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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 affects risk-taking positively, while internal habit and expenditure commitments tend to reduce it. Our microfindings 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.

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, for example, 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

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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), Wachter and Yogo (2010)), habit formation (Constantinides (1990), Campbell and Cochrane (1999)), committed expenditures (Chetty and Szeidl (2007, 2010)), or a "capitalist" taste for wealth (Bakshi and Chen (1996), 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 macrofinance literatures. In this paper, we shed light on which specifications are actually valid at the microlevel.

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, for example, 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 DRRA; a positive exogenous wealth shock triggers investors to select more aggressive asset allocations under this alternative scenario. Cross-sectional data do not permit researchers to disentangle the two interpretations. 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 variation in a household's asset allocation to time variation in the household's financial wealth and characteristics (see, for example, 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

[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).

(Brunnermeier and Nagel (2008), CCS (2009a)),[3] and thus the link between risk-taking and wealth at the microlevel 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 data set 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 to 2002 period. Because twins are much more closely related than random individuals in the population, the data set allows us to control for latent forms of heterogeneity, such as attitudes toward risk, ability, genes, shared background, and expected inheritance, among others. We therefore run portfolio regressions in which yearly twin pair fixed effects are included in the set of 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 affect 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 risky share conditional on participation. Specifically, we run regressions of the participation status and the log risky share on yearly twin pair fixed effects, financial wealth, and other observable characteristics. We 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 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, regardless of whether 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

[3] Brunnermeier and Nagel (2008) instrument time variation 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 (2009a) 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 stock market participation.

is remarkably robust across specifications and provides strong evidence that households exhibit DRRA.

Third, the Swedish data set 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), Fagereng, Gottlieb, and Guiso (2011)). By contrast, our data set 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 for the subsample of identical twins, the subsample for 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% for the full sample of identical and fraternal twins, and reaches 40% for 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, regardless of whether leverage and a large set of characteristics are included as controls. When an investor gets closer to her habit level, her asset allocation becomes 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

[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), Viceira (2001)).

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 microestimates, 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 homogeneous 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 microevidence 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), 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 data set 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

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

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 microfindings. Section V concludes. The Internet Appendix presents details on data construction and estimation methodology.[7]

I. Data and Definitions

A. The Swedish Data Set

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,[8] and the intensity of communication between the twins. We refer the reader to Lichtenstein et al. (2006) and Pedersen, Lichtenstein, and Svedberg (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 data set compiled by Statistics Sweden that we use in earlier work (CCS (2007, 2009a, 2009b)). Until recently, Statistics Sweden and the tax authority had a parliamentary mandate to collect highly detailed information on every resident, including age, gender, marital status, nationality, birthplace, education, municipality, income, and disaggregated wealth, for tax purposes. 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.[9] 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 to 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

[7] The Internet Appendix may be found in the online version of this article.

[8] 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.

[9] To protect privacy, Statistics Sweden provided us with a scrambled version of the household identification number.

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 to 2002 period, corresponding to 11,721 distinct twin pairs.

B. Definitions and Construction of Variables

We 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 for 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 for external habit by the 3-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 is calculated as follows. 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 a 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). The income growth innovation $u_{h,t}$ is defined as the difference between income growth, $\log(L_{h,t}/L_{h,t-1})$, and the fitted value, $b'(x_{h,t} - x_{h,t-1})$. We measure the systematic risk in income at t by the beta coefficient $\beta_{h,t}$ of the income growth innovation relative to the average excess returns on the risky assets that the household holds at t.

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: (i) expected human capital $HC_{h,t}$; (ii) the variance of the transitory component of real income, $\sigma^2_{\varepsilon,h}$; (iii) the variance of the permanent component of real income, $\sigma^2_{\xi,h}$; and (iv) the beta of income growth relative to the risky portfolio, $\beta_{h,t}$.

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 to 2002 period, corresponding to 8,394 distinct twin pairs. The participation decision is investigated in Section V.

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 comparison, 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

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 adult twins participate in risky asset markets, and the second set of columns is based 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 twin siblings. All variables are described in Appendix Table A. The summary statistics reported in this table are computed by winsorizing all nominal variables at the 99^{th} 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

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 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 DRRA, the optimal risky share increases with financial wealth. DRRA is frequently modeled by incorporating a subsistence or habit term into CRRA utility. Under a wide range of assumptions explained in the Internet Appendix (see, for example, 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 both can be explained by adjustment costs in consumption (Chetty and Szeidl (2007), Chetty and Szeidl (2010)). For this reason and given the limitations of the data, we do not attempt to distinguish between habit, subsistence, and commitment, and we generically refer to $X_{h,t}$ as the habit parameter.

