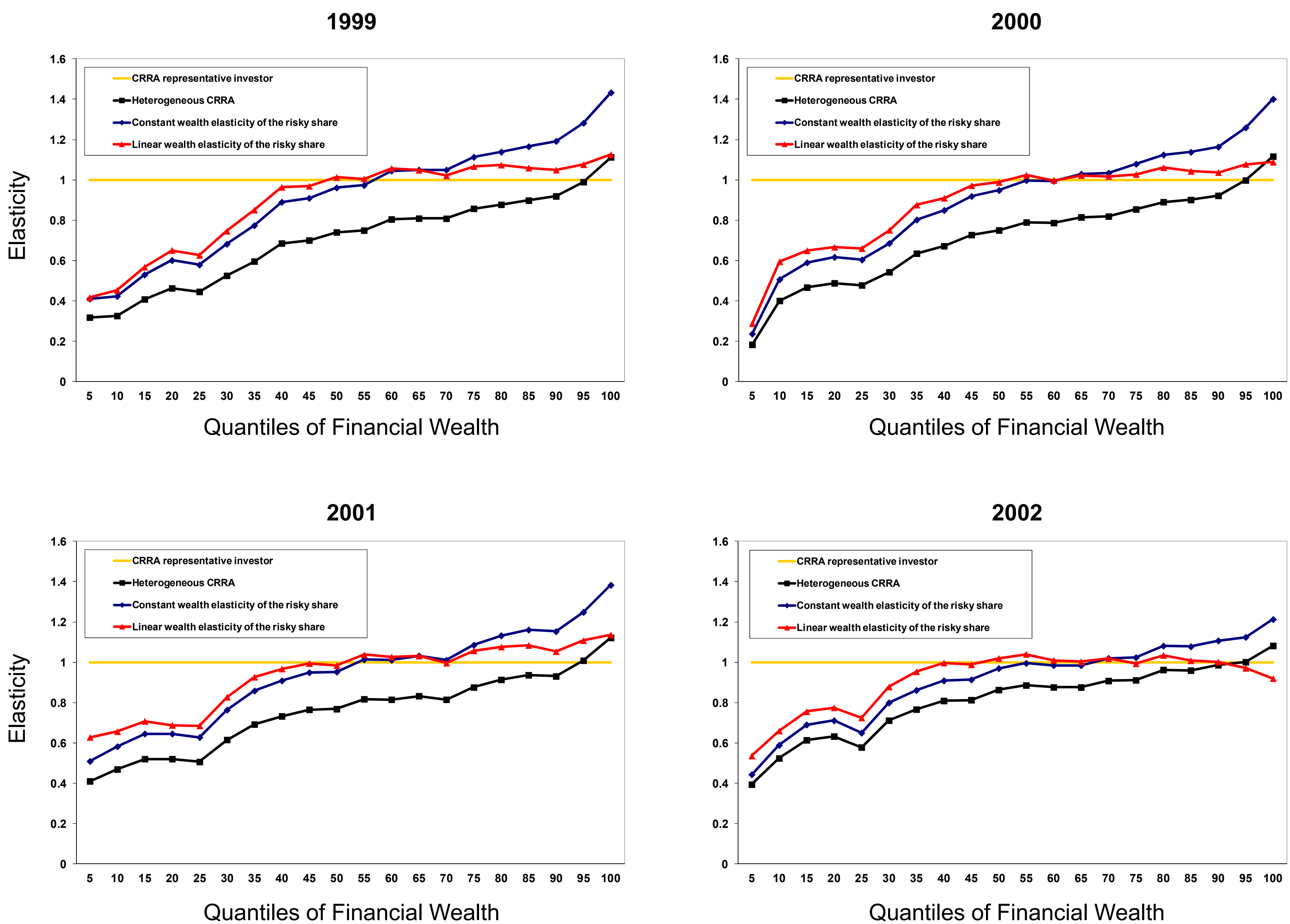

Figure IA.3. Yearly estimates of the aggregate elasticity of participants. The figure illustrates year by year estimates of the elasticity of aggregate risky wealth with respect to the aggregate wealth of participating households. The set of participants before and after the shock is fixed in each yearly simulation.

