Who are the Value and Growth Investors?*

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Abstract

This paper investigates the determinants of value and growth investing in a large administrative panel of Swedish residents over the 1999-2007 period. We document strong relationships between a household's portfolio tilt and the household's financial and demographic characteristics. Value investors have higher financial and real estate wealth, lower leverage, lower income risk, lower human capital, and are more likely to be female than the average growth investor. Households actively migrate to value stocks over the life-cycle and, at higher frequencies, dynamically offset the passive variations in the value tilt induced by market movements. We verify that these results are not driven by cohort effects, financial sophistication, biases toward popular or professionally close stocks, or unobserved heterogeneity in preferences. We relate these household-level results to some of the leading explanations of the value premium.

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ABSTRACT

This paper investigates the determinants of value and growth investing in a large administrative panel of Swedish residents over the 1999-2007 period. We document strong relationships between a household's portfolio tilt and the household's financial and demographic characteristics. Value investors have higher financial and real estate wealth, lower leverage, lower income risk, lower human capital, and are more likely to be female than the average growth investor. Households actively migrate to value stocks over the life-cycle and, at higher frequencies, dynamically offset the passive variations in the value tilt induced by market movements. We verify that these results are not driven by cohort effects, financial sophistication, biases toward popular or professionally close stocks, or unobserved heterogeneity in preferences. We relate these household-level results to some of the leading explanations of the value premium.

JEL Classification: G11, G12.

Keywords: Asset pricing, value premium, household finance, portfolio allocation, human capital.

1 Introduction

A large academic and practitioner literature documents that value stocks outperform growth stocks on average in the United States (Basu 1977, Fama and French 1992, Graham and Dodd 1934) and around the world (Fama and French 1998).[1] The economic explanation of these findings is one of the central questions of modern finance. The value premium may be a compensation for forms of systematic risk other than market portfolio return risk (Fama and French 1992), such as recession risk (Cochrane 1999, Jagannathan and Wang 1996), cash-flow risk (Campbell and Vuolteenaho 2004, Campbell, Polk, and Vuolteenaho 2010), long-run consumption risk (Hansen, Heaton, and Li 2008), or the costly reversibility of physical capital and countercyclical risk premia (Zhang 2005). 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 (Daniel, Hirshleifer, and Subrahmanyam 2001, DeBondt and Thaler 1985, La Porta, Lakonishok, Shleifer, and Vishny 1997).

The extensive empirical literature on the origins of the value premium focuses primarily on stock returns and their relationships to macroeconomic and corporate data. Disentangling theories of the value premium, however, has proven to be challenging on traditional data sets that do not provide individual trades and therefore do not permit to assess the determinants of investor decisions. In this paper, we propose to use the rich information in investor portfolios to shed light on theoretical explanations of the value premium. We make a first step in this direction by investigating 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 portfolio holdings at the level of each stock or fund, along with other forms of wealth, debt, labor income, and employment sector. We document strong empirical relationships between a household's socioeconomic characteristics and the household's tilt toward value or growth stocks. We also uncover new empirical patterns in the dynamics of the portfolio tilt at the yearly and life-cycle frequencies, and relate our various findings to theoretical explanations of the value premium.

The paper makes four main contributions to the literature. First, we show that the value tilt

[1] See also Asness, Moskowitz, and Pedersen (2013), Ball (1978), Basu (1983), Chan, Hamao, and Lakonishok (1991), Fama and French (1993, 1996, 2012), Liew and Vassalou (2000), and Rosenberg, Reid, and Lanstein (1985).

exhibits substantial heterogeneity across households. When we sort investors by the value tilt of their risky asset portfolios, the difference in expected return is about 10% per year between the top and bottom deciles. We document that the value tilt of household portfolios is strongly related to financial and demographic characteristics. Value investors are substantially older, tend to 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, males, entrepreneurs, and educated investors are more likely to invest in growth stocks. These baseline patterns are evident both in the direct stockholdings and the mutual fund holdings of households. Quite strikingly, new entrants exhibit the same strong relationships between the value tilt and characteristics, even though the portfolios of new entrants are formed for the first time and cannot be impacted by past stock market investment decisions. The baseline results are also robust to controlling for the length of risky asset market participation and other measures of financial sophistication. Furthermore, the explanatory power of socioeconomic characteristics is especially high among the minority of households with direct investments in more than four companies, a wealthy group that own the bulk of aggregate equity.

Second, we provide evidence that households actively manage their holdings of growth and value stocks. We report that households dynamically rebalance their exposure to the value factor in response to passive variation in the portfolio tilt at the yearly frequency. At longer horizons, households climb the "value ladder" over the life-cycle, that is they gradually shift from growth to value investing as they become older, wealthier, less levered, and less dependent on human capital. Similar patterns hold for new participants, whose initial portfolios are not passively affected by past market returns.

Third, we document that the relationship between the portfolio tilt and investor characteristics is unlikely to be driven by a bias toward popular or familiar stocks. Consistent with international evidence, the median Swedish household directly invests in a small number of equities. Across households, direct stockholdings tend to concentrate in a limited set of popular firms, toward which less wealthy and less educated households are especially drawn. We document, however, that the set of popular firms contains a mix of growth and value stocks, and that household portfolios of popular firms have heterogeneous tilts. We verify that the baseline relationships between the value loading and characteristics hold strongly in household portfolios of popular stocks, as well as in their portfolios of nonpopular stocks. Moreover, earlier research shows that investors have a propensity to invest in firms that are known to them through their jobs or neighbors (Døskeland and Hvide 2011, Huberman 2001, Massa and Simonov 2006). Consistent with the Norwegian experience (Døskeland and Hvide 2011), professionally close stocks account in Sweden for an average of 16% of direct stockholdings and have substantially heterogeneous weights across households. The baseline relationships between the value tilt and characteristics, however, are observed both in the portfolios of professionally close stocks and in the portfolios of other stocks.

Fourth, we verify the good identification of our results. As in Calvet and Sodini (2014), we use the subsample of Swedish twins to control for latent fixed effects, such as the impact of upbringing, inheritance, or attitudes toward risk. Socioeconomic characteristics have similar coefficients in the twin subsample with yearly twin pair fixed effects as in the general household population. The explanatory power of the regression is of course considerably higher for twins. We also consider various subsamples of households, such as new participants, frequently and infrequently communicating twins, public sector employees, or households employed in growth firms and value firms, and report that investment styles are strongly related to financial and demographic characteristics in all subsamples. Furthermore, we provide evidence that our baseline results are unlikely to be explained by a reverse causality between wealth and the value loading, or by the misspecification of the income process.

The present paper contributes to the growing literature on the relationship between retail investor demand and stock characteristics. Earlier research shows that individual investors prefer stocks that are familiar (Huberman 2001), 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). The dynamics of investment styles chosen by retail investors have also been related to certain types of news and past experience (Kumar 2009, Campbell, Ramadorai, and Ranish 2014). The Swedish panel contains exceptionally high-quality data on individual holdings and socioeconomic characteristics, and allows us to uncover new micro-level patterns in the demand for value and growth stocks from the household sector.

Our portfolio results complement the extensive asset-pricing literature on the value premium, which focuses on stock valuations, corporate data, and aggregate investor forecasts. In particular, we provide household-level support for several leading explanations of the cross-section of returns. Value investors tend to be older than the average participant and have low human capital, low income risk, low leverage, and high financial wealth. These regularities are strikingly consistent with risk-based theories, including the life-cycle implications of the hedging motive (Merton 1973) and the high sensitivity of value stocks to deep recessions (Campbell, Giglio, and Polk 2013, Cochrane 1999). Other empirical regularities documented in the paper can receive complementary risk-based and psychological explanations. For instance, the tilt of entrepreneurs toward growth stocks can be attributed both to a high exposure to business risk (Moskowitz and Vissing-Jørgensen 2002) and a high degree of overconfidence in their decision-making skills (Busenitz and Barney 1997). Overconfidence is more prevalent among men than women (Barber and Odean 2001), and can therefore explain the preference of male investors for growth stocks. Furthermore, a majority of direct stockholders hold a small number of popular stocks, as attention theory predicts (Barber and Odean 2008).