The "spirit of capitalism" (Bakshi and Chen (1996), Carroll (2000, 2002)) offers yet another motivation for DRRA. It proposes that household utility explicitly depends on the ratio of own financial wealth to a benchmark wealth level. 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.[10] The spirit of capitalism implies that financial wealth can impact the risky share through a different channel from the financial wealth-to-consumption habit ratio in (2). This observation motivates using financial wealth as a stand-alone variable in the empirical specification of the risky share.

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

PREDICTION 1: *The risky share increases with financial wealth.*

PREDICTION 2: *The risky share decreases with habit.*

Note that Prediction 1 also holds under the spirit of capitalism specification, (3).

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

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 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 the habit-to-financial wealth ratio. This leads to the following predictions.

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

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

The twin data set 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 Predictions 1 to 4 are all violated.

Human capital represents by far the largest form of wealth held by the average household (see 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 (Merton (1971), Bodie, Merton, and Samuelson (1992), and Cocco, Gomes, and Maenhout (2005)). For instance, if the investor has 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 at low- and medium-wealth levels, the positive relationship between financial wealth and the risky share induced by habit does indeed prevail 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 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) 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 makeup 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.

Accordingly, we 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

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

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 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 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), CCS (2009a)). 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 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 nonetheless investigate if the twin regression (7) is contaminated by residual individual fixed effects. In Sections III and IV we also allow the elasticity η 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.

The richer twin in a pair selects a higher risky share than its poorer sibling, regardless of whether 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 provides a strong indication that households exhibit DRRA. In Section IV we provide further evidence that financial wealth has a causal impact on the risky share and its elasticity.

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

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

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. All variables are described in Appendix Table A. 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			1.39		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

(*Continued*)

Table II—*Continued*

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
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	

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. All variables are described in Appendix Table A.

	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			0.12		−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%	

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 to III, average human capital is \$760,000, the average elasticity η is about 0.20, and average financial wealth is \$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 zero, 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 Table II, Panel A, and Table III, Panel 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 as follows. 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.[11] 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 in part, 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), Fagereng, Gottlieb, and Guiso (2011)). The Swedish data set 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

[11] 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.

investment and a hedge against future rental costs, which has no significant impact empirically.[12]

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 Predictions 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 (Prais and Houthakker (1955), Deaton (1974), Calvet and Comon (2003), Lewbel and Pendakur (2008)). Furthermore, large households have high committed expenditure-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, spirit of capitalism models 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 has a coefficient of −0.04 (t-value = −0.44), and stand-alone financial wealth has 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 stand-alone 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 data set 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 data set permits us to include yearly twin pair fixed effects and thereby control for the common genetic and family 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

[12] 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.

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 $\rho^2 = \text{Var}(\alpha_{i,t} + \eta f_{i,j,t} + \gamma' x_{i,j,t})/\text{Var}(\log w_{i,j,t})$ 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 household 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

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

where ω_α^2, ω_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.[13] We obtain the following results in Panels B of Tables II and III.

(1) 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.
(2) The contribution of observable characteristics, $\omega_f^2 + 2\omega_{f,x} + \omega_x^2$, ranges from 6.9% to 9.16% (= 8.95% − 1.38% + 1.59%) 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 obtain with identical twins.
(3) The cross-terms $\omega_{\alpha,f}$, $\omega_{\alpha,x}$, and $\omega_{f,x}$ are small and not 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

[13] Specifically, letting $\sigma_w^2 = \text{Var}(\log w_{i,j,t})$, we define $\omega_\alpha^2 = \text{Var}(\alpha_{i,t})/\sigma_w^2$, $\omega_f^2 = \text{Var}(\eta f_{i,j,t})/\sigma_w^2$, $\omega_x^2 = \text{Var}(\gamma' x_{i,j,t})/\sigma_w^2$, $\omega_{\alpha,f} = \text{Cov}(\alpha_{i,t}; \eta f_{i,j,t})/\sigma_w^2$, $\omega_{\alpha,x} = \text{Cov}(\alpha_{i,t}; \gamma' x_{i,j,t})/\sigma_w^2$, and $\omega_{f,x} = \text{Var}(\eta f_{i,j,t}; \gamma' x_{i,j,t})/\sigma_w^2$. 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 $\text{Cov}(v_{i,1,t}; v_{i,2,t}) = \text{Var}(\alpha_{i,t})$, 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.

family fixed effects are important, individual financial circumstances play a major role in explaining the risk-taking behavior of households.

To better understand the role of fixed effects, we estimate the twin specification (7) on a "pseudopanel" of randomly matched pairs. As can be seen in the Internet Appendix, random matching produces linear coefficients that are very similar to those 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 pseudopanel (compared to 19% with the 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 data set.

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 those reported in Table III. Twins do not simply mimic each other's behavior but respond to their own economic and financial circumstances, regardless of whether 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 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

Table IV
Communication

The table reports the financial wealth elasticity of the risky share and the variance decomposition estimated on households with twins who communicate infrequently (left set of two 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 the set of all household characteristics and either yearly twin pair fixed effects or yearly fixed effects, estimated on households with a twin (Panel A) or households with an identical twin (Panel B). The full results of the yearly twin regressions are reported in the Internet Appendix.

	Infrequent Communication		Frequent Communication	
Fixed Effect	Yearly Twin Pair	Yearly	Yearly Twin Pair	Yearly
Panel A: All Twins				
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				
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

as a proxy for information differences in risky share regressions, and instead provides further evidence that investors have DRRA.

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 four times higher for frequent communicators as for infrequent communicators, regardless of genetic relationship.[14] By contrast, ω_α^2

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

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 Predictions 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 due to lack of reliable data and identification techniques.

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 Prediction 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.

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.[15] 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

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

[15] 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.

Table V

Elasticity of the Risky Share Across Financial Wealth Quartiles

This table reports the 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 estimation is based on participating households with an adult twin. All variables are described in Appendix Table A.

	(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	

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 Predictions 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 negatively impacts the risky share itself but positively impacts its elasticity. These results are consistent with the models considered in Section II.A. The asset allocation of households with substantial human capital

Table VI

Financial Wealth Elasticity of the Risky Share

This table reports the 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 estimation is based on participating households with an adult twin. All variables are described in Appendix Table A.

	(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			

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 on 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 1990s 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.

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.[16]

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

[16] 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.

Table VII

Lagged Financial and Portfolio Characteristics

This table reports yearly twin pair fixed effects regressions of the 2000 to 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 in 1999 and thereafter remain participants for one or more 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	

of the 1990s. 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 DRRA.

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 using 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 on financial wealth and all the other maintained characteristics are 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 variation in a household's risky share to time variation in its financial wealth (Brunnermeier and Nagel (2008), CCS (2009a), Chiappori and Paiella (2011)). To address portfolio inertia and endogeneity problems, in the Internet Appendix, we develop an instrumental variable estimation method in the style of Arellano and Bond (1991).[17] 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 for external habit by the average income in the same age group *and* the same municipality, or when we 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

[17] CCS (2009a) 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.

capital, defined in equation (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 (Bikhchandani, Hirshleifer, and Welch (1998), Akerlof and Shiller (2010)). 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 microevidence for aggregate risk-taking. We consider exogenous variation in household wealth and compute its impact on the aggregate demand for risky assets. Security prices are fixed and time indices are henceforth suppressed 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 homogeneous 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 microevidence in earlier sections.

The wealth shock modifies the aggregate demand for risky assets from the household sector. Let F denote the 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 homogeneous ($\Delta f_h = g$ for all h). The aggregate elasticity can otherwise be smaller or larger than unity.

In Figure 1, we sort households into 20 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 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. The elasticity ξ is less than one 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 homogeneous 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 microspecification (Scenario 3), poorer investors have a higher elasticity than average; the aggregate elasticity ξ is therefore higher and closer to unity in the 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 is close to the aggregate elasticity obtained with CRRA investors.