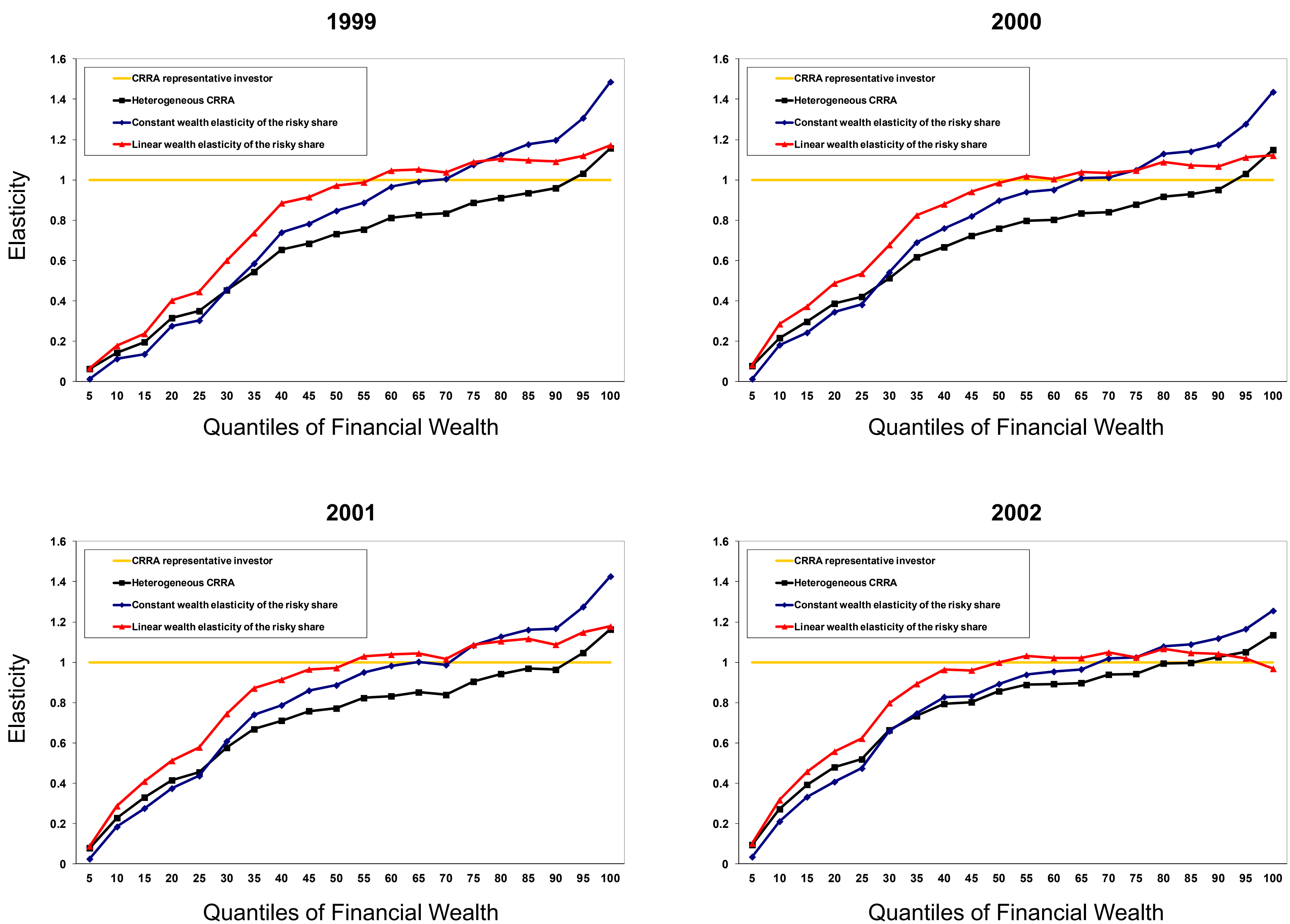

Figure IA.4. Yearly estimates of the aggregate elasticity of participating and nonparticipating households. The figure illustrates year by year estimates of the elasticity of aggregate risky wealth with respect to the aggregate financial wealth of all households. The set of participants before and after the shock is endogenous.