The Swedish data set provides highly detailed information on household financial and demographic characteristics but is somewhat less informative about behavioral biases. With this caveat, a notable conclusion of our study is that the financial circumstances of households impact their value and growth investments in accordance with the predictions of risk-based theories. Wealthy investors with safe incomes and sound balance sheets consciously hold systematic risk other than market portfolio risk because they are in the best position to do so and wish to earn the value premium. Furthermore, socioeconomic variables have higher explanatory power for wealthy investors owning stocks in more than four firms, which suggests that these relationships are conscious and rationally motivated.

The evidence reported in this paper complements the growing body of work showing that retail investors tend to follow the precepts of portfolio theory. Households are known to select a low share of risky assets in their liquid financial portfolios if their labor income is risky, as measured by self-employment (Heaton and Lucas 2000) or income volatility (Betermier, Jansson, Parlour, and Walden 2012, Calvet and Sodini 2014, Guiso, Jappelli, and Terlizzese 1996).[2] Conversely, households choose an aggressive risky share if they have high financial wealth and high human capital (Calvet and Sodini 2014). Furthermore, a majority of investors incur modest welfare losses due to underdiversification (Calvet, Campbell, and Sodini 2007) and actively rebalance these portfolio's shares of liquid financial wealth in response to realized asset returns (Calvet, Campbell, and Sodini 2009a). The present paper documents that financial theory also accounts for the cross-

[2] See Bonaparte, Korniotis, and Kumar (2013) and Knüpfer, Rantapuska, and Sarvimäki (2013).

sectional and time-series properties of household portfolio value tilts.

Finally, the paper sheds light on the potential relationship between genes and value investing. In a recent contribution, Cronqvist, Siegel, and Yu (2013) estimate a variance decomposition of the investment decisions made by identical and fraternal twins, and infer that value investing has a strong genetic component. The present paper replicates these results but also demonstrates their high sensitivity to the frequency of communication between twins. In particular, the so-called genetic component disappears almost entirely among infrequent communicators, which suggests that the variance decomposition severely overestimates the impact of genes. A growing literature in genetics, medicine, and experimental psychology documents substantial interactions between nature and nurture (Ridley 2003), and our findings confirm the fragility of statistical decompositions that ignore these interactions. The empirical evidence in this paper indicates that value and growth investing are not simply encoded in the DNA of retail investors, but are also strongly driven by their financial circumstances and interpersonal communication.

The rest of the paper is organized as follows. Section 2 reviews the portfolio implications of some of the leading explanations of the value premium. Section 3 presents the data and reports summary statistics. Section 4 investigates the characteristics of value and growth investors. Section 5 discusses the economic implications of these findings. In Section 6, we show that investors actively rebalance passive variation in their exposure to the value factor, and, at lower frequencies, actively migrate to value stocks over the life-cycle. Section 7 concludes. A supplementary Internet Appendix (Betermier, Calvet, and Sodini 2014) presents details of data construction and estimation methodology, and reports additional results.

2 Theoretical Motivation

In this section, we review some of the leading theories of the value premium and discuss their implications for portfolio choice.

2.1 Determinants of the Value Premium

The value premium is one of the best documented facts in asset pricing, which has proven to be remarkably persistent over time and across markets.[3] These strong empirical findings have received a number of theoretical explanations.

2.1.1 Systematic Risk

Fama and French (1992, 1995) propose that the value premium is a compensation for a form of systematic risk other than market portfolio return risk. Several possibilities have been considered for the precise nature of this alternative risk (Cochrane 1999). Unlike growth stocks, value stocks exhibit high sensitivity to aggregate labor income and consumption shocks. Conditional versions of the CAPM based on these variables have therefore had success in explaining the value premium (Jagannathan and Wang 1996, Lettau and Ludvigson 2001, Petkova and Zhang 2005, Yogo 2006).[4] Value stocks are also highly exposed to long-run macroeconomic risk (Bansal, Dittmar, and Lundblad 2005, Gulen, Xing, and Zhang 2011, Hansen, Heaton, and Li 2008).[5]

The excess returns of value stocks over growth stocks are informative about changes in investment opportunities. Under the Intertemporal Capital Asset Pricing Model (ICAPM, Merton 1973), a factor that forecasts the distribution of future returns also explains the cross-section of risk premia, as Campbell (1996) emphasizes. Good realizations of the factor are associated with an improvement in investment opportunities, so that assets with a negative loading on the factor provide a hedge against worsening investment opportunities. Consistent with the logic of the ICAPM, good realizations of the value factor predicts high aggregate returns (Campbell and Vuolteenaho 2004) and economic growth (Liew and Vassalou 2000) in U.S. and international data. Growth stocks can

[3] See for instance Asness, Moskowitz, and Pedersen (2013), Capaul, Rowley, and Sharpe (1993), Fame and French (1998, 2012), Griffin (2003), and Liew and Vassalou (2000). Some recent work also shows that the strength of the value premium can be improved by refining the sorting methodology (Asness and Frazzini 2013, Barras 2013, Hou, Karolyi, and Kho 2011).

[4] Eiling (2013), Jagannathan, Kubota, and Takehara (1998), Addoum, Korniotis, and Kumar (2013), and Santos and Veronesi (2006) provide further evidence on the relationship between labor income and the value premium.

[5] Other forms of countercyclical risk can contribute to explaining the value premium. For instance, the variance of idiosyncratic labor income risk is high during recessions (Storesletten, Telmer, and Yaron 2004) and value stocks tend to provide low dividends when the aggregate housing collateral is low (Lustig and van Nieuwerburgh 2005). These mechanisms motivate investors to require a premium in order to hold these stocks.

therefore act as a hedge against low aggregate risk premia.

Fundamentals explanations of the value premium are supported by decompositions of market portfolio returns into cash-flow news and discount-rate news (Campbell and Vuolteenaho 2004). Value stocks have considerably higher exposure to the market's cash-flow risk (bad beta) and lower exposure to the market's discount-rate risk (good beta) than growth stocks. In particular, value stocks are strongly exposed to deep recessions and the persistent reductions in aggregate cash flows that they entail (Campbell, Giglio, and Polk 2013). The poor performance of value strategies during the Great Financial Crisis provides recent evidence that value strategies are indeed highly exposed to deep recession risk. Furthermore, the value loadings of individual stocks are primarily driven by their own cash flows, which confirms that the value premium is rooted in fundamentals (Campbell, Polk, and Vuolteenaho 2010). Overall, the empirical asset-pricing evidence suggests that value stocks are exposed to forms of systematic risk other than market portfolio return risk, which can explain, at least partly, the value premium.

2.1.2 Timing of Cash Flows and Production Risks

The different sensitivities of value and growth stocks to aggregate conditions can be explained by the timing of their cash flows and the dynamics of their production processes. It is for instance well known that value stocks have shorter durations than growth stocks (Cornell 1999, Dechow, Sloan, and Soliman 2004). Consequently, value stocks exhibit low sensitivity to discount-rate risk and high sensitivity to cash-flow risk (Lettau and Wachter 2007), which is consistent with the empirical evidence in Campbell and Vuolteenaho (2004).