The results of Scenarios 2 and 3 reported in Figure 1 are based on the microlevel regressions of the risky share and are therefore subject to estimation

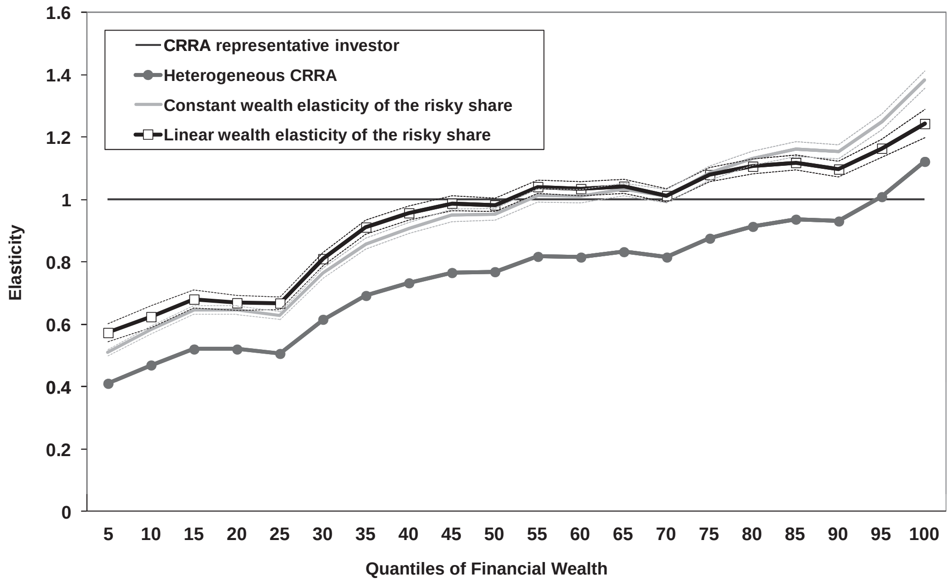

Figure 1. Elasticity of aggregate risky financial wealth computed on the fixed set of 2001 participants. This figure illustrates the elasticity of aggregate risky financial wealth with respect to the aggregate financial wealth of participating households. We consider 20 financial wealth quantiles, and report for each quantile the aggregate elasticity corresponding to an exogenous wealth shock affecting only households in the quantile: $\Delta\log(F_h) = g$ if h is in the quantile and $\Delta\log(F_h) = 0$ otherwise. The set of participants is fixed and all results are reported for 2001. The upper and lower bounds of the 95% confidence interval of aggregate elasticity are reported in dashed lines.

error. For this reason, we depict in dashed lines the 95% confidence intervals 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 homogeneous wealth shock ($\Delta f_h = g$ for all h) is also important for macrofinance applications. In the Internet Appendix, we report that 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) than under the constant elasticity specifications (Scenarios 1 and 2). Since representative-agent models cannot account for distributional effects, this property should help reconcile macromodels with the microevidence.

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

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. All variables are described in Appendix Table A.

	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	

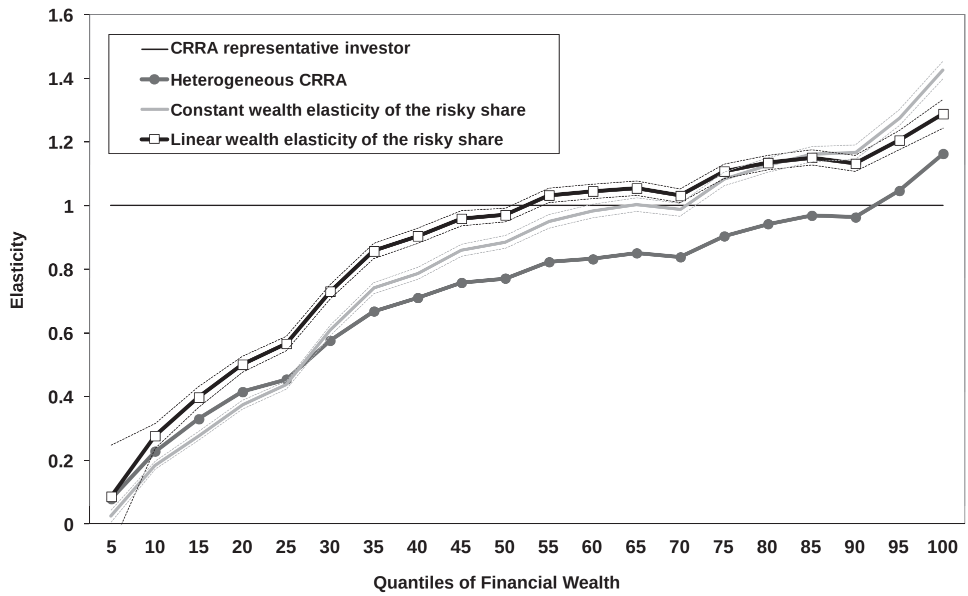

Figure 2. Elasticity of aggregate risky financial wealth with entry and exit. This figure illustrates the elasticity of aggregate risky financial wealth with respect to the aggregate financial wealth of participating and nonparticipating households. We consider 20 financial wealth quantiles, and report for each quantile the aggregate elasticity corresponding to an exogenous positive wealth shock affecting only households in the quantile: $\Delta\log(F_h) = g$ if h is in the quantile and $\Delta\log(F_h) = 0$ otherwise. The set of participants is endogenous and all results are reported for 2001. The upper and lower bounds of the 95% confidence interval of aggregate elasticity are reported in dashed lines.

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[18] 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), Calvet, Gonzalez-Eiras, and Sodini (2004)) remain empirically valid when one controls for yearly twin pair fixed effects.

In Figure 2, we illustrate the elasticity of aggregate risky wealth with respect to aggregate financial wealth computed over the population of participating and

[18] 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)).

nonparticipating households. The 95% confidence bands are reported in dashed lines. In bottom quantiles, risk-taking is low and aggregate elasticity is close to zero for all imputation methods. Under the preferred elasticity specification (Scenario 3), aggregate elasticity remains close to unity over 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.

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 microevidence reported in Sections III and IV. Second, the aggregate elasticity is remarkably stable, regardless of whether one considers homogeneous or concentrated shocks.

VI. Conclusion

In this paper, we conduct the first investigation of the microdeterminants 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 to 2002 period. The twin data allow us to control for latent forms of heterogeneity that are shared by siblings and 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 estimate 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, regardless of whether one controls for characteristics and measurement error or follows households dynamically over time. We estimate the individual labor income process of every household in our sample and find 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 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 document 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 for 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, for example, 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 (Jermann (1998), Boldrin, Christiano, and Fisher (2001)). While the utility specification employed for the representative agent in these models has been questioned (Brunnermeier and Nagel (2008), Chiappori and Paiella (2011)), this paper provides strong evidence in favor of DRRA at the *micro*level. In addition, we investigate the macroimplications of our findings. We show 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 macromodels that approximate well the asset prices generated by a population of heterogeneous DRRA investors.

We document 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 neglect interactions between nature and nurture, may also overestimate 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 reconcile portfolio microdata 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. Macrofinance 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.

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Appendix

Table A

Definitions of Household Variables

This table summarizes the main household variables used in the paper. The education, entrepreneur, and unemployment dummies are computed for the twin in the household. All other characteristics are computed at the household level.

Variable	Description
Cash	Bank account balances and money market funds.
Risky mutual fund	A mutual fund other than a money market fund.
Risky financial assets	Risky mutual funds and directly held stocks.
Risky portfolio	Portfolio of risky financial assets.
Risky share	Proportion of risky assets in the portfolio of cash and risky financial assets.
Financial wealth	Value of holdings in cash, risky financial assets, capital insurance products, derivatives, and directly held bonds, excluding illiquid assets and defined contribution retirement accounts.
Residential real estate wealth	Value of primary and secondary residences.
Commercial real estate wealth	Value of rental, industrial, and agricultural property.
Leverage ratio	Total debt divided by the sum of financial and real estate wealth.
Human capital	Expected present value of future nonfinancial disposable real income.
Permanent income risk	Variance of the permanent component of nonfinancial disposable real income.
Transitory income risk	Variance of the transitory component of nonfinancial disposable real income.
Income innovation	Difference between nonfinancial disposable real income growth and its fitted value.
Beta of income innovation w.r.t. portfolio return	Beta of the household's income innovation with respect to the household's risky portfolio excess return.
Entrepreneur dummy	Dummy variable equal to one if the twin in the household is self-employed.
Unemployment dummy	Dummy variable equal to one if the twin in the household is unemployed.
Internal habit	Three-year moving average of household nonfinancial disposable real income (excluding private pension savings from consideration).
External habit	Three-year moving average of nonfinancial diposable real income in the household's municipality.
High school dummy	Dummy variable equal to one if the twin in the household has a high school degree.
Post–high school dummy	Dummy variable equal to one if the twin in the household has had some post-high school education.
Number of adults	Variable equal to one if the household head lives alone or is a single parent, and to two if the household head has a partner or a spouse.
Number of children	Number of children of the household head or partner/spouse living in the household.
Wealth-weighted gender index	Share of the household's gross financial and real estate wealth owned by male adult in the household.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's web site:

Appendix S1: Internet Appendix.