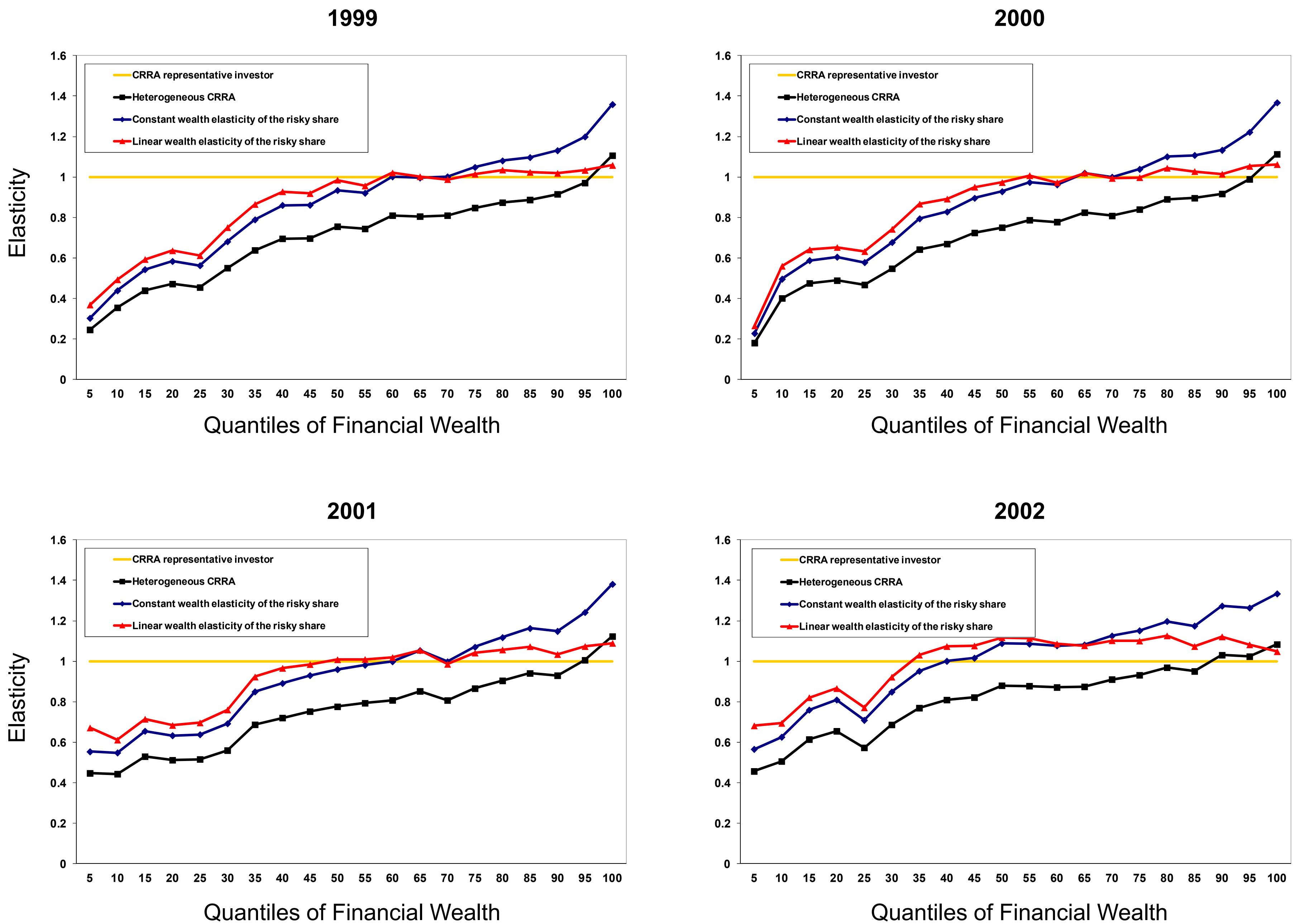

Figure IA.5. Aggregate elasticity of participants computed from panel estimates. The figure illustrates yearly estimates of the elasticity of aggregate risky wealth with respect to the aggregate wealth of participating households. Individual elasticities are computed using panel estimates of the elasticity specifications. The set of participants is fixed in each yearly simulation.