In addition, structural 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, Gomes, Kogan, and Zhang 2003). Cutting physical capital in bad times entails more adjustment costs that expanding physical capital in good times. Assets in place are therefore riskier than growth options, especially in bad times when the price of risk is high. As a result, value stocks are more sensitive than growth stocks to the business cycle (Zhang 2005).[6] Human capital is a key complement of physical capital in the production process and is known to explain

[6]Related channels include operational leverage (Carlson, Fisher, and Giammarino 2004), investment-specific technology (Kogan and Papanikolaou 2012), and the cyclicality of the demand for durable goods (Gomes, Kogan, and Yogo 2009).

the value premium in a conditional CAPM context (Jagannathan and Wang 1996). For this reason, researchers have recently developed structural asset-pricing models that explicitly incorporate human capital (Garleanu, Kogan, and Panageas 2012, Parlour and Walden 2011). Sylvain (2013) 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.

2.1.3 Cognitive Biases

The success of value investing can also originate from the exuberant overpricing of growth stocks and underpricing of value stocks by irrational investors (DeBondt and Thaler 1985, Lakonishok, Shleifer, and Vishny 1994, La Porta, Lakonishok, Shleifer, and Vishny 1997, Shleifer 2000). These mistakes can be explained by the representativeness heuristic uncovered in the psychological literature, that is the tendency to pay more attention to recent events than Bayesian updating would imply (Kahneman and Tversky 1973). In the context of equity markets, companies that have recently performed well tend to be overpriced growth or "glamour" stocks, while companies that have recently performed poorly tend to be underpriced value stocks. Overconfidence, that is the tendency to overestimate the accuracy of available information, is a complementary explanation of the cross-section of returns. Overconfident investors overprice stocks following positive news and underprice stocks following negative news, so that valuation ratios can predict future returns (Daniel, Hirshleifer, and Subrahmanyam 2001). These behavioral interpretations are consistent with biases in stock analyst expectations (La Porta 1996, La Porta, Lakonishok, Shleifer, and Vishny 1997, Greenwood and Sheifer 2013, Skinner and Sloan 2002) and with the pricing impact of measures of investor sentiment (Baker and Wurgler 2006).

2.2 Portfolio Implications

Risk-based and behavioral explanations of the value premium have important implications for portfolio choice. The topic, however, has remained relatively unexplored until now, presumably because of the technical challenges involved and the complex nature of the value premium. We now summarize existing results and conjecture possible relationships when formal results are not yet available.

Consistent with the ICAPM, the value factor forecasts future aggregate returns, so investors can use growth stocks to hedge against adverse variations in future investment opportunities while earning lower expected returns. Since the hedging motive is stronger for investors with longer horizons, young households should pick growth stocks, while mature households should pick value stocks. Lynch (2001), Jurek and Viceira (2011), and Larsen and Munk (2012) demonstrate the validity of this logic for a finite-horizon investor with constant relative risk aversion.

The optimal portfolio of risky assets may be impacted by household characteristics other than age. Since value stocks carry systematic risk other than market portfolio return risk, intuition suggests that high book-to-market ratio stocks should be picked by investors who have a strong capacity to bear risk, such as investors with high liquid financial wealth, high real estate wealth, and low leverage. Conversely, growth stocks should be picked by investors with a limited capacity to bear systematic risk, for instance because they own low financial and real estate wealth or have high leverage. Such tilts naturally arise in a habit-formation model with time-varying opportunities (Munk 2008). The hedging demand then depends on an effective risk aversion coefficient driven by wealth and consumption habit, and, as a result, the optimal loading on the value factor is an increasing function of wealth.

Human capital represents a large fraction of the overall wealth of most individuals, but its theoretical impact on the value tilt has not been widely studied. Intuition suggests that conflicting forces drive the relationship between human capital and the value tilt. On the one hand, to the extent that it is a safe form of wealth, human capital increases the financial security of households and should therefore tilt the risky asset portfolio toward value stocks. On the other hand, if income is sensitive to recession risk, human capital should reduce the value tilt of the risky asset portfolio. In his Presidential Address to the American Finance Association, Cochrane (2011) gives the following explanation of the value premium: "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." Value stocks should therefore be held by investors with relatively safe jobs, while growth stocks should be held by individuals with recession-sensitive incomes, such as entrepreneurs and small business owners.

Two additional mechanisms may link human capital to the value tilt. First, the wage income of rich households is highly exposed to aggregate fluctuations (Parker and Vissing-Jørgensen 2009, 2010). Households with high human capital should therefore tilt their portfolios toward growth stocks. Second, aggregate human capital is positively correlated with aggregate physical capital at the macro level (Baxter and Jermann 1997). If human capital and physical capital are also risk substitutes at the micro level, households with substantial human capital should allocate their financial wealth away from the physical capital risk embedded in value stocks, and should instead aggressively invest in growth stocks.

Cognitive biases have a number of important implications for portfolio choice. Consider for instance the assumption that the superior performance of value stocks is due to expectational errors, such as representativeness heuristic and overconfidence.[7] The psychology literature documents that cognitive biases tend to attenuate with experience in sufficiently regular environments (Hogarth 1987, Kahneman 2011, Oskamp 1965).[8] To the extent that the relative performance of value and growth stocks is sufficiently regular to be learned, households with longer financial market experience should be less prone to cognitive biases and exhibit a stronger tilt toward value stocks. Moreover, overconfidence is generally more pronounced among men (Barber and Odean 2001) and entrepreneurs (Busenitz and Barney 1997, Cooper, Woo, and Dunkelberg 1988), which suggest that men and entrepreneurs should favor growth stocks. In the next sections, we test the portfolio implications of these theories on Swedish portfolio data.

3 Data and Construction of Variables

This section presents the security and household data, and defines the main variables used throughout the paper.

3.1 Local Fama and French Factors

We use stock market data for the 1985 to 2009 period provided by 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. We also use Datastream to compute free-float adjusted market shares.

[7] See Barberis and Thaler (2003) for a review.

[8] Malmendier and Nagel (2011) provide some evidence that younger or less experienced investors are especially likely to extrapolate from recent financial data.

We focus on stocks with at least 2 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 Scandinavian exchanges in 2003.[9] 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 excess return between the market portfolio and the risk-free rate defines the market factor MKT_t.

The local value, size, and momentum factors are constructed by following the methodology of Fama and French (1993) and Carhart (1997). We sort the stocks traded on the major exchanges according to their book-to-market values, market size and past returns. We then compute the value factor HML_t, the size factor SMB_t, and the momentum factor MOM_t in months $t = 1 \cdots, T$, as is fully explained in the Internet Appendix.

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

$$r_{i,t} = a_i + b_i MKT_t + v_i HML_t + s_i SMB_t + m_i MOM_t + e_{i,t},$$

where $r_{i,t}$ denotes the excess return of asset i in month t, and $e_{i,t}$ are uncorrelated to the factors. Estimated loadings are winsorized at -5 and +5. The value premium is substantial in Sweden: the average annual return on the HML portfolio is about 10% over the 1985 to 2009 period, which is in the range of country estimates reported in Liew and Vassalou (2000).

3.2 Household Panel Data

The Swedish Wealth Registry is an administrative data set compiled by Statistics Sweden, which has been used in earlier work (Calvet, Campbell, and Sodini 2007, 2009a, 2009b, Calvet and Sodini 2014). 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

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

the worldwide assets owned by the resident at year-end from 1999 to 2007. Real estate, debt, bank accounts, and holdings of mutual funds and stocks are provided for each property, account or security. Statistics Sweden provides a household identification number for each resident, which allows us to group residents by living units.[10] The age and gender variables used in the rest of the paper refer to the household head.

We consider households that participate in risky asset markets and satisfy the following requirements. Disposable income is strictly positive, financial wealth is at least 1,000 kronor (approximately \$140), and total wealth is at least 3,000 kronor (approximately \$420). The household head, defined as the individual with the highest income, is between 25 and 85 years old. Finally, five years of household income data are available. Unless stated otherwise, the results are based on an unbalanced, random sample of approximately 70,000 households satisfying these requirements observed at the yearly frequency between 1999 and 2007.

We also use a panel of twins satisfying the same requirements. The Swedish Twin Registry, which is administered by the Karolinska Institute in Stockholm, is the largest twin database in the world. It provides the genetic relationship (fraternal or identical) of each twin pair, and the intensity of communication between the twins. The twin database also allows us to identify twin siblings in the Swedish Wealth Registry, so that all financial and demographic characteristics are available in the twin panel.

3.3 Definition of Main Variables

3.3.1 Financial Portfolio

We use the following definitions throughout the paper. Cash consists of bank account balances and Swedish money market funds.[11] 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 for which less than 3 months of returns are available.

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

[11] Financial institutions are required to report the bank account balance at year-end if the account yields less 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 period). We impute unreported cash balances by following the method used in Calvet, Campbell, and Sodini (2007, 2009a, 2009b) and Calvet and Sodini (2014), as we explain in the Internet Appendix.

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

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

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

where $w_{h,i,t}$ denotes the weight of asset i in household h's risky portfolio at time t. We will also refer to $v_{h,t}$ as the HML loading or the value tilt. We similarly compute the value loading of the fund and stock portfolios. The methodology captures time variation in $v_{h,t}$ driven by time variation in portfolio weights, while taking advantage of the long time series available for individual asset returns. The use of an unconditional pricing model guarantees that the value tilts of individual firms, v_i, are constant over the sample period and therefore do not generate time variation in the portfolio loading, $v_{h,t}$. Thus, our estimates of active management of the value tilt by households will not be contaminated by exogenous changes in firm value tilts during the 1999 to 2007 sample period.

3.3.2 Financial Wealth and Real Estate

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 the household's total debt divided by the household's financial and real estate wealth.

3.3.3 Human Capital

We consider a labor income specification based on Carroll and Samwick (1997) and accounting for the persistence of income shocks:

$$\log(L_{h,t}) = a_h + b' x_{h,t} + \theta_{h,t} + \varepsilon_{h,t}, \tag{2}$$

where $L_{h,t}$ denotes real income of household h in year t, 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 bins defined by (i) the immigration dummy, (ii) the gender dummy, and (iii) educational attainment. We estimate the fixed-effects estimators of a_h and b in each bin, and then compute the maximum likelihood estimators of ρ_h, $\sigma^2_{\xi,h}$ and $\sigma^2_{\varepsilon,h}$ using the Kalman filter on each household income series.

In the portfolio-choice literature (e.g., Cocco, Gomes, and Maenhout 2005), it is customary to assume that the household observes the transitory and persistent components of income. Since the characteristics $x_{h,t}$ are deterministic, labor income $\log(L_{h,t})$ then has conditional stochastic component

$$\eta_{h,t} = \xi_{h,t} + \varepsilon_{h,t}, \tag{3}$$

and conditional variance

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

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

We define expected human capital as

$$HC_{h,t} = \sum_{n=1}^{T_h} \Pi_{h,t,t+n} \frac{\mathbb{E}_t(L_{h,t+n})}{(1+r)^n}, \tag{4}$$

where T_h denotes the difference between 100 and the age of household h at date t, and $\Pi_{h,t,t+n}$ denotes the probability that the household head h is alive at $t+n$ conditional on being alive at t. We make the simplifying assumption that no individual lives longer than 100. The survival probability is computed from the life table provided by Statistics Sweden. The discount rate is set equal to $r = 5\%$ per year. We have verified that our results are robust to alternative choices of r. Detailed descriptions of the labor income and human capital imputations are provided in the Internet Appendix.

3.4 Summary Statistics

Table I, Panel A, reports summary statistics on the financial and demographic characteristics of 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). All summary statistics are computed 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 household owning risky assets has a 46-year old head and a yearly income of $\$45,000$. It owns $\$50,000$ in liquid financial wealth, $\$155,000$ in gross residential and commercial real estate wealth, and $\$955,000$ in human capital. The vast majority of risky asset participants (88%) hold mutual funds, while 59% of them directly own stocks.

Direct stockholders have on average substantially higher financial ($\$65,000$) and real estate wealth ($\$190,000$) than general risky asset market participants. There is also considerable heterogeneity among direct stockholders. Households owning 1 or 2 stocks own modest levels of financial wealth ($\$35,000$). By contrast, households owning at least 5 different stocks have substantially higher financial wealth ($\$125,000$) and education attainment than the average participant.

In Table I, Panel B, we report summary statistics on household financial portfolios. 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 panel also shows substantial heterogeneity across investors. Households owning directly 1 or 2 stocks have substantially lower risky shares than owners of more diversified stock portfolios. Concentrated stock portfolios represent a small fraction of household financial wealth and the corresponding diversification losses are modest, as documented in Calvet, Campbell, and Sodini (2007).

The direct investments of the household sector are concentrated in a small number of popular stocks. Specifically, we compute the aggregate value of household direct holdings in each stock, and classify a stock as *popular* if it is one of the top 10 holdings in at least one year during the 1999 to 2007 sample period. Popular stocks, which account for 59% of the Swedish stock market, represent 71% of the average household stock portfolio in 2003. Thus, household direct stockholdings concentrate in a small number of popular companies. Furthermore, the popular share is more pronounced for portfolios with one or two stocks (79%) than for portfolios with at least five stocks (57%).

Households may favor professionally close stocks for familiarity or informational reasons. 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 indicates that households are not heavily tilted toward stocks in their employment sector. This estimate is consistent with the evidence from Norway (Døskeland and Hvide 2011).

The aggregate household portfolio is constructed by adding up the stock and fund holdings of risky asset market participants. In the bottom rows of Table I, Panel B, we report the fraction of the aggregate portfolio held by specific subsets of investors. The share of risky asset market participants is by definition equal to unity. Households owning 5 stocks or more represent 17% of the population of risky asset market participants but own 36% of aggregate mutual fund holdings, 54% of the aggregate risky portfolio, and 80% of aggregate direct stockholdings. Thus, households with at least 5 stocks play an important role in determining the aggregate household demand for risky assets. For this reason, we will pay special attention to this wealthy subgroup in the rest of the paper.

In Figure 1, we sort firms by market capitalization, and for each size bucket we report the fraction of the firm's stocks owned directly by Swedish households (solid bars) and the fraction of firms in the size bucket (solid line). Households directly own 30% to 50% of firms with a market capitalization up to 100 million U.S. dollars, and a smaller fraction of larger firms. Since small companies represent a large fraction of the overall population of companies, the aggregate demand from the household sector is substantial and can therefore have a sizable impact on stock prices.

4 Empirical Evidence on Value and Growth Investors

In this section, we investigate the value tilts of household portfolios in the administrative panel. We first analyze the cross-sectional distribution of the value loading. We then document the relationships between a household's value tilt and the household's financial and demographic characteristics. The present section documents new empirical regularities and Section 5 relates them to theoretical explanations of the value premium.

4.1 Cross-Sectional Distribution of the Value Loading

In Table II, we report the cross-sectional distribution of the value loading for individual stocks and household portfolios at the end of 2003. Individual stocks have widely heterogeneous loadings, ranging from -3.22 (10th percentile) to 0.94 (90th percentile). The median loading is -0.37 and the equal-weighted average loading is -0.87. The distribution of the value loading is thus negatively skewed across individual stocks. We next consider value-weighted portfolios. The value-weighted portfolio coincides by construction with the SIXRX index and has a value loading of -0.15 in 2003, which is substantially higher than the equal-weighted average loading of a stock.[12] The different value loadings of the equal- and value-weighted portfolios are of course explained by the large number of small growth stocks. The value-weighted portfolio of all Swedish mutual funds has a loading of -0.10 in 2003, which is close to the estimate for the market index. A portfolio with a loading between -0.15 and -0.10 in 2003 is therefore neutral relative to the Swedish market portfolio.

Household portfolios also exhibit substantially heterogeneity in value loadings. Among risky asset market participants, the value loading of the risky portfolio ranges from -0.94 (10th percentile) to 0.10 (90th percentile), which corresponds to a difference in expected returns of about 10% per year. The median loading is approximately neutral at -0.18, so the cross-sectional loading distribution is negatively skewed. Subgroups of investors produce relatively similar estimates. Stock portfolios have more dispersed value loadings than risky portfolios, with estimates ranging from -1.20 (10th percentile) to 0.39 (90th percentile). Fund portfolios are centered around the neutral benchmark and are less dispersed than risky or stock portfolios, as intuition suggests.

The aggregate risky portfolio containing all the stocks and funds owned by Swedish households has a loading of -0.26, which confirms that the household sector as a whole exhibits only a mild growth tilt. Table II indicates that the aggregate mutual fund portfolio has a neutral loading of -0.18. The slight tilt of the aggregate risky portfolio therefore originates from the aggregate stock portfolio, which has a loading of -0.36. Moreover, whether we consider stocks or funds, the

[12]As equation (1) 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.

equal-weighted average household has a stronger growth tilt than that its wealth-weighted counterpart. A natural explanation is that low-wealth households invest in growth stocks, while wealthier households invest in value stocks. We test this explanation in the next section.

4.2 What Drives the Value Tilt?

Table III maps the relationships between portfolio tilts and socioeconomic variables. We estimate 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. We compute the value loading 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 characteristics in column (4). Standard errors are clustered at the household level.

The regressions reveal that financial characteristics are strongly related to the value loading. The financial wealth coefficient is positive and strongly significant for the risky, stock and fund portfolios. Households with more liquid financial wealth tend to select financial portfolios with a value tilt. The financial wealth coefficient reaches its highest value for the stock portfolio, which suggests that wealthy households primarily achieve this tilt by investing directly in value stocks. This finding is consistent with the fact that the value loadings of mutual funds themselves tend to concentrate around the neutral benchmark (see Table II). In the Internet Appendix, we verify that the link between financial wealth and the value loading is not due to reverse causality by regressing the value loading on lagged values of financial wealth. Thus, the empirical evidence indicates that financial wealth has a positive impact on the value loading. In Section 4.3.5, we verify the robustness of this result to latent heterogeneity by using twin data.

Real estate is also associated with value investing. Residential and commercial real estate have positive regression coefficients, which are significant for the risky and stock portfolios. Since home ownership is usually financed by a mortgage, it is also important to consider the impact of debt. We report that households with a high leverage ratio tend to invest directly in growth stocks, while no tilt is apparent in the risky and fund portfolios. Financial and real estate wealth are therefore associated with a value tilt, while debt is associated with a growth tilt in the stock portfolio. We investigate later in the section if the interaction between real estate and leverage also drives the financial portfolio.

Human capital and labor income are strongly related to the value loading. Households with high current income $L_{h,t}$ and high expected human capital $HC_{h,t}$ (as defined in equation (4)) tilt their financial portfolios toward growth stocks; these relationships are significant for all three types of portfolios. Income risk measures also have strongly negative coefficients: households with high income volatility or with a head who is either self-employed or unemployed are prone to selecting growth stocks. In the Internet Appendix, we verify that these results are robust to regressing the value tilt on the persistent and transitory components of income risk, $\sigma_{\xi,h}$ and $\sigma_{\varepsilon,h}$, instead of the total volatility σ_h. Current income, expected human capital, and the volatility of the income process therefore all tilt household financial portfolios toward growth stocks.

Demographic characteristics are also significant. The age of the household head tends to increase the value loading. Younger households tend to go growth and older households tend to go value, primarily through direct stockholdings. Section 6 provides further evidence on the connection between the value tilt and age. The gender variable is strongly significant; men tend to have a growth tilt and women a value tilt. Immigrants and educated households also have a tendency to go growth, which suggests that the value loading is not just driven by sophistication.

Table III raises some immediate questions about real estate and family size, which are important for the interpretation of the results and their connections with risk-based theories. Real estate is both (i) a form of wealth that can prompt households to aggressively invest in equities with systematic risk exposures, such as value stocks, and (ii) a source of risk that can discourage households from purchasing systematically risky stocks. The strength of these two channels is likely influenced by leverage. In Table IV, Panel A, we regress the value loading of the financial portfolio on the leverage ratio, log residential real estate, log commercial real estate, the leverage ratio interacted with log residential real estate, the leverage ratio interacted with log commercial real estate, and all the other characteristics considered in Table III. The full regression is reported in the Internet Appendix. Leverage as a standalone variable has a strongly negative impact on the value loading, which is significant for all portfolios. For households with low leverage, residential and commercial real estate tilt the risky and stock portfolios toward value stocks. By contrast, for households with high leverage, both forms of real estate tilt the financial portfolio toward growth stocks.

Family size also plays an ambiguous role in the baseline regressions of Table III. On the one hand, households with secure jobs and financial prospects are more likely to decide to have children; thus family size can be viewed as a predictor of sound future financial conditions and can therefore co-vary positively with value investing in the cross-section. On the other hand, children are a source of random needs and other forms of background risk that can discourage value investing. We now use a panel of 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 and should tilt the portfolio toward growth stocks. In Table IV, 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 dummy has positive coefficients, the twin dummy has a negative impact on the loadings of all three portfolios. Thus, the unexpected birth of an additional child tilts the portfolio toward growth stocks.

Overall, the regressions in Tables III and IV provide substantial evidence that the portfolio value loading co-varies with financial and demographic characteristics. Value investors tend to have high financial and real estate wealth, low leverage, low income risk, and low human capital; they are also and more likely to be older and female. Conversely, young males with risky income and high human capital are more likely to go growth. We now verify the robustness of these baseline results to alternative hypotheses.

4.3 Identification and Robustness Checks

4.3.1 Portfolio Concentration

In Table V, we investigate whether the baseline results are mechanical implications of portfolio concentration. We reestimate the baseline regression on five separate groups of investors: mutual fund owners in column (1), direct stockholders in column (2), and direct stockholders sorted by the number of firms that they own in columns (3) to (5). The baseline results remain valid in all groups. Furthermore, the explanatory power of the regression is substantially higher for households owning more stocks. Thus, wealthier, more educated direct stockholders holding at least three different stocks are prone to selecting value tilts that are well explained by their financial and demographic characteristics.

4.3.2 Popular Stocks

As Table I shows, household portfolios are dominated by a handful of popular firms. We now assess the potential implications of popular stocks for the baseline results of Section 4.2. Table VI reports the 10 stocks that are most widely held by Swedish households at the end of 2003. For each of these 10 firms, we compute the percentage of direct stockholders owning it, the stock's percentage of aggregate household financial wealth, the stock's percentage of the Swedish stock market, the stock's percentage of the Swedish free float, the stock's value loading, and the percentile of the stock's book-to-market ratio. Popular stocks are a mix of growth stocks and value stocks, regardless of whether one classifies stocks by value loading or book-to-market percentile.

In the first two sets of columns of Table VII, we reestimate the baseline regression for the portfolio of popular stocks directly held by households in column (1), and the portfolio of non-popular stocks in column (2). For both portfolios, characteristics have the same impact as in the baseline regression. In the Internet Appendix, we verify that the baseline results also hold among households that invest either 100% or 0% of their stock portfolios in popular firms. We conclude that the relationship between the value loading and characteristics is unlikely to be driven by popular stocks. Furthermore, the explanatory power of the regression in Table VII is substantially higher for non-popular stocks, suggesting that investors with broad portfolios select their value tilts more deliberately than other investors.

4.3.3 Professionally Close Stocks

We next ask if professionally close stocks, which represent 16% of household stock portfolios, can account for the relationship between the value loading and financial characteristics. In columns (3) and (4) of Table VII, we reestimate the baseline regression separately on the portfolio of professionally close stocks and on the portfolio of other stocks. Our baseline results are apparent in both portfolios.

It is interesting to assess if our findings are driven by investors working in specific sectors or are instead broad phenomena that can be observed in all industries. In the Internet Appendix, we consider subsamples of households working in the public sector or in pools of companies sorted according to the value loading of workers with only 1 stock, the value loading of employee incomes, or the employees' shares of professionally close stocks. Quite strikingly, the results obtained from every subsample are consistent with the baseline results of Table III. In the Internet Appendix, we verify that the baseline results also remain valid for households with extreme shares of professionally close stocks. Thus, the baseline results are unlikely to be driven by holdings of professionally close stocks.

4.3.4 Financial Market Experience

Age has a positive coefficient in the baseline regression, which indicates that *ceteris paribus* older households tend to invest in value stocks. Risk-based theories provide a possible explanation for age effects through investment horizons. Another interpretation is that age simply proxies for financial market experience. Naive new investors might purchase overpriced growth stocks, learn that these stocks are bad deals, and then progressively migrate toward value stocks as time goes by. Learning can thus create a positive cross-sectional correlation between age and value investing, which is unrelated to the investment horizon channel.

Table VIII reports regressions that include both age and the number of years of risky asset market participation in the set of explanatory variables. Specifically, we consider households that participate in risky asset markets in 2007, and regress the 2007 value loading on age, the number of years since entry, the value loading in the year of entry, and the other usual characteristics in 2007. The coefficient on the number of years since entry is significantly *negative* for all portfolios, which is inconsistent with the simple learning story.[13] Thus, financial market experience, measured by the number of years in risky asset markets, induces a growth tilt and, more importantly, cannot explain away the positive link between age and the value tilt. 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 the value tilt.

Table VIII also sheds light on the dynamics of the portfolio tilt during the participation period.

[13]The panel does not allow us to observe entry to financial markets prior to 1999. In the Internet Appendix, we verify that the results are unchanged when we regress the value loading on a dummy for 1999 participation, the measure number of participation years, and all the other characteristics in Table VIII, which shows that the limitations of the experience variable are not a cause for concern.

The value loading in the entry year has a positive and strongly significant impact on the value loading in 2007, as one might expect. Furthermore, the impact of other characteristics remain significant and are consistent with our earlier results when we control for the initial loading. This suggests that the value loading is not simply driven by the initial portfolio in the year of entry, but also depends on financial and demographic characteristics in the subsequent participation period.

One potential concern with Table VIII is that our definition of financial experience might be collinear to age. In the Internet Appendix, we remove age from the list of control variables and verify that the relationship between participation years and the value tilt remains negative. Section 6 provides further evidence on the relationship between age and value investing.

4.3.5 Latent Heterogeneity

The panel regressions presented until now include yearly, industry, and county fixed effects. One might worry, however, that household characteristics merely proxy for latent traits or cohort effects. For this reason, we estimate on the twin panel regressions of the form:

$$v_{k,1,t} = \alpha_{k,t} + b' x_{k,1,t} + e_{k,1,t}, \tag{5}$$

$$v_{k,2,t} = \alpha_{k,t} + b' x_{k,2,t} + e_{k,2,t}, \tag{6}$$

where $v_{k,s,t}$ denote the value loading of sibling $s \in \{1,2\}$ in pair k at date t, $\alpha_{k,t}$ is a yearly pair fixed effect of twin pair k, $x_{k,s,t}$ denotes the vector of yearly characteristics of sibling s, and $e_{k,s,t}$ is an orthogonal error. The yearly twin pair fixed effect captures the common effects 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. Since twin siblings have the same age, the twin regression naturally controls for cohort effects. Calvet and Sodini (2014) apply this methodology to the determinants of the risky share,[14] and we now use it to check the robustness of our baseline value loading results.

In Table IX, we regress the value loading on yearly twin pair fixed effects and household characteristics. Consistent with the baseline results in Table III, twins with high financial and real estate wealth and low income, low human capital, and low income risk tends to go value. In the

[14] Cesarini, Dawes, Johannesson, Lichtenstein, and Wallace (2009), Cesarini, Johannesson, Lichtenstein, Örjan Sandewall, and Wallace (2010), and Barnea, Cronqvist, and Siegel (2010) also use twins to investigate risk-taking.

Internet Appendix, we show that these results also hold on the subsample of identical twins. Thus, the main empirical regularities reported in the paper are robust to the inclusion of yearly twin pair fixed effects.

The twin regression has a substantially higher adjusted R^2 coefficient than the baseline regression. For the stock portfolio, socioeconomic characteristics and year, industry, and county fixed effects explain 4% of the cross-sectional variation in the value loading among the general population (Table III). By contrast, characteristics and yearly twin pair fixed effects account for 23% of the cross-sectional variation of the stock portfolio value tilt among twins (Table IX). Large increases in adjusted R^2 are also obtained for the risky and fund portfolios.

Thus, yearly twin pair fixed effects have a major impact on the portfolio tilt, but do not modify the baseline relationships between the value loading and socioeconomic characteristics. In the next section, we discuss the possible origins of the high explanatory power of yearly twin pair fixed effects.

4.3.6 Communication and Genes

The twin panel obtained from the Karolinska Institute contains detailed information on the frequency of communication between twins. We classify a twin pair as "high communication" if the frequency of mediated communication and the frequency of unmediated communication are both above the median, and as "low communication" otherwise.

In Table X, we sort twin pairs into high and low communication bins, and reestimate in each bin the baseline regression of the value loading on characteristics and year, industry and county fixed effects. The relationships between the value loading and characteristics are generally consistent with the baseline results in each bin. In the Internet Appendix, we obtain similar results when we use yearly twin pair fixed effects. Thus, communication does not impact the relationship between the value tilt and socioeconomic variables. Moreover, the adjusted R^2 is substantially higher in the presence of yearly twin pair fixed effects, reaching 30% for the stock portfolio of frequently communicating twins.

The high adjusted R^2 of the twin regressions could suggest that value investing has genetic origins, as has been recently proposed by Cronqvist, Siegel, and Yu (2013) on the basis of a genetic decomposition. Specifically, in the ACE model considered by Cronqvist, Siegel, and Yu (2013), the value loading $v_{k,s}$ of sibling s in pair k is assumed to be the sum of a genetic component $a_{k,s}$, a common component c_k, and an idiosyncratic component $\varepsilon_{k,s}$:

$$v_{k,s} = a_{k,s} + c_k + \varepsilon_{k,s},$$

which satisfy the following identification conditions. The twin correlation of the genetic component, $Corr(a_{k,1}; a_{k,2})$, equals 1 for identical twins and $1/2$ for fraternal twins. The cross-sectional variance of the genetic component, σ_a^2, is the same in the group of identical twins as in the group of fraternal twins. Similarly, the variance of the common component, σ_c^2, and the variance of the idiosyncratic component, σ_ε^2, are the same for fraternal and identical twins. Furthermore, the components $a_{k,s}$, c_k, and $\varepsilon_{k,s}$ are mutually uncorrelated. Under this model, the twin correlation of the value loading, $Corr(v_{k,1}; v_{k,2})$, is $\rho_I = (\sigma_c^2 + \sigma_a^2)/(\sigma_c^2 + \sigma_a^2 + \sigma_\varepsilon^2)$ for identical twins, and $\rho_F = (\sigma_c^2 + \sigma_a^2/2)/(\sigma_c^2 + \sigma_a^2 + \sigma_\varepsilon^2)$ for fraternal twins. The rescaled correlation difference,

$$2(\rho_I - \rho_F) = \frac{\sigma_a^2}{\sigma_c^2 + \sigma_a^2 + \sigma_\varepsilon^2}, \tag{7}$$

quantifies the contribution of the genetic component to the cross-sectional variance of the value loading according to ACE.

Table XI reports the ACE decomposition of the value loading for all twins as well as for twins sorted twins by communication frequency. We consider both the value loading itself ("No controls") and the residual of a regression of the value loading on characteristics ("With controls"). For all twins, the contribution of the genetic component ranges between 10 and 17% for the stock and the risky portfolios, and is slightly lower for the fund portfolio, regardless of whether or not we consider the value loading itself or its residual in the baseline regression. These estimates confirm the findings of Cronqvist, Siegel, and Yu (2013).

The table also reveals that the estimated contribution of the genetic component, given by (7), is highly sensitive to communication. For all three portfolios, the genetic share reaches 35% for frequent communicators but disappears almost entirely among infrequent communicators, with estimates that do not exceed 1% across specifications.[15] These low estimates are especially surprising if ACE is correctly specified, because purely genetic effects should not depend on communication.

[15] The estimator of the genetic share (7) is the rescaled difference between two sample correlations. It can therefore take negative values if the estimate of ρ_I is lower than the estimate of ρ_F in a particular sample. In fact, under the null

The table indicates that the so-called genetic component of the ACE model is unlikely to be purely driven by genes. Instead, the genetic share estimate (7) incorporates other effects, such as the substantial impact of communication on portfolio decisions.

One could argue that the communication frequency itself has genetic origins, so that the results of Table XI could be construed as evidence that value investing is driven by genes. However, by equation (7), the genetic share is zero if and only if the twin correlation of the value loading is the same for identical and fraternal pairs: $\rho_I = \rho_F$. Thus, a genetic theory of value investing needs to explain why infrequently communicating twins have the same loading correlations regardless of genetic makeup, which seems to be challenging task.

The sensitivity of the ACE decomposition is related to one of the well-known shortcomings of ACE, namely that it neglects interactions between genetic and environmental variables. Interactions between nature and nurture are known to be empirically important in medicine and experimental psychology (Ridley 2003). The modern view in these fields is that genes cause a predisposition to certain behaviors or diseases, which develop only in particular environments. Table XI shows that the clean dichotomy between nature and nurture is equally elusive in the context of value investing.

Overall, the section uncovers strong relationships between a household's value loading and the household's financial and demographic characteristics. We show that these empirical regularities are unlikely to be explained away by genes, communication, latent traits, experience or certain types of stocks. We interpret these findings in the next section, and empirically investigate the dynamics of the value tilt in Section 6.

5 Interpretation of the Empirical Determinants of the Value Tilt

We now relate our empirical results to the asset-pricing explanations of the value premium reviewed in Section 2.

hypothesis

$$H_0: \ \rho_I = \rho_F,$$

the estimator of the genetic share converges asymptotically to a centered normal as the number of pairs goes to infinity. *Negative* estimates of the so-called genetic share are then asymptotically as likely as positive estimates.

5.1 Risk Aversion, Wealth, and Background Risk

Risk-based theories imply that household portfolio tilts are partly determined by financial wealth, leverage, background risk, and other variables affecting their willingness to take financial risk. Quite remarkably, the empirical impact of financial variables on the portfolio tilt is generally in accordance with the predictions of risk-based theories, as we now explain. Liquid financial wealth is positively related to the value loading across participants (Table III) and in the twin panel (Table IX). In the Internet Appendix, we regress the value loading on lagged financial wealth and verify that our results are unlikely to be driven by a reverse causality between the value loading and financial wealth. The empirical evidence therefore indicates that financial wealth has a positive impact on the value loading. As early studies (e.g., Calvet and Sodini 2014) document and as Table III confirms, financial wealth is also associated with high risky shares. These results suggest that wealthier households adopt value strategies because they are more risk tolerant and therefore more prone to bearing the systematic risk (other than market portfolio risk) embedded in value stocks. In particular, our findings are consistent with Munk (2008)'s model of portfolio choice with habit formation.

The positive relationship between financial wealth and the value tilt holds in all subgroups of investors, including the wealthy group of stockholders owning 5 stocks or more (Table V). Furthermore, educated households favor growth stocks, even more so if they have studied economics. We have also provided evidence that financial wealth does not proxy for financial market experience. Thus, growth investing is not the restricted turf of unsophisticated investors, and the positive relationship between financial wealth and value investing is unlikely to be driven only by sophistication.

Our results on real estate, leverage, and family size provide additional support for risk-based interpretations of value investing. Unlevered households with real estate tend to invest in value stocks, while leveraged households tend to purchase growth stocks. As a form of wealth, real estate encourages households to tilt their portfolios toward value stocks in order to earn the value premium. By contrast, households with substantial leverage choose a lower risky share and tilt their risky portfolios toward growth stocks in order to reduce their systematic exposure, thus giving up the value premium. The unexpected birth of a child also induces a growth tilt, which is consistent with the lower resources per-capita and higher idiosyncratic needs that the arrival of a newborn entails.

5.2 Income and Human Capital

Growth stocks are picked by households with risky incomes, as measured by the income volatility σ_h, self-employment, or unemployment. This empirical regularity can be viewed as a consequence of background risk if labor income is uncorrelated to the value factor. The growth tilt may also be a hedge against future income shocks if household income and the value factor are positively correlated.

To assess these mechanisms, we regress the stochastic component of income, defined by (3), on the returns of the pricing portfolios:

$$\eta_{h,t} = \lambda_h' f_t + \tilde{\eta}_{h,t}, \tag{8}$$

where $f_t = (1, MKT_t, HML_t, SMB_t, MOM_t)'$. In Table XII, Panel A, we decompose income variance into systematic and idiosyncratic components: $\text{Var}(\eta_{h,t}) = \text{Var}(\lambda_h' f_t) + \text{Var}(\tilde{\eta}_{h,t})$. The idiosyncratic share, $\text{Var}(\tilde{\eta}_{h,t})/\text{Var}(\eta_{h,t})$, is close to 80%. Most of labor income risk is idiosyncratic, so that the pricing portfolios can only provide a limited hedge against fluctuations in income. As a consequence, one expects that the value tilt is driven more strongly by idiosyncratic income risk than by systematic income risk.

In Table XII, Panel B, we confirm this intuition by regressing the portfolio tilt, $v_{h,t}$, on the loading of income on the value factor, λ_h, and idiosyncratic labor income variance, $\text{Var}(\tilde{\eta}_{h,t})$, where λ_h, and $\tilde{\eta}_{h,t}$ are defined in (8). Idiosyncratic variance is by far the most significant variable and negatively impacts the portfolio loadings. Thus, households with substantial idiosyncratic labor income risk select low risky shares and tilt away from value stocks. In future work, it would be interesting to refine the analysis by taking into account the cointegration of the stock and labor markets, as in Benzoni, Collin-Dufresne, and Goldstein (2007).

The effect of human capital on the value tilt provides further evidence of an income risk effect. In Section 2.2, we have explained that human capital plays an ambiguous role because it is both a form of wealth and a form of risk. The empirical evidence strongly suggests that human capital tilts the portfolio toward growth stocks, so that the risk channel dominates. Furthermore, we report that labor income is weakly correlated to the value factor at the micro level (Table XII), while human capital and physical capital are strongly correlated at the macro level (Baxter and Jermann 1997). These contrasting results suggest that the idiosyncratic risks that dominate household labor income risk aggregate out at the macro level. These results provide guidance for building general equilibrium models that can account for the empirical evidence on the value premium and household micro data.

5.3 Intertemporal Hedging and Horizon Effects

The portfolio choice literature on the value factor focuses on intertemporal hedging and time horizon effects (Jurek and Viceira 2011, Larsen and Munk 2012, Lynch 2001). Indeed, if value stocks outperform growth stocks when aggregate expected returns improve, market participants can use growth stocks as a hedge against adverse variation in investment opportunities. Since the hedging motive is stronger for investors with longer horizons, portfolio theory predicts that young investors should hold growth stocks and old investors should hold value stocks.

As the results reported in Section 4 show, age is positively and significantly related to the value loading. This relationship is observed even when we control for real estate, debt, financial market experience, human capital, income risk, and other socioeconomic characteristics that vary with age. Our baseline results thus provide strong empirical support for one the main predictions of portfolio choice models incorporating the value factor, the positive link between age and value investing. In Section 6, we will investigate the life-cycle variation in the value tilt and its relationship to age, financial wealth, human capital, and other socioeconomic characteristics.

5.4 Overconfidence

The impact of gender sheds light on behavioral and risk-based explanations of value investing. Women tend to select low risky shares and invest in value stocks, while men tend to select aggressive risky shares and go growth. These patterns cannot easily be explained by differences in risk aversion alone, since a risk-averse investor should choose both a lower risky share and tilt the risky portfolio toward growth stocks in a model such as Munk (2008). A likely explanation is that men are more overconfident than women and therefore tend to favor glittering growth stocks. The positive link between self-employment and growth investing can also be viewed as evidence of overconfidence, since entrepreneurs are generally known to be overconfident in their financial decision-making abilities (Busenitz and Barney 1997, Cooper, Woo, and Dunkelberg 1988). In the Internet Appendix, we reestimate the baseline regression on the subsample of households with a male head and on the subsample of households with a self-employed head. The two groups are especially prone to overconfidence according to earlier studies. The baseline results, however, hold in both subsample and are therefore unlikely to be driven by cross-sectional differences in overconfidence alone.

6 Dynamics of the Value Tilt

This section investigates the dynamics of the portfolio tilt. We show that at the yearly frequency, households actively rebalance their exposure to the value factor in response to passive variation in their portfolio tilt. At longer horizons, households progressively switch from growth stocks to value stocks as they get older, a migration which we coin the "value ladder." We also quantify the respective impact of age and other characteristics on the value loading over the life-cycle.

6.1 Active Rebalancing at the Yearly Frequency

We now consider passive and active variation in the value tilt of household portfolios. Calvet, Campbell, and Sodini (2009a) define active and passive changes of the risky share, and provide strong evidence that households actively rebalance the passive variation in the risky share due to realized asset returns. We now apply a similar methodology to the portfolio tilt of the risky, stock, and fund portfolios.

We begin with definitions of passive and active rebalancing of the value tilt. Consider household h with portfolio weights $w_{h,i,t-1}$ $(i = 1,\dots,I)$ at the end of year $t-1$. If the household did not trade during the following year, the share of asset i at the end of year t would be

$$w^P_{h,i,t} = \frac{w_{h,i,t-1}\,(1+r_{i,t})}{\sum_{j=1}^{I} w_{h,j,t-1}\,(1+r_{j,t})}, \tag{9}$$

where, for every $j \in \{1,\dots,I\}$, $r_{j,t}$ denotes the rate of return on asset j between $t-1$ and t. By equation (1), the value loading of the passive household at the end of year t would then be:

$$v_{h,t}^{P} = \sum_{i=1}^{I} w_{h,i,t}^{P} v_i. \tag{10}$$

The data set reports the actual loading $v_{h,t}$. We can therefore decompose the actual change of the portfolio value loading, $v_{h,t} - v_{h,t-1}$, as the sum of active and passive changes:

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

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

Table XIII regresses the active change, $a_{h,t}$, on (i) the passive change, $p_{h,t}$, (ii) the lagged value loading, $v_{h,t-1}$, and (iii) either no characteristics or all other 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. These estimates imply that the average household actively undoes passive variation in the value loading, presumably because it has a sense of the target value loading that it would like to achieve. Overall, Table XIII confirms that households actively rebalance the passive variation in their value tilt, as portfolio theory (Lynch 2001, Munk 2008) implies.

6.2 Value Ladder over the Life-Cycle

Figure 2 illustrates life-cycle variation in the value loading. We sort households into 9 cohorts based on the year of birth, and plot for each cohort the yearly average wealth-weighted value loading over the 1997 to 2007 period. The figure is based on all Swedish households that directly hold stocks during the period and satisfy the basic requirements stated in Section 3.2. Households are weighted by financial wealth because this aggregation method has the strongest implications for asset pricing. All value loadings in a given year are demeaned in order to control for changes in the average loading of individual stocks, which are caused by the exit of some stocks from the stockmarket and the entry of new stocks.

We observe that young households select growth portfolios and older households choose value portfolios. The dependence between the value loading and age is therefore positive, which confirms the positive coefficient on age in the baseline regression of Table III and the other results reported in Section 4. The relationship between the loading and age is also strikingly linear, which is also consistent with our baseline specification. Furthermore, for all cohorts, there is a tendency for households to migrate toward higher loadings as time goes by. Figure 2 illustrates the value ladder for the stock portfolio. In the Internet Appendix, we show that a similar ladder exists for the risky portfolio. We also plot the equal-weighted value loading of household portfolios and obtain that the results are similar to the wealth-weighted estimates in Figure 2.

One may ask if the value ladder is due to exogenous drifts to which stockmarket participants are passively exposed. In order to control for such effects, a natural solution is to consider the value tilt of new participants in the year they enter risky asset markets. In Table XIV, we regress the stock portfolio value loading on household characteristics. Consistent with the baseline results, the exposure to the value factor increases with financial wealth, commercial real estate, and age, and decreases with human capital, income risk, self-employment, and unemployment. In particular, age has a significantly positive coefficient: older entrants select a higher value loading than younger entrants, which confirms that pure horizon effects are empirically important.

We next assess if the relationship between the value loading and age is driven by specific age groups. In Table XV, we regress the value loading on cumulative age dummies, cumulative age dummies for new entrants, and all characteristics other than age. The cumulative age dummies corresponding to all participants are strictly positive and almost all significant. Moreover, the relationship between a participant's age and its value loading is approximately linear, consistent with the baseline results in Section IV.

The age dummies of new entrants are primarily insignificant. One interesting exception is the dummy variable for new entrants aged 30 or more, which is significantly negative. Since the age dummy coefficients are cumulative, this result simply implies that all new entrants have a significant bias toward growth stocks. Since the other coefficients are insignificant, age does not seem to impact differences in the value tilt between preexisting participants and new entrants. