Who are the Value and Growth Investors?*

Sebastien Betermier, Laurent E. Calvet, and Paolo Sodini

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Abstract

This paper investigates value and growth investing in a large administrative panel of Swedish residents. We show that over the life-cycle, households progressively shift from growth to value as they become older and their balance sheets improve. Furthermore, investors with high human capital and high exposure to macroeconomic risk tilt their portfolios away from value. While several behavioral biases seem evident in the data, the patterns we uncover are overall remarkably consistent with the portfolio implications of risk-based theories of the value premium.

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*Betermier: Desautels Faculty of Management, McGill University, 1001 Sherbrooke St West, Montreal, QC H3A 1G5, Canada, sebastien.betermier@mcgill.ca. Calvet: Department of Finance, HEC Paris, 1 rue de la Libération, 78351 Jouy-en-Josas Cedex, France; calvet@hec.fr. Sodini: Department of Finance, Stockholm School of Economics, Sveavägen 65, Box 6501, SE-113 83 Stockholm, Sweden, Paolo.Sodini@hhs.se. We are grateful to Kenneth Singleton (the Editor), the Associate Editor, and two anonymous referees for many insightful comments. We thank Stephan Jank, Claus Munk, Per Östberg, Jonathan Parker, Sébastien Pouget, Stefan Ruenzi, and Shaojun Zhang for helpful discussions. We also acknowledge constructive comments from Laurent Barras, John Campbell, Chris Carroll, Luigi Guiso, Marcin Kacperczyk, Bige Kahraman, Hugues Langlois, Anthony Lynch, Alex Michaelides, Ben Ranish, David Robinson, Johan Walden, and seminar participants at the City University of Hong Kong, Copenhagen Business School, HEC Lausanne, HEC Montréal, HEC Paris, Imperial College Business School, Lund University, McGill University, Peking University, the Securities and Exchange Commission, the Swedish School of Economics, the Toulouse School of Economics, Université de Sherbrooke, the University of Helsinki, the University of Southern Denmark, the 2013 Norges Bank Household Finance Workshop, the 2014 IFM2 Math Finance Days, the 2014 China International Conference in Finance, the 2014 NBER Summer Institute Asset Pricing Workshop, the 2014 European Conference on Household Finance, the 2015 Cologne Colloquium on Financial Markets, and the 2015 Annual Meeting of the European Finance Association. We thank Statistics Sweden and the Swedish Twin Registry for providing the data. The project benefited from excellent research assistance by Nikolay Antonov, Pavels Berezovkis, Milen Stoyanov, Tomas Thörnqvist, and especially Andrejs Delmans. This material is based upon work supported by Agence Nationale de la Recherche, the HEC Foundation, Riksbank, the Social Sciences and Humanities Research Council of Canada, Vinnova, and the Wallander and Hedelius Foundation.

1 Introduction

A large academic and practitioner literature documents that value stocks outperform growth stocks on average in the United States and around the world (Basu 1977, Fama and French 1992, 1998, Graham and Dodd 1934).[1] The economic explanation of these findings is one of the central questions of modern finance. As Fama and French (1992, 1995) suggest, the value premium may be a compensation for forms of systematic risk other than market portfolio return risk, such as fluctuations in aggregate labor income and consumption (Cochrane 1999, Jagannathan and Wang 1996, Lettau and Ludvigson 2001, Lustig and van Nieuwerburgh 2005, Petkova and Zhang 2005, Yogo 2006), cash-flow risk (Campbell and Vuolteenaho 2004), the costly reversibility of physical capital (Zhang 2005), long-run consumption risk (Bansal, Dittmar, and Kiku 2009, Bansal, Dittmar, and Lundblad 2005, Bansal, Kiku, Shaliastovich, and Yaron 2014, Hansen, Heaton, and Li 2008), or displacement risk (Garleanu, Kogan, and Panageas 2012). The underperformance of growth stocks relative to value stocks may also be evidence that investors are irrationally exuberant about the prospects of innovative glamour companies (DeBondt and Thaler 1985, Lakonishok, Shleifer, and Vishny 1994).[2]

The extensive empirical literature on the value premium focuses primarily on stock returns and their relationships to macroeconomic and corporate variables. Disentangling theories of the value premium, however, has proven to be challenging on traditional data sets that do not provide individual holdings and therefore do not permit researchers to assess the determinants of investor decisions.[3] The present paper proposes to use the rich information in investor portfolios to shed light on theoretical explanations. We investigate value and growth investing in a highly detailed administrative panel, which contains the disaggregated holdings and socioeconomic characteristics of all Swedish residents between 1999 and 2007. The data set reports portfolios at the level of each stock or fund, along with other forms of wealth, debt, labor income, and employment sector.

The paper makes several contributions to the literature. First, we show that the value tilt exhibits

[1]See also Asness, Moskowitz, and Pedersen (2013), Ball (1978), Fama and French (1993, 1996, 2012), and Liew and Vassalou (2000).

[2]We refer the reader to the Internet Appendix for a detailed review of the literature.

[3]See Liu, Lu, Sun, and Yan (2015) for a recent discussion.

substantial heterogeneity across households. When we sort investors by the value tilt of their risky asset portfolios, the difference in expected returns between the top and bottom deciles is approximately equal to the value premium.

Second, we relate the value tilt to household characteristics. Value investors are substantially older, have higher financial wealth, higher real estate wealth, lower leverage, lower income risk, lower human capital, and are also more likely to be female, than the average growth investor. By contrast, men, entrepreneurs, and educated investors are more likely to invest in growth stocks. These baseline patterns are evident both in stock and mutual fund holdings. The explanatory power of socioeconomic characteristics is highest for households that invest directly in at least five companies, a wealthy subgroup that owns the bulk of aggregate equity and may therefore have the greatest influence on prices.

Third, over the life-cycle, households climb the "value ladder", i.e. they gradually shift from growth to value investing as their investment horizons shorten and their balance sheets and human capital evolve. The life-cycle migration in the value loading is economically significant, amounting on average to half the value premium for the stock portfolio and a quarter of the premium for the risky portfolio, which also includes equity mutual funds. In both cases, we attribute 60% of the value ladder to age, 20% to changes in balance sheets, and 20% to human capital. The value ladder is made possible by active rebalancing, which allows households to mitigate the impact of realized returns and revert to their slow-moving target. The relationships between the value loading and characteristics are also evident in the portfolios of new participants, which are not passively affected by past returns.

Fourth, we document a strong link between the value loadings of households and the macroeconomic exposures of their employment sectors. Specifically, we uncover that a single macroeconomic factor, per-capita aggregate income growth, explains on average 88% of the time-series variation of per-capita income in any given 2-digit SIC industry. Households employed in sectors with *high* exposures to the macroeconomic factor tend to select portfolios of stocks and funds with *low* value loadings. We obtain similar results when we use industry exposures to the value factor itself as measures of systematic risk. Furthermore, we show that cross-sectoral differences in loadings are more pronounced for young households than for mature households, consistent with the intuition that human capital risk is primarily born by the young. As a result, the value ladder is empirically steeper in more cyclical industries.

Fifth, we provide a battery of robustness checks. We document that the equities most widely held by households are a mix of growth stocks and value stocks, and we show that the relationships between portfolio tilts and investor characteristics are not driven by these stocks. We verify that our results are unlikely to be due to investor experience or stock characteristics other than the value loading, such as professional proximity, the dividend yield, taxes, firm age, skewness, and size. As in Calvet and Sodini (2014), we use the subsample of Swedish twins to control for latent investor fixed effects, such as family background, upbringing, inheritance, or attitudes toward risk. The sensitivities of the value loading to socioeconomic characteristics are similar in the twin subsample as in the general household population, regardless of whether or not the twins communicate frequently or infrequently with each other.[4]

The patterns we uncover appear remarkably consistent with the portfolio implications of risk-based theories. The strong negative relationship between a household's value loading and its macroeconomic exposure provides *direct* support in favor of the hedging motive. Households in cyclical sectors go growth, which reduces their overall exposures to aggregate income risk. To the best of our knowledge, this paper is the first to find evidence of a hedging demand of any kind in the risky portfolio of individual investors.

The value ladder provides further validation of the hedging motive. Over the life-cycle, the household becomes less dependent on human capital and its hedging demand gets progressively weaker, as the model of Lynch and Tan (2011) suggests. The value ladder should therefore be more pronounced in more cyclical industries. The empirical evidence confirms these predictions. Other types of hedging demands might also contribute to explaining the value ladder. For instance, to the extent that investment opportunities are time-varying, households should behave more myopically and have weaker hedging demands as their investment horizons shorten (Brennan, Schwartz, and

[4]We also note that the tilts of twin pairs are highly sensitive to communication, which allows us to reject Cronqvist, Siegel, and Yu (2015)'s assertion that value investing is largely driven by genes.

Lagnado 1997, Campbell and Viceira 2000, Jurek and Viceira 2011, Larsen and Munk 2012, Lynch 2001). The value ladder is therefore consistent with life-cycle variation in a variety of hedging demands.

The positive effects of sound balance sheets on portfolio value tilts are also consistent with portfolio theory. More financially secure households should generally be better able to tolerate investment risk (see, e.g., Kihlstrom, Romer, and Williams 1981), and their hedging demands should therefore represent only a small fraction of their risky portfolios (Ingersoll 1987). Consistent with these predictions, we document that households with high financial wealth, low debt, and low background risk tend to invest their financial wealth aggressively in risky assets and select risky portfolios with a value tilt.

These empirical regularities can be integrated into a unified equilibrium model. We develop a stylized model of the value tilt, based on a version of the Intertemporal Capital Asset Pricing Model (Merton 1973), that includes labor income and discount-rate risks. The analysis is qualitative but demonstrates that the relationships between the value tilt and variables such as age, wealth, human capital, and income risk can arise in a general equilibrium setting.

The Swedish data set provides highly detailed information on household finances and demographics but is somewhat less informative about psychological traits. With this caveat, we find that sentiment-based explanations of the value premium also help to explain the portfolio evidence. Overconfidence, which is more prevalent among men than women (Barber and Odean 2001), is consistent with the growth tilt of male investors. As attention theory predicts (Barber and Odean 2008), a majority of direct stockholders hold a small number of popular stocks. Furthermore, some of the portfolio evidence can receive complementary risk-based and psychological explanations. For instance, the growth tilt of entrepreneurs can be attributed both to exposure to private business risk (Heaton and Lucas 2000, Moskowitz and Vissing-Jørgensen 2002) and to marked overconfidence in own decision-making skills (Busenitz and Barney 1997). The paper therefore complements the literature showing that retail investors favor assets with certain characteristics[5] and adjust their investment styles to news and past experience (Kumar 2009a, Campbell,

[5]Households are known to favor stocks that are familiar (Døskeland and Hvide 2011, Huberman 2001, Massa and

Ramadorai, and Ranish 2014).

The paper analyzes the value tilt both at the household and cohort levels, which allows us to identify the forms of heterogeneity that have the strongest impact on aggregate demand and might therefore drive prices. We document that socioeconomic characteristics explain at most 8% of the variation of the portfolio tilt across households, but the average R^2 increases to 70% when we investigate the tilt at the cohort level. Thus, unexplained heterogeneity largely aggregates out. Moreover, characteristics tied to risk-based theories, such as age, financial wealth, debt, and human capital account almost entirely for the value ladder. These findings suggest that risk-based explanations of the value premium are quantitatively important both at the micro and macro levels.

The patterns we uncover contribute to the growing body of work showing the relevance of portfolio theory for explaining household financial behavior. Retail investors allocate a high share of liquid financial wealth to risky assets if they have high financial wealth and human capital (Calvet and Sodini 2014), earn safe labor incomes (Betermier, Jansson, Parlour, and Walden 2012, Calvet and Sodini 2014, Guiso, Jappelli, and Terlizzese 1996), and are not entrepreneurs (Heaton and Lucas 2000).[6] Households actively rebalance their financial portfolios in response to realized returns (Calvet, Campbell, and Sodini 2009a). Furthermore, a majority of households incur small welfare losses from underdiversification (Calvet, Campbell, and Sodini 2007). We document here that financial theory also accounts for the cross-sectional and time-series properties of household portfolio styles.

The rest of the paper is organized as follows. Section 2 presents the data and reports the cross-sectional distribution of the value loading. Section 3 empirically investigates how the value tilt relates to the demographic and financial characteristics. Section 4 links the employment sector to the value tilt of the financial portfolio. Sections 5 and 6 develop the equilibrium model and relate the evidence to risk- and sentiment-based explanations of the value premium. Section 7 presents robustness checks and Section 8 concludes. An Internet Appendix (Betermier, Calvet, and Sodini 2015) discusses methodological details and additional empirical results.

Simonov 2006), geographically and culturally close (Grinblatt and Keloharju 2001), attention-grabbing (Barber and Odean 2008), or connected to products they consume (Keloharju, Knüpfer, and Linnainmaa 2012).

[6]See also Angerer and Lam (2009) and Bonaparte, Korniotis, and Kumar (2014).

2 Data and Summary Statistics

2.1 Local Fama and French Factors

Data on Nordic stock markets for the 1985 to 2009 period are available from FINBAS, a financial database maintained by the Swedish House of Finance. The data include monthly stock returns, market capitalizations at the semiannual frequency, and book values at the end of each year. Free-float adjusted market shares are available from Datastream. We focus on stocks with at least two years of available data. We exclude stocks worth less than 1 krona, which filters out very small firms. For comparison, the Swedish krona traded at 0.1371 U.S. dollar on 30 December 2003. We end up with a universe of approximately 1,000 stocks, out of which 743 are listed on one of the four major Nordic exchanges in 2003.[7]

The return on the market portfolio is proxied by the SIX return index (SIXRX), which tracks the value of all the shares listed on the Stockholm Stock Exchange. The risk-free rate is proxied by the monthly average yield on the one-month Swedish Treasury bill. The market factor MKT_t is the market return minus the risk-free rate in month t. The local value, size, and momentum factors are constructed as in Fama and French (1993) and Carhart (1997). We sort the stocks traded on the major Nordic exchanges by book-to-market value, market size, and past performance, and then use these bins to compute the value factor HML_t, the size factor SMB_t, and the momentum factor MOM_t, as is fully explained in the Internet Appendix.

We index stocks and funds by $i \in \{1, \ldots, I\}$. For every asset i, we estimate the four-factor model:

$$r_{i,t}^e = a_i + b_i MKT_t + v_i HML_t + s_i SMB_t + m_i MOM_t + u_{i,t}, \tag{1}$$

where $r_{i,t}^e$ denotes the excess return of asset i in month t and $u_{i,t}$ is a residual uncorrelated to the factors. Estimated loadings are winsorized at -5 and +5. The value premium is substantial in Sweden: HML_t averages to about 10% per year over the 1985 to 2009 period, which is consistent

[7] The major Nordic exchanges are the Stockholm Stock Exchange, the Copenhagen Stock Exchange, the Helsinki Stock Exchange, and the Oslo Stock Exchange.

with the Sweden estimate in Fama and French (1998) and is also in the range of country estimates reported in Liew and Vassalou (2000).

The Swedish value factor has the same key properties as its U.S. counterpart. As the Internet Appendix shows, Swedish value stocks have positive CAPM-alphas, as (1) implies. The Swedish value factor, HML_t, predicts future GDP and income growth, consistent with the international evidence in Liew and Vassalou (2000). Furthermore, the value loading of a stock is tightly related to characteristics that can be easily observed by investors. Value stocks have higher book-to-market (B/M) ratios, lower price-to-earnings (P/E) ratios, and higher dividend yields and leverage ratios than growth stocks. These relationships give credence to the view that sophisticated retail investors can distinguish between value and growth stocks and may have a sense of the risk and return tradeoffs involved with these stocks.

2.2 Household Panel Data

The Swedish Income and Wealth Registry is an administrative data set compiled by Statistics Sweden, which has previously been used in household finance (Calvet, Campbell, and Sodini 2007, 2009a, 2009b). Statistics Sweden and the tax authority had until 2007 a parliamentary mandate to collect highly detailed information on every resident. Income and demographic variables, such as age, gender, marital status, nationality, birthplace, education, and municipality of residence, are available on December 31 of each year from 1983 to 2007. The disaggregated wealth data include the worldwide assets owned by the resident at year-end from 1999 to 2007. Real estate, debt, bank accounts, stockholdings, and mutual fund investments are observed at the level of each property, account, or security.

Statistics Sweden assigns a household identification number to each resident, which allows us to group residents by living units. We define the household head as the adult with the highest income. The age, gender, education and immigration variables used in the paper refer to the household head, as is commonly assumed in the literature (see, e.g., Calvet and Sodini 2014, Campbell 2006, Guiso, Jappelli and Terlizzese 1996).

We focus on households that participate in risky asset markets. Unless stated otherwise, the results are based on a representative random sample of approximately 70,000 households observed at the yearly frequency between 1999 and 2007. The data requirements imposed on households and the method used to construct the random panel are fully explained in the Internet Appendix.

For identification purposes, we also use a twin panel from the Swedish Twin Registry, the largest twin database in the world. The registry provides the genetic relationship (fraternal or identical) of each pair and the intensity of communication between the twins. As in Calvet and Sodini (2014), we have merged the twin data base with the Swedish Income and Wealth Registry, so that all financial and demographic characteristics are available for the twin panel.

2.3 Definition of Main Variables

2.3.1 Financial Assets and Real Estate

We use the following definitions throughout the paper. Cash consists of bank account balances and Swedish money market funds.[8] Risky mutual funds refer to all funds other than Swedish money market funds. Risky financial assets consist of directly held stocks and risky mutual funds. We exclude assets with less than 3 months of return data from the portfolio analysis.

For every household h, the risky portfolio contains risky financial assets. The risky share is the fraction of risky financial assets in the portfolio of cash and risky financial assets. A market participant has a strictly positive risky share.

The *value loading of the risky portfolio* at time t is the weighted average of individual asset loadings:

$$v_{h,t} = \sum_{i=1}^{I} w_{h,i,t} v_i, \tag{2}$$

where $w_{h,i,t}$ denotes the weight of asset i in household h's risky portfolio at time t. We will oc-

[8] Financial institutions are required to report the bank account balance at year-end if the account yields more than 100 Swedish kronor during the year (1999 to 2005 period), or if the year-end bank account balance exceeds 10,000 Swedish kronor (2006 and 2007). We impute unreported cash balances by following the method used in Calvet, Campbell, and Sodini (2007, 2009a, 2009b) and Calvet and Sodini (2014), as is explained in the Internet Appendix.

casionally call $v_{h,t}$ the HML loading or the value tilt. The value loadings of the *fund* and *stock* portfolios are similarly defined. The estimation methodology takes advantage of (i) the detailed yearly data available for household portfolios, which permit the calculation of $w_{h,i,t}$, and (ii) the long monthly series available for individual assets, which permit the precise estimation of v_i.

Another advantage of the approach is that under the unconditional pricing model (1), individual firms have constant value loadings, v_i, so that time variation in household portfolio loading, $v_{h,t}$, in (2) is driven exclusively by time variation in portfolio weights, $w_{h,i,t}$. Thus, in Section 3, our estimates of active management of the value tilt by households are not contaminated by exogenous changes in firm tilts over the 1999-2007 household sample period.

We measure the household's financial wealth at date t as the total value of its cash holdings, risky financial assets, directly held bonds, capital insurance, and derivatives, excluding from consideration illiquid assets such as real estate or consumer durables, and defined contribution retirement accounts. Also, our measure of wealth 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 total debt divided by financial and real estate wealth.

2.3.2 Human Capital

We consider a labor income specification based on Carroll and Samwick (1997) that accounts for the persistence of income shocks. Specifically, we assume that the real income of household h in year t, denoted by $L_{h,t}$, satisfies

$$\log(L_{h,t}) = a_h + b' x_{h,t} + \theta_{h,t} + \varepsilon_{h,t}, \tag{3}$$

where a_h is a household fixed effect, $x_{h,t}$ is a vector of age and retirement dummies, $\theta_{h,t}$ is a persistent component, and $\varepsilon_{h,t}$ is a transitory shock distributed as $\mathcal{N}(0, \sigma^2_{\varepsilon,h})$. The persistent component

$\theta_{h,t}$ follows the autoregressive process:

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

where $\xi_{h,t} \sim \mathcal{N}(0, \sigma^2_{\xi,h})$ is the persistent shock to 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 conduct the estimation separately on household bins sorted by (i) immigration status, (ii) gender, and (iii) educational attainment. We compute the fixed-effects estimators of a_h and b in each bin, and then estimate ρ_h, $\sigma^2_{\xi,h}$ and $\sigma^2_{\varepsilon,h}$ by maximum likelihood on each household income series.

As is customary in the portfolio-choice literature (e.g., Cocco, Gomes, and Maenhout 2005), we assume that the household observes both the persistent and transitory components of income. At a given date $t-1$, the household knows the contemporaneous component $\theta_{h,t-1}$ and next-period characteristics $x_{h,t}$. The period-t log labor income, $\log(L_{h,t})$, therefore has conditional stochastic component

$$\eta_{h,t} = \xi_{h,t} + \varepsilon_{h,t}, \tag{4}$$

and conditional variance

$$\sigma^2_h = \mathrm{Var}_{t-1}[\log(L_{h,t})] = \sigma^2_{\xi,h} + \sigma^2_{\varepsilon,h}.$$

We call σ_h the *conditional volatility of income* and use it as a measure of income risk.

We define expected human capital as

$$HC_{h,t} = \sum_{n=1}^{T_h} \Pi_{h,t,t+n} \frac{\mathbb{E}_t(L_{h,t+n})}{(1+r)^n}, \tag{5}$$

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 alive at t is still alive at date $t+n$. We make the simplifying assumption that no individual lives longer than 100. The survival probability is imputed from the life table provided by Statistics Sweden. The discount rate r is set equal to 5% per year. Detailed descriptions of the labor income and human capital imputations are provided in the Internet Appendix.

2.4 Summary Statistics on Participating Households

Table I reports summary statistics on risky asset market participants (first set of columns), mutual fund owners (second set of columns), direct stockholders (third set of columns), and direct stockholders sorted by the number of stocks that they own (last set of columns) at the end of 2003. To facilitate comparison, we convert all financial variables into U.S. dollars using the exchange rate at the end of 2003 (1 Swedish krona = $0.1371).

The average participating household has a 46-year old head and a yearly income of $45,000. It owns about 1 year of income in liquid financial wealth, 3 years of income in real estate wealth, and 21 years of income in human capital. Within the financial portfolio, the average participant has a risky share of 40%, owns 4 different mutual funds, and directly invests in 2 or 3 firms. These estimates are similar to the average number of stocks in U.S. household portfolios (Barber and Odean 2000, Blume and Friend 1975). The vast majority of risky asset participants (90%) hold mutual funds, while 60% of them own stocks directly.

About half of direct stockholders invest in 1 or 2 companies; they have lower financial wealth ($35,000) and slightly lower risky shares than the average investor. These households tend to invest in a small group of companies. We classify a stock as *popular* if it is one of the 10 most widely held by the household sector in at least one year between 1999 and 2007. Popular stocks, which account for 59% of the Swedish equity market, represent 79% of the direct holdings of households with 1 or 2 stocks. The diversification losses of these households are modest, however, because concentrated stock portfolios represent only a small fraction of their financial wealth.[9]

By contrast, almost 30% of direct stockholders own at least 5 different stocks. This subgroup is important for the following reasons. Households with at least 5 stocks have high education levels and exhibit no bias toward popular stocks. They have substantially higher financial wealth ($125,000) and select a higher risky share (61%) than the average investor, and correspondingly own the bulk of aggregate equity. In the bottom rows of Table I, Panel B, we report the fraction of the aggregate portfolio held by specific subsets of investors. The aggregate portfolio is constructed

[9]See Calvet, Campbell, and Sodini (2007) for a detailed analysis.

by adding up the stock and fund holdings of all participants. Households owning 5 stocks or more, which represent only 17% of all participants, own 36% of aggregate mutual fund holdings and 80% of aggregate direct stockholdings. They therefore account for a substantial fraction of the household demand for risky assets. Polkovnichenko (2005) similarly shows that a minority of diversified wealthy households hold the bulk of aggregate equity in the United States.

Households are not heavily tilted toward stocks in their employment sector. We classify a stock as *professionally close* to household *h* if it has the same 1-digit Standard Industrial Classification code as the employer of one of the adults in *h*. The average direct stockholder allocates 16% of the stock portfolio to professionally close companies, which is rather modest and consistent with the evidence from Norway (Døskeland and Hvide 2011).

Swedish households own a sizable fraction of Swedish firms, as Figure 1 illustrates. We sort firms by market capitalization, and for each size bucket we report the fraction of firms in the size bucket (solid line) and the fraction of equity owned directly by Swedish households (solid bars). Households directly own 30% to 50% of firms with a market capitalization up to 100 million U.S. dollars, and directly own a smaller fraction of larger firms.[10] For the majority of Swedish companies, the aggregate demand from the household sector is therefore substantial and can potentially have a sizable impact on stock prices.

2.5 The Cross-Section of Value Tilts

Individual Stocks. Table II reports the value loadings of stocks listed on the Stockholm Stock Exchange at the end of 2003. The loadings range from -3.22 (10th percentile) to 0.94 (90th percentile), with a median of -0.37. The distribution of the value loading across individual stocks is therefore highly heterogenous and negatively skewed. The value-weighted (VW) portfolio of Swedish stocks, which by construction coincides with the SIXRX market index, has a value loading of -0.15 in 2003.[11] We will therefore view a value loading of -0.15 in 2003 as being neutral.

[10] In the Internet Appendix, we verify that the share of equity held by the household sector is nearly identical for value and growth firms.

[11] As equation (2) implies, the value loading of the SIXRX index can vary from year to year because the universe of listed stocks changes over time and the value loadings of individual stocks are time-invariant over the period.

The equal-weighted (EW) average stock loading is more negative than its VW counterpart, which stems from the large number of small growth stocks.

Household Portfolios. Like individual stocks, household portfolios exhibit substantial heterogeneity in the value loading. Among participants, the loading of the risky portfolio ranges from -0.94 (10th percentile) to 0.10 (90th percentile); the implied expected return differential is therefore approximately equal to the value premium.[12] The median loading is nearly neutral at -0.18, so the distribution of the risky portfolio loading is negatively skewed. Cross-sectional heterogeneity is slightly more pronounced for the stock portfolio tilt, as intuition suggests.

The value-weighted average risky portfolio has a loading of -0.26, which confirms that the household sector as a whole exhibits only a mild growth tilt. This slight tilt originates from the aggregate *stock* portfolio, which has a loading of -0.36, while the aggregate *fund* portfolio is neutral. Moreover, whether we consider stocks or funds, the EW average household has a more negative tilt than that its VW counterpart. A natural explanation is that low-wealth households invest in growth stocks, while high-wealth households invest in value stocks. We further explore this explanation in the next section.

3 Life-Cycle Variation in the Value Tilt

3.1 The Value Ladder

In Figure 2, we illustrate that households progressively switch from growth to value investments over the life-cycle, a phenomenon which we call the "value ladder." The figure is based on the risky portfolio (Panel A) and the stock portfolio (Panel B) of all Swedish households owning, respectively, risky assets or equities during the period. We sort households by birthyear into 9 cohorts, and for each cohort we plot in solid line the average VW value loading between 1999 and

[12] In the Internet Appendix, we report standard errors for the loading percentiles and infer that their difference are highly significant. We also show that the return differential is slightly higher for households owning 5 stock or more, which suggests that heterogeneous loadings are not simply the by-product of portfolio underdiversification.

2007.[13] Cohort loadings are demeaned each year in order to control for variation in the average loading of individual stocks due to new listings and delistings. The dotted lines plot the predicted cohort loadings based on pooled panel regressions, as is discussed in Section 3.3.

The value ladder is economically substantial. Figure 2 indicates that between the ages of 30 and 70, the value loading of the risky portfolio varies by 0.23 and the value loading of the stock portfolio varies by 0.48. The corresponding return differentials are, respectively, a quarter of the value premium (2.3% per year) for the risky portfolio and half the value premium (4.9% per year) for the stock portfolio.

The striking linearity between the value loading and age suggests that the ladder is more likely to originate from life-cycle variation in age and other characteristics than from combinations of time and cohort fixed effects. We know that in panel data, it is generally not possible to disentangle between age, cohort, and time effects, simply because the age variable of household h in year t is the difference between the observation year, t, and the birth year, B_h (see, e.g., Ameriks and Zeldes (2004)). The value ladders in Figures 2 reveal, however, a remarkably tight structure: the loading in year t of an investor born in year B coincides with the loading at $t+n$ of an investor born in year $B+n$. The combined effect of age, cohort, and time effects can therefore be written as a function of age alone. As we discuss in the Internet Appendix, cohort and year fixed effects would have to offset each other exactly in order to generate such an empirical structure, which can only occur in a very limited (zero-measure) subset of the parameter space.

In the remainder of this Section, we run pooled panel regressions of the value loading on household characteristics and show that changes in age, human capital and financial characteristics over the life-cycle explain almost entirely the dynamics of the value ladder. We document that these results also hold among new entrants and that maintained participants actively rebalance the value tilt of their financial portfolios, which implies that the value ladder is not due to inertia.

[13] We weigh households by financial wealth because this aggregation method has the strongest implications for asset pricing. Similar ladders exist with EW cohorts, as the Internet Appendix shows.

3.2 Demographic and Financial Determinants

Baseline Regressions. In Table III, we report pooled regressions of a household's value loading on the household's characteristics and year, industry, and county fixed effects. The industry fixed effect is the 2-digit Standard Identification Code of the household head. The first three columns consider the value loading of (1) the risky portfolio, (2) the stock portfolio, and (3) the fund portfolio. In column (4), we regress the risky share on characteristics. The estimation is conducted on the random panel of risky asset market participants, and standard errors are clustered at the household level.

Households with more liquid financial wealth tend to have a higher value tilt than other households. The financial wealth coefficient is positive and strongly significant for all three portfolios. It is the highest for the stock portfolio, which suggests that wealthy households achieve a value tilt primarily via direct stockholdings. This finding is consistent with the fact that mutual funds tend to have fairly neutral value loadings (see Table II).

Households with high current income $L_{h,t}$ and high expected human capital $HC_{h,t}$ (as defined in equation (5)) tilt their financial portfolios toward growth stocks. These relationships are significant for all three portfolios. Measures of income risk also have strongly negative coefficients: households with high income volatility and a self-employed or unemployed head are prone to selecting growth stocks.

Demographic characteristics are significantly related to the value tilt. The age of the household head tends to increase the value loading in the regressions. Younger households tend to go growth and older households tend to go value, primarily through direct stockholdings. The gender variable is strongly significant: men have a growth tilt and women a value tilt. Immigrants and educated households both tend to go growth, which suggests that the value loading is not just driven by sophistication.

Investor Subgroups. In Table IV, we reestimate the baseline regression on five separate groups of investors: (1) mutual fund owners, (2) direct stockholders, and (3) to (5) direct stockholders sorted by the number of firms that they own. The baseline results remain valid in all groups.

Furthermore, the explanatory power of the regression is twice as high for households with at least 3 stocks as for households with 1 or 2 stocks. Thus, diversified stockholders, who own the bulk of aggregate equity, tend to select value tilts that are best explained by their financial and demographic characteristics.

Real Estate and Leverage. The baseline regressions raise some immediate questions about real estate and leverage, which are important for the interpretation of the results and their connections with risk-based theories. In Table III, real estate has a positive but small effect for the risky and stock portfolios, and no effect for the fund portfolio. Likewise, leverage has a negative effect on the value loading of the stock portfolio, but no effect for the risky and the fund portfolios. These weak results are potentially due to the fact that real estate is both (i) a form of wealth and (ii) a source of background risk, and the net effect is likely influenced by the level of leverage.

In Table V, Panel A, we obtain stronger results by interacting demeaned real estate with demeaned leverage. The leverage ratio as a standalone variable has a strongly negative impact on the value loading, which is significant for all portfolios. For unlevered households, residential and commercial real estate tilt the risky and stock portfolios toward value stocks, whereas for levered households, both forms of real estate tilt the financial portfolio toward growth stocks.

Family Size. Like leverage, family size plays an ambiguous role in the baseline regressions of Table III. On the one hand, households with secure jobs and sound financial prospects are more likely to decide to have children; thus family size can be viewed as a predictor of sound financial conditions. On the other hand, as in Love (2010) and Cocco, Gomes, and Lopes (2015), we can view children as a source of background expenditure risk.

We use twins to disentangle the two effects. Our identification strategy is that while the decision to have a child is endogenous, the arrival of twins is an exogenous financial shock that could not be fully anticipated. In Table V, Panel B, we accordingly modify the baseline regression by including a dummy variable for having children and a dummy variable for having twins. While the child variable has a positive coefficient, the twin variable has a negative impact on the value loading for all three portfolios. Thus, the unexpected birth of an additional child tilts the portfolio toward growth stocks.

The regressions in Tables III to V provide substantial evidence that the portfolio value loading co-varies with financial and demographic characteristics. Value investors have high financial and real estate wealth, low leverage, low income risk, and low human capital; they are also more likely to be older and female. Conversely, young males with risky income and high human capital are more likely to go growth.

3.3 Economic Significance

We now use the baseline regressions to assess how age, human capital, and other financial characteristics contribute to the value ladder. In Table VI, we consider a household with a 30-year-old head, to which we assign the average wealth-weighted characteristics of his age group in 2003. We also consider households with 50- and a 70-year old heads that have the average characteristics of their age groups. The estimates in Table III allow us to quantify how characteristics drive the life-cycle variation in the value loading.

The table reveals that life-cycle changes in age, human capital, and financial characteristics all tend to increase the value loading, and account almost entirely for the amplitude of the value ladder. For both the risky and stock portfolios, age captures about 60% of the life-cycle variation in the value loading. The decumulation of human capital between 30 and 70 drives 20% of the life-cycle variation of the loading, while the accumulation of financial wealth accounts for the remaining 20%. Other characteristics, such as real estate, have more marginal impacts.[14] In the Internet Appendix, we show that the impact of real estate and leverage is substantially stronger when their interaction is taken into account.

In Figure 2, we illustrate the predicted average loading (dotted lined) and observed average loading (solid lines) of cohorts between 1999 and 2007. Each line plots the average loading of households in a given cohort, weighted by financial wealth. We compute the predicted values by

[14]Demographic characteristics other than age, such as immigration status or educational attainment, vary across cohorts but are not expected to vary over the life-cycle of a typical household. Moreover, as Table V shows, the impact of family size is not accurately measured by the regression coefficient in Table III. We include all characteristics in Table VI for completeness, but we observe that demographic characteristics other than age only have a marginal impact on the value loading and therefore have no impact the conclusions of this section.

using the linear coefficients of the baseline regression applied to the set of characteristics used in Table VI: age, financial characteristics and human capital. Consistent with Table VI, these variables explain the ladder with good accuracy, both for the risky and for the stock portfolios. In the Internet Appendix, we regress the predicted loading on the actual loading for each cohort. The R^2 coefficient is substantial, averaging 66% for the risky portfolio and 74% for the stock portfolio. Thus, socioeconomic characteristics, which have only limited explanatory power at the household level, have strong implications for the value loading at the cohort level and may therefore substantially impact asset prices.

3.4 New Entrants and Active Rebalancing

We verify that the value ladder is not simply due to inertia by considering the portfolios of new entrants and by documenting active rebalancing in the portfolios of maintained participants.

New Entrants. A natural identification strategy is to consider new participants in the year they enter risky asset markets, because their portfolios are not impacted by past returns, past investment decisions, inertia, and other mechanical effects. In the Appendix, we regress the portfolio value loading of new participants on their characteristics and find that all the results are consistent with the baseline regressions and the value ladder.

Active Rebalancing at the Yearly Frequency. In order to climb the value ladder over the life-cycle, households presumably need to rebalance their portfolios at shorter horizons to mitigate the impact of realized returns and revert to their slow-moving target. For this reason, we now investigate passive and active variation in the value tilt of household portfolios.[15] Consider household h with portfolio weights $w_{h,i,t-1}$ $(i = 1,\ldots,I)$ at the end of year $t-1$. If the household did not trade during the following year, the share of each asset i at the end of year t would be

$$w^P_{h,i,t} = \frac{w_{h,i,t-1}(1+r_{i,t})}{\sum_{j=1}^{I} w_{h,j,t-1}(1+r_{j,t})},$$

[15] Calvet, Campbell, and Sodini (2009a) apply a similar methodology to the dynamics of the risky share.

and the portfolio value loading would then be $v_{h,t}^P = \sum_{i=1}^I w_{h,i,t}^P v_i$. We can therefore decompose the actual change of the portfolio value loading as:

$$v_{h,t} - v_{h,t-1} = a_{h,t} + p_{h,t}.$$

where $a_{h,t} = v_{h,t} - v_{h,t}^P$ denotes the active change and $p_{h,t} = v_{h,t}^P - v_{h,t-1}$ the passive change.

In Table VII, we regress the active change, $a_{h,t}$, on the passive change, $p_{h,t}$, the lagged value loading, $v_{h,t-1}$, and either no characteristics or all lagged characteristics. The passive change has a negative and highly significant coefficient for all portfolios, regardless of whether or not one controls for household characteristics. Specifically, the passive change coefficient is -0.36 for the risky portfolio, is slightly stronger for the stock portfolio, and is slightly weaker for the fund portfolio. Thus, households actively fight the passive variation generated by realized returns, which confirms that the value ladder is not purely driven by inertia.

4 Systematic Labor Income Risk and the Value Tilt

The baseline regressions indicate that labor income volatility tends to tilt the financial portfolio toward growth stocks. We now investigate if the value loading is driven by forms of systematic risk to which households employed in different industries are heterogeneously exposed.

4.1 Industry Sensitivities

For every two-digit SIC sector s, let $L_{s,t}$ denote per-capita income in year t, which we compute using all workers in the sector. The sector's per-capita income growth is

$$\ell_{s,t} = \log(L_{s,t}) - \log(L_{s,t-1}).$$

The growth rate of per-capita income in the economy is similarly $\bar{\ell}_t = \log(\bar{L}_t) - \log(\bar{L}_{t-1})$, where $\bar{L}_t$ is average per-capita income in year t.

Table VIII, Panel A, documents that income growth is strongly correlated across sectors.[16] We estimate the linear specification:

$$\ell_{s,t} = \alpha_s + \varphi_s \overline{\ell_t} + \varepsilon_{s,t} \tag{6}$$

for each of the 70 sectors, and report the distribution of the sensitivity, φ_s, and the coefficient of determination, R^2, across regressions. The R^2 coefficients of the 70 regressions are generally high and average 0.88. Thus, aggregate income growth, $\overline{\ell_t}$, is an important factor explaining the panel of sectoral growth rates. The sensitivity, φ_s, is heterogeneous across sectors, ranging from 0.81 (10th percentile) to 1.22 (90th percentile).

4.2 Industry Variation in the Value Loading

In Table VIII, Panel B, we regress a household portfolio's value tilt, $v_{h,t}$, on the household sensitivity to the macro factor, $\varphi_{h,t}$, the conditional volatility of household income, $\sigma_{h,t}$, and all the other characteristics in the baseline regression. The household sensitivity, $\varphi_{h,t}$, is the average sensitivity of its members weighted by labor income, as is explained in the Internet Appendix.

The table shows that households working in cyclical sectors tend to reduce their portfolio value tilts. These results are especially strong for the risky portfolio, which further confirms that household tilts are not simply the by-product of a preference for certain types of stocks. Economic significance is substantial. For instance, as Table VIII shows, the income exposures of sectors in the 10th and 90th percentiles differ by about 0.4, which corresponds to an absolute difference in household portfolio loading of $0.2 \times 0.4 = 0.08$. As a comparison, this estimate slightly exceeds the change in loading induced by the life-cycle decumulation of human capital (Table VI).

We make several observations about these results. First, we impute household sensitivities from industry data because household income growth has a large idiosyncratic component and the direct measurement of household sensitivity entails large estimation error, as is further explained in the Internet Appendix. Second, our approach is motivated by earlier research showing that the value factor correlates positively with future economic growth and labor income in U.S. and international

[16]We thank the referee for encouraging us to investigate income risk at the sector level.

data (Liew and Vassalou 2000). In the Internet Appendix, we replicate these earlier results on Swedish data, even though the available time series are relatively short. We also consider a direct measure of risk, the sensitivity of labor income to the lagged value factor itself, and similarly obtain that the portfolio value loading is negatively related to the labor income sensitivity to HML.

4.3 The Value Ladder Across Industries

In Table IX, we further illustrate economic magnitudes by reporting the average risky portfolio loading of households sorted by age and industry sensitivity. The estimates are equal-weighted averages in 2003. When we compare households in the top half and bottom half of industry sensitivity, we observe that the portfolio loading spread averages to 0.11 among 30-year-olds and to 0.04 among 60-year-olds. Macroeconomic risk thus has a stronger impact on the risky portfolio if the household is young. A possible interpretation is that young households have a large stock of human capital and are therefore especially sensitive to the cyclicality of their industries.

These results suggest that the shape of the value ladder should vary across industries. In Figure 3, we correspondingly illustrate the average value loading of the risky portfolio in the most cyclical and least cyclical industries for the nine cohorts observed over the 9-year sample period. The figure is based on wealth-weighted estimates over the full sample period. The value ladder is indeed steeper in cyclical industries. Furthermore, the value ladders join up for older households, consistent with the intuition that older households have weak hedging needs regardless of their employment sectors.

5 Relation to Risk-Based Theories

In this Section, we show that the empirical evidence is consistent with some of the leading risk-based explanations of the value premium. The central tenet of the rational approach is that the value premium is a compensation for forms of systematic risk (other than market portfolio return risk) to which value and growth stocks are heterogeneously exposed. The HML factor has been shown to comove positively with several forms of systematic risk, such as aggregate labor income (Jagannathan and Wang 1996), economic growth (Koijen, Lustig, and Van Nieuwerburgh 2014, Liew and Vassalou 2000), aggregate returns (Campbell and Vuolteenaho 2004), and technological shocks (Berk, Green, and Naik 1999) in U.S. and international data. Portfolio theory implies that such risks can generate hedging demands and induce tilts in the risky portfolios of investors, as is well known from static mean-variance optimization with non-tradable assets (Mayers 1972) or dynamic portfolio choice (Merton 1973).

5.1 Hedging Demands

Direct Evidence on Income Risk. Section 4 provides direct evidence of a hedging demand by showing that households working in sectors with *high* exposures to the macro factor select risky financial portfolios with *low* HML exposures, just as the hedging motive implies. Self-employment induces an additional growth tilt, presumably because small businesses are especially sensitive to recession risk.

To the best of our knowledge, our paper is the first to provide direct evidence of a hedging demand of any kind in the risky portfolios of households. It also lends support to the link between the value premium and income risk, which has been the subject of a vast asset-pricing literature.[17] In his Presidential Address to the American Finance Association, Cochrane (2011) develops the following interpretation of the value factor: "If a mass of investors has jobs or businesses that will be hurt especially hard by a recession, they avoid stocks that fall more than average in a recession." The present paper confirms Cochrane's prediction.

Age Effects. The relationship between portfolio tilts and age is a natural implication of the hedging motive. Since long-term investors are less myopic than short-term investors, the hedging motive is theoretically stronger for younger than for older households, as the portfolio literature

[17] Jagannathan and Wang (1996), Lettau and Ludvigson (2001), Palacios-Huerta (2003), Petkova and Zhang (2005), and Santos and Veronesi (2006) develop conditional versions of the CAPM and C-CAPM that incorporate aggregate income growth and can price the Fama and French portfolios. Complementing these empirical studies, Parlour and Walden (2011) and Sylvain (2013) derive general equilibrium models in which risky labor income drives the cross-section of book-to-market ratios and risk premia.

emphasizes (Brennan, Schwartz, and Lagnado 1997, Campbell and Viceira 2000). A ladder of portfolio tilts can hence arise in a wide class of environments.

Given the direct evidence in Section 4, we can naturally relate the value ladder to aggregate income risk. This view is further reinforced by the evidence in Figure 3 that the value ladder is steeper in industries with high sensitivities to the macro factor. Indeed, in a life-cycle setting, a young agent facing high state risk has a strong hedging motive, which progressively weakens as the agent ages and becomes more myopic. This suggests that the slope of the value ladder is primarily driven by the hedging motive of the young and is therefore steeper in more cyclical industries.[18] The data confirm this theoretical prediction.

Other forms of state risk may also contribute to the value ladder. The asset-pricing literature documents that growth stocks provide a hedge against adverse variation in investment opportunities. Since young investors face higher reinvestment risk than old investors, the young should be tilted toward growth and the old toward value. Jurek and Viceira (2011), Larsen and Munk (2012), and Lynch (2001) develop this logic in calibrated portfolio-choice settings. Put slightly differently, since value stocks have shorter durations than growth stocks (Cornell 1999, Dechow, Sloan, and Soliman 2004, Lettau and Wachter 2007), young investors should hold long-duration growth stocks while old investors should select short-duration value stocks.[19] The value ladder is consistent with these mechanisms.

Human Capital. In addition to these results, we uncover that high expected human capital is associated with a growth tilt in the financial portfolio. This relationship is strong in all the specifications considered in this paper and the Internet Appendix. Intuition suggests that human capital is both a form of wealth, which in principle might induce a value tilt, and a form of risk, which in the data induces a growth tilt. We can offer several possible explanations for the dominance of the risk channel, which build on the extensive literature relating the value premium to the production process.[20] Since human capital is a key complement of physical capital in production, households

[18]Lynch and Tan (2011) demonstrate this logic in a calibrated portfolio-choice model in which the investor faces labor income risk and can trade a riskless and a risky asset.

[19]Campbell and Viceira (2001) apply a similar logic to bond investments.

[20]Production-based asset pricing models have had success in relating the sensitivity of a firm's traded equity to the firm's physical assets and growth options (Berk, Green, and Naik 1999, Carlson, Fisher, and Giammarino 2004,

with high levels of human capital should tilt away from the physical capital in value firms and invest instead in growth firms.[21] A complementary explanation is that human capital is highly risky because it is exposed to tail risks and innovation shocks that are difficult to anticipate and measure ex ante, as in the theoretical models of Garleanu, Kogan, and Panageas (2012) and Kogan, Papanikolaou, and Stoffman (2013). The strong empirical link between human capital and growth investing is a novel empirical fact that deserves further theoretical research.

5.2 Risk Aversion, Wealth, and Background Risk

Since the value factor comoves positively with financial conditions, value stocks should be picked by investors with a strong capacity to bear risk, for instance because they have high liquid financial wealth, high real estate wealth, and low leverage. These investors should be effectively more risk-tolerant (Kihlstrom, Romer, and Williams 1981) and their hedging demands should only represent a small fraction of their risky portfolios, as Ingersoll (1987) shows.

Quite remarkably, the empirical evidence in Section 4 confirms that value stocks are picked by investors with strong balance sheets. Liquid financial wealth is positively related to the value loading across participants (Table III), including the wealthy group of stockholders owning 5 stocks or more (Table IV). As in earlier studies, financial wealth is also associated with high risky shares (Table III). These results are consistent with the view that wealthier households adopt value strategies because they are effectively more risk tolerant and therefore more prone to bearing the systematic risk embedded in value stocks.

Expected utility theory implies a link between effective risk tolerance and the level of background risk. The regression results on family size, income risk, self-employment, and immigration status all give empirical support to this prediction. The unexpected birth of a child induces a growth tilt, consistent with the view that the arrival of a newborn entails lower resources per-capita and higher idiosyncratic needs. High income volatility also creates a growth tilt. Indeed, the volatility

Gomes, Kogan, and Yogo 2009, Zhang 2005). We refer the reader to the Internet Appendix for a full discussion.