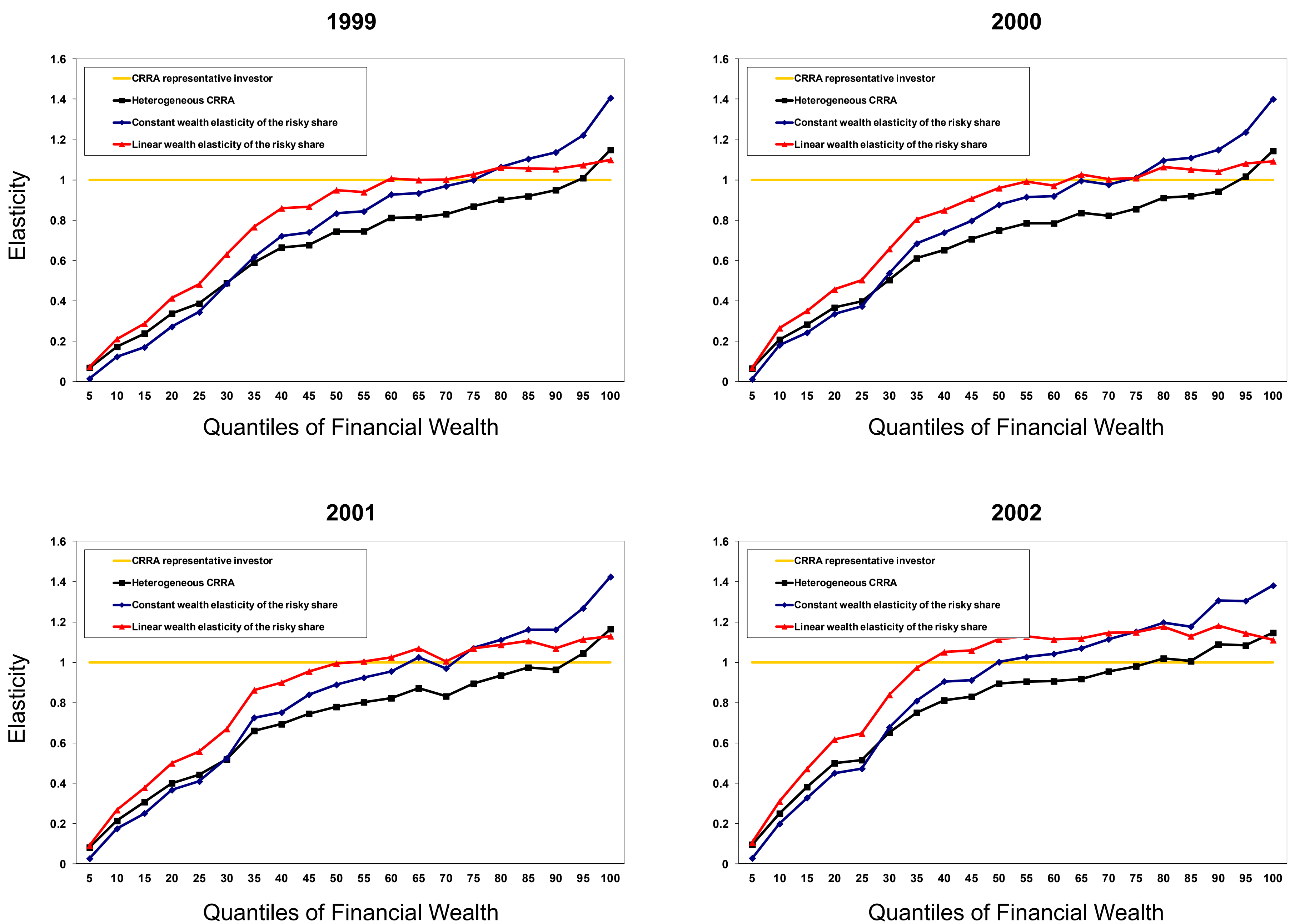

Figure IA.6. Aggregate elasticity of all households computed from panel estimates. The figure illustrates yearly estimates of the aggregate elasticity of participating and nonparticipating households. Individual elasticities are computed using panel estimates of the elasticity specifications. The set of participants before and after the shock is endogenous.

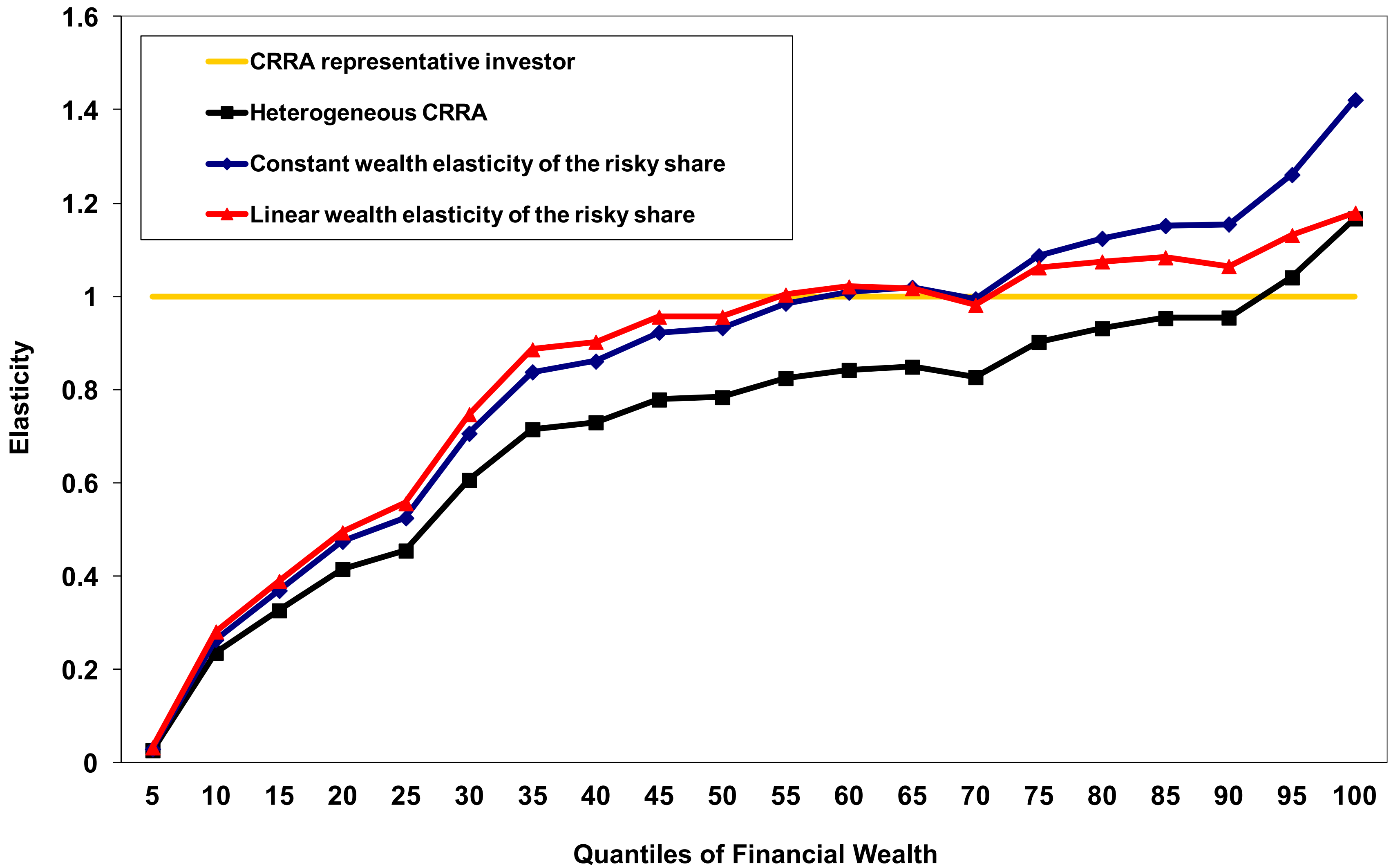

Figure IA.7. Aggregate elasticity in response to a negative wealth shock with exit. This figure illustrates the elasticity of aggregate risky financial wealth with respect to negative shocks to the financial wealth of participating and nonparticipating households The set of participants is endogenous and all results are reported for the year 2001.

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