[21] Baxter and Jermann (1997) show that human capital is positively correlated with aggregate physical capital at the macro level. Sylvain (2013) accordingly develops a general equilibrium model with both human and physical capital investment, and shows that value stocks endogenously exhibit a high sensitivity to human capital risk.

of real disposable income at the household level is substantial in Sweden, with an average of 16% per year (Table I) and is primarily idiosyncratic, as we show in the Internet Appendix. Similarly, entrepreneurs and immigrants exhibit a growth tilt, presumably because of substantial idiosyncratic risk in business assets and income.[22]

5.3 Intergenerational Effects

The value ladder has a natural interpretation in an overlapping generations equilibrium context. Participants gradually sell their growth stocks and migrate toward value stocks. The growth stocks must therefore be absorbed by new entrants. In the Appendix, we verify that the value ladder of new entrants is located below and is parallel to the value ladder of preexisting participants. Specifically, we verify that (i) all new entrants have a significant bias toward growth stocks and (ii) age does not impact the difference between the tilt of preexisting participants and the tilt of new entrants. Thus, new entrants absorb the *growth* stocks of preexisting participants. At the other end of the ladder, the portfolios of the deceased contain *value* stocks that surviving investors can purchase. New entrants and inheritances therefore permit the migration from growth stocks to value stocks over the life-cycle.

5.4 Household Tilts in Partial and General Equilibrium

We now show that all the empirical results can be integrated into a unified equilibrium model in the style of Merton (1974), Long (1974) and Breeden (1979). The economy, which we fully specify in the Internet Appendix, consists of K state variables, I risky assets, and a set of investors with finite horizons and heterogeneous lifespans. The model accommodates a wide range of overlapping generations structures. We do not attempt to calibrate it but note that when the state variables consist of the market price of risk and aggregate labor income, the model can relate the HML portfolio to labor income risk, as in Jagannathan and Wang (1996), and to time-varying returns, as

[22]In the Internet Appendix, we provide further evidence that idiosyncratic volatility is high in Sweden and that immigrants and entrepreneurs have significantly higher levels of income risk than other households.

in Campbell and Vuolteenaho (2004).[23] In both cases, value stocks are more exposed to state risk than growth stocks.

The following portfolios play an important role in the analysis. The tangency portfolio $\boldsymbol{\tau_t}$ maximizes the Sharpe ratio of a myopic (or short-lived) agent. The k^{th} mimicking portfolio is the portfolio with the highest absolute correlation with the k^{th} state variable. We denote by $\boldsymbol{f_{k,t}}$ the zero-sum portfolio that is long the k^{th} mimicking portfolio and short the tangency portfolio. The long-short portfolios $\boldsymbol{f_{k,t}}$ can be viewed as "factor portfolios" analogous to HML.

The optimal portfolio of an individual investor h is determined by diversification and hedging. The shares of risky wealth held in each risky asset, $\boldsymbol{\omega_t^h} \in \mathbb{R}^I$, satisfy

$$\boldsymbol{\omega_t^h} = \boldsymbol{\tau_t} + \sum_{k=1}^{K} \frac{\eta_{k,t}^h}{w_t^h} \boldsymbol{f_{k,t}}, \tag{7}$$

where each coefficient $\eta_{k,t}^h$ quantifies the investor's sensitivity to state variable k and $w_{h,t}$ denotes the risky share. The investor's deviation from the tangency portfolio is substantial if the ratios $\eta_{k,t}^h/w_t^h$ are large, that is if hedging demands are strong and represents a substantial fraction of the risky portfolio.

Equilibrium Tilts. In general equilibrium, households hold the market portfolio, $\boldsymbol{m_t}$, and heterogeneous positions in the factor portfolios:

$$\boldsymbol{\omega_t^h} = \boldsymbol{m_t} + \sum_{k=1}^{K} \left(\frac{\eta_{k,t}^h}{w_t^h} - \frac{\eta_{k,t}^m}{w_t^m} \right) \boldsymbol{f_{k,t}}, \tag{8}$$

where each coefficient $\eta_{k,t}^m/w_t^m$ denotes the relative sensitivity of the *aggregate* investor to the k^{th} factor. While the aggregate investor holds the market portfolio, each investor h tilts toward or away from the k^{th} factor if its relative sensitivity to the state variable, $\eta_{k,t}^h/w_t^h$, differs from the average sensitivity $\eta_{k,t}^m/w_t^m$. The more sensitive investor deviates from the market portfolio by insuring against state risk, whereas the less sensitive investor earns a higher average return than the market portfolio by selling insurance against state risk.

[23] Breeden (1979) and Cochrane (2007) show that labor income risk can easily be incorporated into the ICAPM.

In the context of HML, equation (8) illustrates why young investors with risky incomes and weak balance sheets should tilt their financial portfolios away from value. As we discussed in Section 5.1, young investors generally have higher sensitivities $\eta_{k,t}^h$ than old investors. When aggregate income is a state variable, the sensitivity $\eta_{k,t}^h$ is strong if the household is exposed to high systematic risk in labor income or has a large stock of human capital. Moreover, investors with weak balance sheets and high levels of background risk typically have low risky shares,[24] which means that their relative sensitivity to all state variables, $\eta_{k,t}^h/w_t^h$, is high. Young investors with risky incomes and weak balance sheets should therefore select risky portfolios that are dominated by hedging demands and, consequently, exhibit growth tilts, as is evident in the data.

6 Relation to Sentiment-Based Theories

While the baseline results are generally remarkably consistent with the predictions of risk-based models, some of our results suggest that psychological factors are also at play. Sentiment-based explanations consider that investors exuberantly overprice growth ("glamour") stocks and underprice value stocks ("fallen angels"), which explains the long-run success of value investing. Several psychological biases may account for such mispricing. Investors may be overconfident and overestimate the accuracy of available information. They may also pay more attention to recent events than Bayesian updating would imply (Kahneman and Tversky 1973). Investor with such biases tend to overprice stocks following positive news and underprice stocks following negative news, so that valuation ratios can predict future returns (Daniel, Hirshleifer, and Subrahmanyam 2001, La Porta, Lakonishok, Shleifer, and Vishny 1997, Shleifer 2000).

Cognitive biases have a number of potential implications for portfolio choice. Men and entrepreneurs are known to be especially prone to overconfidence (Barber and Odean 2001, Busenitz and Barney 1997, Cooper, Woo, and Dunkelberg 1988) and should therefore favor growth stocks. The evidence in Section 3.2 confirms these predictions. Women tend to select low risky shares and invest in value stocks, while men tend to select aggressive risky shares and go growth. These gen-

[24]The optimal risky share is low if the investor has high risk aversion, holds little liquid wealth, earns a risky income, and has high debt, as Campbell and Viceira (2000) and the references therein show.

der patterns cannot easily be explained by differences in risk aversion alone, since a risk-tolerant investor should choose both a high risky share and a value tilt. The positive empirical link between entrepreneurship and growth investing might similarly be explained by overconfidence.

The growth tilt of immigrants can be attributed to both behavioral biases and cultural effects. Calvet, Campbell, and Sodini (2007) show that immigrants bear more idiosyncratic risk in their financial portfolios, and Carroll, Rhee, and Rhee (1999), Christelis, Georgarakos, and Haliassos (2013), and Haliassos, Jansson, and Karabulut (2015) document that cultural effects impact immigrant savings rates, leverage, and equity and real estate investments. Our work uncovers that behavioral and cultural effects might also drive the value tilt. However, these effects do not drive the baseline results, as we verify in the Internet Appendix.

7 Identification and Robustness Checks

We now present a battery of robustness checks. Unless stated otherwise, all additional tests are reported in the Internet Appendix.

7.1 Stock Characteristics

Popular and Professionally Close Stocks. A potential concern is that in Sweden, a handful of firms dominate the stock market and household portfolios (Table I). In Table X, we report the characteristics of the 10 stocks that are most widely held by Swedish households at the end of 2003. These popular equities are a mix of growth and value, regardless of whether one classifies stocks by value loading or book-to-market ratio. The baseline results hold on both portfolios of popular stocks and portfolios of non-popular stocks. We similarly verify that professionally close stocks, which represent 16% of household stock portfolios, do not drive the relationships between the value loading and characteristics.

Dividends. One may ask if the value tilt picks up retail demand for dividend-paying or tax-advantaged stocks unrelated to HML. For example, Graham and Kumar (2006) use U.S. brokerage data to show that the demand for high dividend yield stocks increases with age and decreases with income, which they interpret as evidence of age and tax clienteles. In Sweden, capital losses are deductible and the tax rate is 30% on both capital gains and dividends, so the tax clientele story is not as clear as in the United States. Furthermore, the baseline results hold on sub-portfolios of stocks sorted by dividend yields, including the 50% of stocks that pay no dividends.

Taxes. We investigate the potential impact of tax optimization strategies by considering two identification methods. First, the wealth tax, which was levied on Swedish households until 2007, applied to stocks in the A list of the Stockholm Stock Exchange but not to the smaller stocks in the O list. The baseline results hold both for portfolios of A-listed stocks and for portfolios of O-listed stocks. Second, until 2004, Swedish households were levied inheritance and gift taxes at death, but these taxes did not apply to O-listed stocks. The baseline results nonetheless hold in the subperiod that follows the repeal of the inheritance tax (2005-2007). Tax optimization strategies are therefore unlikely to explain our results.

Firm Age. A possible interpretation of the value ladder is that young households invest in young firms while old households invest in old firms, without consideration of HML. This mechanism, however, is unlikely to explain our baseline results for two main reasons. First, since we use unconditional estimates of firm loadings, our results cannot be contaminated by exogenous changes in firm value tilts between 1999 and 2007. Consequently, the age story cannot explain the drift from growth to value in the portfolio of each cohort illustrated in Figure 2. Second, we show that the baseline results hold both for the portfolio of "young" stocks (listed for less than 10 years) and for the portfolio of "old" stocks (listed for at least 20 years). Thus, firm age does not drive our results.

Skewness. A recent literature suggests that the demand for positively-skewed "lottery" stocks could explain the under-diversification of household portfolios (Goetzmann and Kumar 2008, Kumar 2009b, Mitton and Vorkink 2007, Polkovnichenko 2005). While lottery stocks tend to be small and young growth stocks, it is unlikely that the value tilt is explained by preference for skewness. First, the demand for lottery stocks is relatively small. Kumar (2009b) estimates that the average share invested in lottery-stocks is less than 4% of household risky portfolios. We observe a similar pattern in Table I. Among households that own 1 or 2 stocks directly, the amount invested in smaller non-popular stocks only represents $1,000 out of a financial wealth of $37,000. Second, households choose similar value tilts in their stock and fund portfolios (Table III), which is inconsistent with the implications of portfolio theory when investors have preference for skewness (Langlois 2013, Mitton and Vorkink 2007). Third, Table IV and the Internet Appendix show that our results are the strongest among households with more diversified portfolios and are evident in the portfolios of popular and old stocks, which do not include typical lottery stocks. Thus, preference for skewness alone cannot explain our main results.

7.2 Investor Characteristics

Financial Market Experience. A possible explanation of the value ladder is that new investors naively purchase overpriced growth stocks, learn that they are bad deals, and then progressively migrate toward value stocks as time goes by.[25] We show that a measure of experience, the number of years since entry, has a significantly *negative* impact on the value loading and cannot explain away the effect of other characteristics, which is inconsistent with the simple learning story. In a recent study, Campbell, Ramadorai, and Ranish (2014) consider an Indian brokerage data set containing highly detailed information on individual trades, but no socioeconomic characteristics. They show that the returns experienced by a household drive its future portfolio style. Our results indicate that the number of years spent on financial markets cannot explain away the relationship between age and value investing.

Latent Heterogeneity. The twin panel allows us to check that the characteristics do not merely proxy for latent traits or cohort effects. We estimate the specification:

$$v_{k,1,t} = \alpha_{k,t} + b' x_{k,1,t} + e_{k,1,t}, \tag{9}$$

$$v_{k,2,t} = \alpha_{k,t} + b' x_{k,2,t} + e_{k,2,t}, \tag{10}$$

where $v_{k,j,t}$ denote the value loading of sibling $j \in \{1,2\}$ in pair k at date t, $\alpha_{k,t}$ is a yearly pair fixed

[25]The psychology literature documents that cognitive biases attenuate with experience in sufficiently regular environments (Kahneman 2011). Malmendier and Nagel (2011) provide some evidence that younger or less experienced investors are especially likely to extrapolate from recent financial data.

effect, $x_{k,j,t}$ denotes the vector of yearly characteristics of sibling j, and $e_{k,j,t}$ is an orthogonal error. Yearly twin pair fixed effect capture the impact of time, such as age or stock market performance, as well as similarities between the twins, such as common genetic makeup, family background, upbringing, and expected inheritance.[26] Consistent with the intuition that latent heterogeneity is quantitatively important, the twin regressions have substantially higher adjusted R^2 coefficients than the baseline regression, reaching 27% for the stock portfolio of identical twins (compared to 4% in Table III). The coefficients on characteristics are nonetheless fully consistent with the baseline regressions, which shows that latent heterogeneity does not drive our results.

Communication. The twin panel contains detailed information on the frequency of communication between twins. In the Internet Appendix, we sort twin pairs by their communication frequencies, and reestimate the baseline regression in each communication bin. The reported regressions are consistent with the baseline results, which indicates that communication is unlikely to drive the relationship between the value tilt and socioeconomic variables.

Genes. We use the twin communication data to reject the claim that value investing is largely driven by genes. Cronqvist, Siegel, and Yu (2015) consider a model in which the value loading of twin s in pair k is the sum of three *independent* components: a so-called "genetic" component, $a_{k,s}$, a common component, c_k, and an idiosyncratic component $\varepsilon_{k,s}$.[27] On this basis, they attribute 30% of the cross-sectional variation of the value loading to the component $a_{k,s}$. We show that this estimate is highly sensitive and drops down to less than 1% among infrequent communicators. The model used by Cronqvist, Siegel, and Yu (2015) is therefore severely misspecified, because a purely genetic component should not fully depend on communication. "Genetic" models of the *risky share* are similarly flawed, as Calvet and Sodini (2014) explain.

[26] Calvet and Sodini (2014) apply this methodology to the determinants of the risky share.

[27] That is, $v_{k,s} = a_{k,s} + c_k + \varepsilon_{k,s}$. The twin correlation, $Corr(a_{k,1}; a_{k,2})$, is assumed to be 1 for identical twins and $1/2$ for fraternal twins.

7.3 Other Robustness Checks

In the Internet Appendix, we verify that the baseline results are not contaminated by multicollinearity of household characteristics, are unlikely to be due to a reverse causality between wealth and the value loading, and hold for both households and individual investors. Our findings are robust to controlling for the size loading, using alternative definitions of household income processes, or distinguishing between the persistent and transitory components of income risk. We show that our results also hold for the value loading relative to the U.S. value factor, as the ICAPM with international financial integration implies.

8 Conclusion

An extensive asset-pricing literature relates the value premium to a wide range of macroeconomic risks. This paper documents that strong patterns exist in the portfolio value loadings of retail investors. Over the life-cycle, households progressively shift from growth to value as they become older and their balance sheets improve. Furthermore, investors with high human capital and high exposure to macroeconomic risk tilt their portfolios away from value. While several behavioral biases seem evident in the data, the patterns we uncover are remarkably consistent with the portfolio implications of risk-based theories of the value premium.

The results provide new directions for future research on the value factor. The data reveal that growth investing is tightly linked to aggregate income risk and human capital. One might seek to match these patterns in a calibrated life-cycle model, for instance by building on the frameworks of Benzoni, Collin-Dufresne, and Goldstein (2007) and Lynch and Tan (2011). Our findings also suggest that powerful general equilibrium effects are at play in the cross-section and the dynamics of value tilts. The development of overlapping generations models matching these features in the style of Garleanu, Kogan, and Panageas (2012) and Kogan and Papanikolaou (2014) are natural extensions of our work. Finally, our results suggest that demographic changes may have major implications for the value premium, which will be investigated in further research.

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Table I
Summary Statistics

The table reports summary statistics on the financial and demographic characteristics (Panel A) and portfolio characteristics (Panel B) of participating Swedish households at the end of 2003. We consider risky asset market participants (first set of columns), mutual fund holders (second set of columns), direct stockholders (third set of columns), and direct stockholders sorted by the number of stocks that they own (last set of three columns). For each characteristic, we report the cross-sectional mean and standard deviation in each sample. The bottom rows of Panel B tabulate the fraction of the aggregate wealth of risky asset market participants held by specific groups of investors. The calculations are based on the representative panel of households over the 1999 to 2007 period defined in Section 2.2. All variables are described in Table A.

Panel A: Financial and Demographic Characteristics

	All Participants		Fundholders		Stockholders		Stockholders Sorted By Number of Stocks Owned		
							1-2	3-4	5+
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Mean	Mean
Financial Characteristics									
Financial wealth ($)	48,849	121,578	50,614	121,099	66,478	152,690	37,123	60,091	126,493
Residential real estate wealth ($)	137,108	184,525	138,327	179,024	165,020	215,680	129,854	169,241	229,107
Commercial real estate wealth ($)	19,581	112,626	19,520	111,890	27,255	135,585	21,598	30,115	36,131
Leverage ratio	0.66	1.13	0.65	1.09	0.53	0.91	0.65	0.46	0.34
Human Capital and Income Risk									
Human capital ($)	955,680	515,879	972,402	513,389	993,114	545,932	929,517	1,030,770	1,089,285
Income ($)	46,184	31,316	46,785	30,687	50,066	37,029	44,902	51,133	59,183
Self-employment dummy	0.04	0.20	0.04	0.19	0.05	0.22	0.05	0.05	0.05
Unemployment dummy	0.08	0.27	0.07	0.26	0.07	0.25	0.08	0.06	0.05
Conditional income volatility	0.16	0.12	0.16	0.11	0.17	0.12	0.17	0.17	0.18
Demographic Characteristics									
Age	46.27	10.73	46.06	10.69	47.60	10.58	46.82	47.55	49.12
Male household head dummy	0.64	0.48	0.63	0.48	0.69	0.46	0.66	0.70	0.73
High school dummy	0.85	0.36	0.85	0.35	0.86	0.35	0.84	0.86	0.90
Post-high school dummy	0.37	0.48	0.37	0.48	0.42	0.49	0.35	0.42	0.53
Economics education dummy	0.12	0.32	0.12	0.32	0.13	0.34	0.12	0.14	0.16
Immigration dummy	0.08	0.27	0.08	0.26	0.08	0.27	0.08	0.09	0.07
Family size	2.53	1.40	2.61	1.40	2.52	1.37	2.42	2.56	2.69
Number of observations	71,639	71,639	62,972	62,972	42,153	42,153	22,522	7,786	11,845

Table I
Summary Statistics - *Continued*

Panel B: Portfolio Characteristics

	All Participants		Fundholders		Stockholders		Stockholders Sorted By Number of Stocks Owned		
							1-2	3-4	5+
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Mean	Mean
Portfolio Characteristics									
Risky share	0.40	0.27	0.42	0.26	0.46	0.27	0.37	0.49	0.61
Share of direct stockholdings in risky portfolio	0.29	0.37	0.19	0.28	0.49	0.37	0.44	0.48	0.58
Share of popular stocks	0.71	0.37	0.71	0.36	0.71	0.37	0.79	0.71	0.57
Share of professionally close stocks	0.16	0.32	0.16	0.31	0.16	0.32	0.15	0.17	0.18
Number of stocks	2.59	5.15	2.53	5.30	4.40	6.10	1.35	3.42	10.85
Number of funds	4.11	4.51	4.68	4.53	4.55	5.19	3.49	4.90	6.34
Share of Aggregate Wealth									
Risky portfolio	1.00		0.94		0.86		0.18	0.13	0.54
Stock portfolio	1.00		0.85		1.00		0.09	0.11	0.80
Fund portfolio	1.00		1.00		0.75		0.25	0.14	0.36
Number of observations	71,639	71,639	62,972	62,972	42,153	42,153	22,522	7,786	11,845

Table II
Cross-Sectional Distribution of the Value Loading

The table reports summary statistics on the cross-sectional distribution of the value loading at the end of 2003 for some of the main categories of assets and household portfolios used in the paper. For each category, the columns report (i) the value-weighted and equal-weighted means of the value loading, (ii) the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentiles, and (iii) the spread between the top and bottom deciles. The first row considers stocks listed on the Stockholm Stock Exchange and the second row considers all Swedish risky mutual funds. The next sets of rows consider the risky, stock, and fund portfolios held by, respectively, risky asset market participants, fundholders, and direct stockholders.

	Value Loading							
	Means		Cross-Sectional Distribution					Spread
	Value-Weighted	Equal-Weighted	10th	25th	50th	75th	90th	(90th - 10th)
Assets								
Stocks listed on Stockholm Stock Exchange	-0.15	-0.87	-3.22	-1.57	-0.37	0.09	0.94	4.16
Funds	-0.10	-0.15	-0.41	-0.26	-0.10	0.01	0.20	0.61
Households								
All participants								
- Risky portfolio	-0.26	-0.30	-0.94	-0.46	-0.18	0.00	0.10	1.04
- Stock portfolio	-0.36	-0.58	-1.20	-1.09	-0.53	0.11	0.39	1.58
- Fund portfolio	-0.18	-0.20	-0.57	-0.30	-0.14	0.00	0.08	0.65
Fundholders								
- Risky portfolio	-0.25	-0.25	-0.71	-0.40	-0.17	-0.01	0.09	0.80
- Stock portfolio	-0.35	-0.57	-1.17	-1.06	-0.52	0.10	0.38	1.55
- Fund portfolio	-0.18	-0.20	-0.57	-0.30	-0.14	0.00	0.08	0.65
Direct stockholders								
- Risky portfolio	-0.28	-0.38	-1.07	-0.61	-0.24	-0.02	0.11	1.18
- Stock portfolio	-0.36	-0.58	-1.20	-1.09	-0.53	0.11	0.39	1.58
- Fund portfolio	-0.19	-0.22	-0.58	-0.33	-0.16	-0.03	0.07	0.65

Table III
Panel Regression of the Value Loading on Characteristics

This table reports pooled regressions of the value loading on household characteristics and year, industry, and county fixed effects. The value loading is computed at the level of the risky portfolio in column (1), the stock portfolio in column (2), and the fund portfolio in column (3). We regress the risky share on the same characteristics and fixed effects in column (4). The computations are based on the representative panel of households over the 1999 to 2007 period defined in Section 2.2. All variables are described in Table A. Standard errors are clustered at the household level.

	Dependent Variable: Value Loading						Dependent Variable:	
	Risky Portfolio (1)		Stock Portfolio (2)		Fund Portfolio (3)		Risky Share (4)	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Financial Characteristics								
Log financial wealth	0.017	12.44	0.050	16.15	0.012	14.57	0.095	135.95
Log residential real estate	0.001	1.75	0.003	4.55	0.000	-0.27	0.000	3.32
Log commercial real estate	0.001	3.97	0.007	12.36	0.000	0.43	-0.002	-11.89
Leverage ratio	0.000	0.30	-0.008	-1.73	-0.001	-0.98	-0.008	-14.46
Human Capital and Income Risk								
Log human capital	-0.052	-9.50	-0.103	-9.50	-0.021	-6.63	0.016	5.92
Log income	-0.046	-11.35	-0.044	-5.75	-0.029	-12.87	-0.062	-29.50
Self-employment dummy	-0.034	-4.41	-0.037	-2.66	-0.011	-2.62	-0.047	-13.49
Unemployment dummy	-0.017	-3.99	-0.021	-2.03	-0.005	-1.97	-0.012	-5.92
Conditional income volatility	-0.353	-21.84	-0.338	-10.98	-0.116	-13.28	-0.062	-9.24
Demographic Characteristics								
Age	0.003	16.02	0.009	23.50	0.001	5.53	-0.002	-26.14
Male household head dummy	-0.062	-18.48	-0.106	-13.57	-0.013	-5.85	0.014	8.62
High school dummy	-0.014	-3.38	-0.035	-3.43	-0.006	-2.16	0.023	11.20
Post-high school dummy	-0.016	-4.64	0.016	2.00	-0.015	-6.89	0.034	19.95
Economics education dummy	-0.027	-5.94	-0.011	-1.09	-0.014	-4.76	0.011	4.69
Immigration dummy	-0.066	-11.13	-0.135	-10.33	-0.003	-0.95	-0.007	-2.61
Family size	0.036	24.60	0.024	7.42	0.017	19.23	-0.007	-10.44
Adjusted R^2	2.37%		3.95%		0.94%		16.57%	
Number of observations	589,561		331,693		523,798		589,561	

Table IV
Value Loadings of Investor Subgroups

This table reports pooled regressions of the value loading of the risky portfolio on household characteristics and year, industry, and county fixed effects estimated over different subsets of investors. The regressions are similar to the baseline regressions in Table III, but we consider subgroups of risky asset market participants: fund holders in column (1), direct stockholders in column (2), and direct stockholders sorted by the number of owned stocks in columns (3) to (5). The subgroups are obtained from the representative panel of households over the 1999 to 2007 period defined in Section 2.2. All variables are described in Table A. Standard errors are clustered at the household level.

	Dependent Variable: Value Loading of Risky Portfolio									
					Stockholders Sorted by Number of Stocks Owned					
	Fundholders (1)		Stockholders (2)		One or Two Stocks (3)		Three or Four Stocks (4)		Five or More Stocks (5)	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Financial Characteristics										
Log financial wealth	0.010	9.27	0.047	19.97	0.040	11.82	0.091	16.70	0.067	18.18
Log residential real estate	0.000	-0.45	0.002	4.48	0.002	2.65	0.002	2.01	0.004	4.92
Log commercial real estate	0.001	2.34	0.003	7.50	0.004	8.40	0.002	3.38	0.001	0.99
Leverage ratio	-0.001	-0.96	-0.010	-3.03	-0.005	-1.28	-0.028	-3.42	-0.041	-5.15
Human Capital and Income Risk										
Log human capital	-0.039	-9.29	-0.073	-9.15	-0.068	-5.84	-0.060	-3.54	-0.067	-5.87
Log income	-0.047	-15.12	-0.043	-7.38	-0.047	-5.63	-0.036	-2.73	-0.044	-5.29
Self-employment dummy	-0.025	-4.51	-0.024	-2.29	-0.024	-1.48	-0.014	-0.65	-0.027	-1.90
Unemployment dummy	-0.009	-2.83	-0.031	-3.93	-0.042	-3.91	-0.012	-0.75	-0.017	-1.47
Conditional income volatility	-0.247	-20.98	-0.403	-17.01	-0.379	-10.78	-0.444	-9.81	-0.413	-12.88
Demographic Characteristics										
Age	0.002	16.78	0.005	17.40	0.005	11.92	0.005	8.88	0.005	11.65
Male household head dummy	-0.037	-14.08	-0.085	-16.28	-0.077	-10.47	-0.113	-11.20	-0.076	-9.96
High school dummy	-0.009	-2.76	-0.024	-3.46	-0.029	-3.20	-0.008	-0.57	-0.013	-1.15
Post-high school dummy	-0.019	-6.75	0.005	0.90	-0.003	-0.38	0.016	1.62	0.021	2.71
Economics education dummy	-0.020	-5.47	-0.018	-2.75	-0.035	-3.54	-0.014	-1.06	0.011	1.19
Immigration dummy	-0.031	-6.93	-0.120	-12.39	-0.115	-8.65	-0.108	-5.76	-0.138	-9.46
Family size	0.025	22.24	0.040	17.74	0.046	14.54	0.038	8.36	0.030	9.00
Adjusted R^2	2.02%		4.45%		3.50%		7.54%		7.22%	
Number of observations	523,798		331,693		175,707		59,697		96,289	

Table V
Alternative Risk Measures

This table reports the effects of additional real estate, leverage, and family size variables on the value loading in the presence of year, industry, and county fixed effects. Panel A includes measures of demeaned real estate wealth interacted with demeaned leverage. We conduct this estimation on the representative panel of households over the 1999 to 2007 period defined in Section 2.2. Panel B includes a dummy variable for having a child during the year and a dummy variable for having twins during the year. The estimation is conducted on a separate sample that includes all households with newborn twins. The regressions are otherwise similar to the baseline regression in Table III, and the full estimation details and results are available in the Internet Appendix. All variables are described in Table A. Standard errors are clustered at the household level.

Panel A: Real Estate Interacted with Leverage

	Dependent Variable: Value Loading					
	Risky Portfolio (1)		Stock Portfolio (2)		Fund Portfolio (3)	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Log residential real estate	0.000	1.37	0.003	3.79	0.000	-0.44
Log commercial real estate	0.001	2.01	0.007	9.87	0.000	-0.88
Log residential real estate × Leverage ratio	-0.001	-4.28	-0.004	-4.88	0.000	-1.40
Log commercial real estate × Leverage ratio	-0.001	-3.13	0.000	-0.45	-0.001	-3.48
Leverage ratio	-0.012	-4.11	-0.040	-5.10	-0.004	-2.29

Panel B: Children

	Dependent Variable: Value Loading					
	Risky Portfolio (1)		Stock Portfolio (2)		Fund Portfolio (3)	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Dummy for having children	0.087	17.21	0.028	2.17	0.03	8.20
Dummy for having twins	-0.020	-2.63	-0.039	-1.83	-0.01	-1.15

Table VI
Economic Significance

This table reports the impact on the value loading of life-cycle variation in age and financial characteristics. We use as benchmarks a 30-year old household head, a 50-year-old household head, and a 70-year old household head, to which we assign the average characteristics of households in their respective cohorts in 2003. The impact of changes in characteristics is assessed using the baseline regression coefficients in Table III. All variables are described in Table A.

	Risky Portfolio		Stock Portfolio		Fund Portfolio	
	30→50	50→70	30→50	50→70	30→50	50→70
Observed change in value loading	0.09	0.14	0.23	0.25	0.02	0.04
Predicted change						
Financial Characteristics						
Log financial wealth	0.015	0.008	0.042	0.022	0.010	0.005
Log residential real estate	0.001	0.000	0.005	-0.003	0.000	0.000
Log commercial real estate	0.001	0.004	0.010	0.025	0.000	0.000
Leverage ratio	0.000	0.000	0.002	0.001	0.000	0.000
Human Capital and Income Risk						
Log human capital	0.024	0.037	0.048	0.073	0.010	0.015
Log income	-0.006	-0.009	-0.006	-0.008	-0.004	-0.006
Self-employment dummy	0.000	-0.009	0.000	-0.009	0.000	-0.003
Unemployment dummy	0.000	0.001	0.000	0.001	0.000	0.000
Conditional income volatility	-0.004	0.000	-0.003	0.000	-0.001	0.000
Demographic Characteristics						
Age	0.055	0.055	0.177	0.177	0.012	0.012
Male household head dummy	-0.001	-0.018	-0.001	-0.031	0.000	-0.004
High school dummy	0.001	0.002	0.003	0.006	0.001	0.001
Post-high school dummy	0.001	0.007	-0.001	-0.007	0.001	0.006
Economics education dummy	0.002	-0.001	0.001	0.000	0.001	-0.001
Immigration dummy	0.000	0.003	0.000	0.007	0.000	0.000
Family size	-0.035	-0.015	-0.024	-0.011	-0.016	-0.007
Change due to age and wealth characteristics	**0.090**	**0.094**	**0.278**	**0.287**	**0.028**	**0.027**
Fraction due to age	**61.12%**	**58.10%**	**63.61%**	**61.54%**	**41.14%**	**42.90%**
Fraction due to financial characteristics	**18.56%**	**11.58%**	**21.34%**	**15.83%**	**37.68%**	**21.85%**
Fraction due to human capital and income	**20.31%**	**30.32%**	**15.05%**	**22.63%**	**21.18%**	**35.25%**

Table VII
Active Rebalancing of the Value Loading

This table reports pooled regressions of the active change in the value loading on (i) the passive change in the value loading and (ii) the lagged value loading. We conduct the analysis at the level of the risky portfolio in columns (1) and (2), the stock portfolio in columns (3) and (4), and the fund portfolio in columns (5) and (6). For each portfolio, we report the regression with and without lagged households characteristics. All variables are demeaned each year. The computations are based on the representative panel of households over the 1999 to 2007 period defined in Section 2.2. Standard errors are clustered at the household level.

	Dependent Variable: Active Change of Value Loading											
	Risky Portfolio				Stock Portfolio				Fund Portfolio			
	(1)		(2)		(3)		(4)		(5)		(6)	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Value Loading Variables												
Passive change in the value loading	-0.356	-27.63	-0.356	-27.61	-0.372	-27.30	-0.375	-27.40	-0.283	-27.95	-0.284	-27.98
Lagged value loading	-0.116	-41.95	-0.119	-42.55	-0.078	-38.24	-0.082	-39.15	-0.110	-54.30	-0.111	-54.41
Lagged Financial Characteristics												
Log financial wealth			0.002	4.81			0.005	6.08			0.000	0.90
Log residential real estate			0.000	1.97			0.001	3.71			0.000	-1.96
Log commercial real estate			0.000	1.64			0.001	5.09			0.000	1.65
Leverage ratio			0.001	2.30			0.000	-0.04			0.000	0.22
Lagged Income												
Log human capital			-0.020	-14.49			-0.031	-12.31			-0.009	-11.79
Log income			-0.002	-1.58			0.008	3.21			0.000	0.36
Self-employment dummy			-0.006	-2.79			-0.006	-1.51			-0.001	-0.69
Unemployment dummy			-0.004	-2.28			-0.004	-1.27			0.000	0.00
Conditional income volatility			-0.051	-11.21			-0.028	-3.61			-0.011	-4.92
Lagged Demographic Characteristic												
Family size			0.006	14.40			0.001	1.83			0.002	9.10
Adjusted R^2	6.85%		0.070		5.27%		0.054		7.06%		0.071	
Number of observations	406,561		406,561		221,143		221,143		355,443		355,443	

Table VIII
Systematic Labor Income Risk

This table investigates the factor structure of industry-level income growth and its implications for household financial portfolios. For each of the 70 two-digit industries, we regress sectoral income growth on aggregate income growth and report in Panel A the distribution of the corresponding slopes and R^2 coefficients. Panel B reports pooled regressions of the household portfolio value loading on (i) the loading of household income on aggregate income, (ii) conditional income volatility, and (iii) other standard characteristics, and year, industry, and county fixed effects. The household income loading is defined as the weighted average loading of the sectors in which the adults in the household are employed. The full results are reported in the Internet Appendix. The computations are based on the representative panel of households over the 1999 to 2007 period defined in Section 2.2. Standard errors are clustered at the household level.

Panel A: Cross-Sectional Distribution of Income Exposure to Aggregate Income Shocks

	Mean	10th	25th	50th	75th	90th
Loading of sectoral income on aggregate income	1.03	0.81	0.95	1.05	1.15	1.22
R^2	0.88	0.74	0.83	0.92	0.95	0.96

Panel B: Income Exposure to Aggregate Income Shocks

	Dependent Variable: Value Loading					
	Risky Portfolio (1)		Stock Portfolio (2)		Fund Portfolio (3)	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Loading of sectoral income on aggregate income	-0.205	-10.05	-0.200	-3.86	-0.077	-5.54
Conditional income volatility	-0.342	-20.45	-0.330	-10.30	-0.111	-12.23

Table IX
Value Loadings of Households Sorted by Age and Industry Exposure

The table reports the average value loading of the risky portfolios held by households sorted by age and industry sensitivity in 2003. All the value loadings are equally-weighted and demeaned by the 2003 average. The first set of three columns consider households with industry sensitivities in the bottom 10%, 25%, and 50%, the next set of three columns consider households with industry sensitivities in the top 50%, 25%, and 10%, and the last column reports the value spread between the bottom and top halves of industry sensitivity. The last row reports the amplitude of the value ladder in each industry sensitivity bucket.

	Least Cyclical Industries			Most Cyclical Industries			Spread
	Bottom			Top			(Bottom 50% -
	10%	25%	50%	50%	25%	10%	Top 50%)
Age:							
30	-0.02	-0.01	-0.01	-0.12	-0.16	-0.13	0.11
40	0.02	0.02	0.02	-0.04	-0.08	-0.08	0.06
50	0.02	0.03	0.03	0.00	-0.02	-0.05	0.03
60	0.09	0.10	0.09	0.05	0.03	0.04	0.04
Spread (Age 60 - Age 30)	0.11	0.11	0.10	0.17	0.19	0.17	

Table X
Stocks Most Widely Held by Swedish Households

The table reports the ten stocks that are most widely held by Swedish households at the end of 2003. Stocks are sorted by the proportion of households that hold them directly (first column). We also report the stock's percentage of aggregate household direct stockholdings (second column), the stock's percentage of the total market capitalization of all firms listed on Swedish exchanges (third column), the stock's percentage of the free float-adjusted market capitalization of all firms listed on Swedish exchanges (fourth column), the stock's value loading (fifth column), and the percentile of the stock's book-to-market ratio (sixth column). The analysis is conducted on the representative panel defined in Section 2.2. In the bottom row, we consider the aggregate household portfolio of popular stocks and report its share of aggregate household stock wealth, its share of the Swedish stockmarket, its value loading, and the average book-to-market ratio percentile of popular stocks weighted by their shares of the aggregate household stock wealth (imputed from the second column).

	% of Stockholders Owning Company	% of Household Stock Wealth	% of Swedish Stockmarket	% of Swedish Free Float	Value Loading	B/M Quantile
Ericsson	60.46%	21.69%	7.49%	8.70%	-1.22	25.41%
Telia	46.50%	4.02%	6.48%	4.16%	-1.00	44.19%
Swedbank	24.54%	3.76%	2.74%	2.75%	0.11	46.85%
SEB	23.57%	5.52%	2.69%	3.14%	0.74	56.21%
Volvo	14.58%	5.00%	3.18%	3.36%	0.41	68.94%
H&M	11.39%	4.75%	5.21%	3.76%	-0.07	4.29%
Billerud	10.78%	1.11%	0.22%	0.25%	-0.06	46.26%
AstraZeneca	9.66%	5.38%	4.81%	3.79%	0.09	68.23%
Nokia	8.71%	3.78%	23.77%	31.14%	-0.08	14.69%
Investor	8.61%	2.48%	1.95%	1.59%	0.27	80.77%
Aggregate portfolio of popular stocks		57.49%	58.53%	62.64%	-0.41	39.21%

Table A
Definition of Household Variables

This table summarizes the main household variables used in the paper.

Variable	Description
Cash	Bank account balances and Swedish money market funds.
Fund portfolio	Portfolio of mutual funds other than Swedish money market funds.
Stock portfolio	Portfolio of directly held stocks.
Risky portfolio	Combination of the stock and fund portfolios.
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 defined-contribution retirement accounts.
Share of popular stocks	Fraction of the stock portfolio invested in public firms which were one of the ten most widely held in at least one year between 1999 and 2007.
Share of professionally close stocks	Fraction of the stock portfolio invested in firms with the same 1-digit industry code as an adult household member's current employer.
Number of stocks	Number of assets in the stock portfolio.
Number of funds	Number of assets in the fund portfolio.
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 non-financial disposable real income.
Income	Total household disposable income.
Self-employment dummy	Dummy variable equal to one if the household head is self-employed.
Unemployment dummy	Dummy variable equal to one if the household head is unemployed.
Conditional income volatility	Standard deviation of the total income shock, defined as the sum of the persistent and transitory income shocks in a given year.
Loading of sectoral on aggregate income	Sensitivity of a sector's per-capita income growth to the growth rate of per-capita income in the overall economy.
Age	Age of the household head.
Male household head dummy	Dummy variable equal to one if the household head is male.
High school dummy	Dummy variable equal to one if the household head has a high school degree.
Post-high school dummy	Dummy variable equal to one if the household head has had some post-high school education.
Economics education dummy	Dummy variable equal to one if the household head received education in a field related to economics and management.
Family size	Number of people living in the household.

Figure 1
Percentage of Public Equity Directly Held by Households

This figure illustrates (i) the percentage of firm market capitalizations owned directly by Swedish households at the end of 2003 as function of firm size (solid bars and left axis), and (ii) the distribution of firm size (solid line and right axis). The calculations are based on the 352 firms listed on Swedish exchanges and all Swedish households that own stocks at the end of 2003.

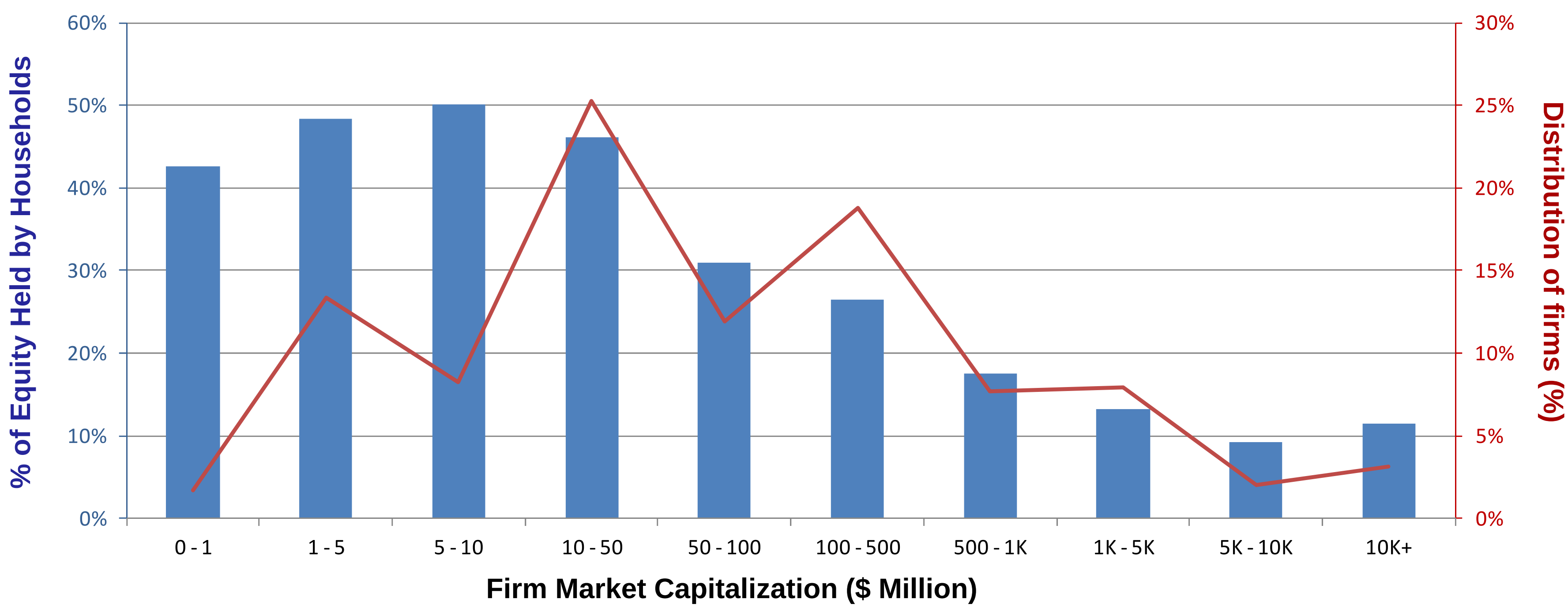

Figure 2
The Value Ladder

This figure illustrates the value loading of the risky portfolio (left panel) and stock portfolio (right panel) for different cohorts of households. Each solid line corresponds to the average loadings of households in a given cohort, weighted by financial wealth. Each dotted line is the corresponding predicted value loading, obtained by using age, wealth variables, and human capital multiplied by the household-level baseline regression coefficients in Table **III**. A cohort is defined as a 5-year age bin. The first cohort contains households with a head aged between 30 and 34 in 1999, while the oldest cohort has a head aged between 70 and 74 in 1999. The loadings of all households in year *t* are demeaned to control for changes in the composition of the Swedish stock market. Panel A is based on the panel of all Swedish risky asset market participants and Panel B on the panel of all Swedish direct stockholders over the 1999 to 2007 period.

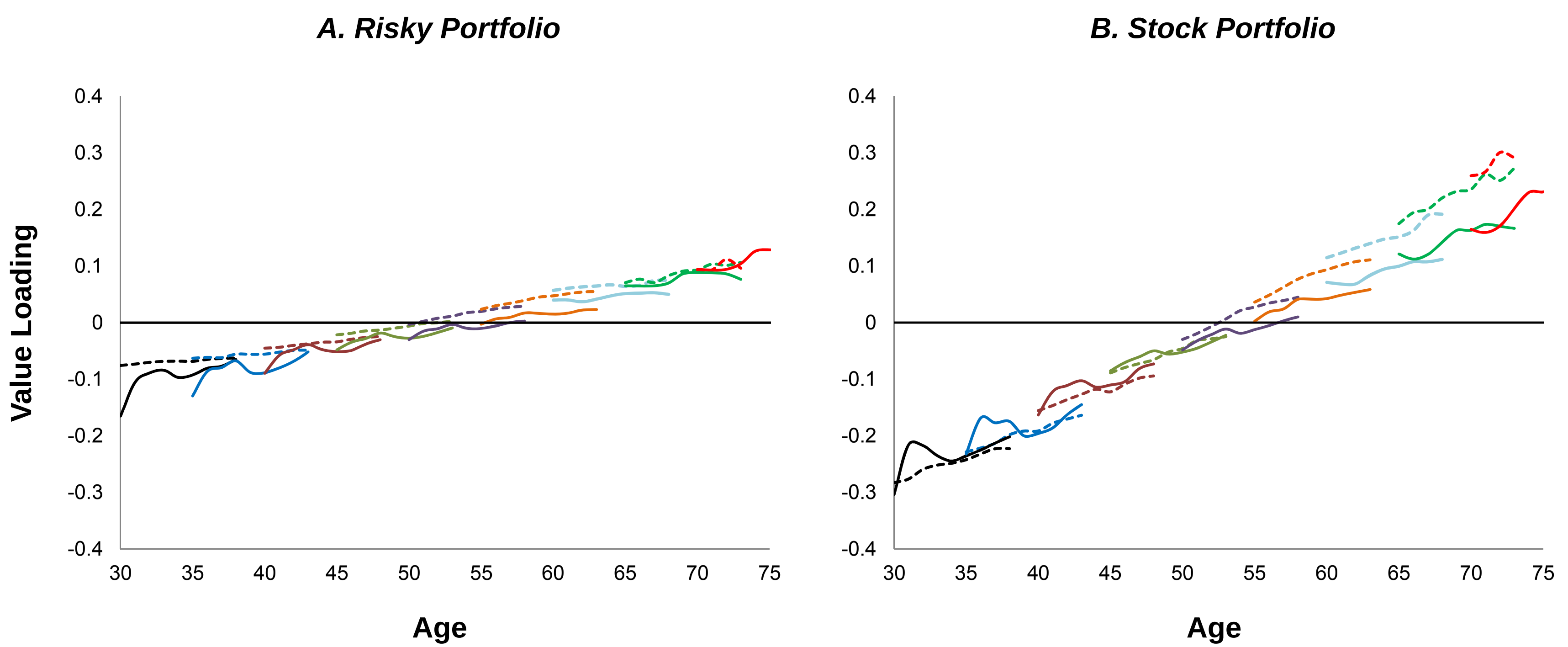

Figure 3
The Value Ladder Across Industries

This figure illustrates the value loading of the risky portfolio for cohorts of households in the top 25% (solid lines) and the bottom 25% (dotted lines) of industry sensitivity. We measure industry sensitivity by regressing per-capita income growth in the industry on per-capita income growth in the economy. Each line corresponds to a given cohort, defined as a 5-year age bin. The first cohort contains households with a head aged between 30 and 34 in 1999, while the oldest cohort has a head aged between 70 and 74 in 1999. The loadings of all households in year *t* are demeaned to control for changes in the composition of the Swedish stock market. A cohort's loading in year *t* is the wealth-weighted average year-*t* loading of households in the cohort. The figure is based on the panel of all Swedish risky asset market participants over the 1999 to 2007 period.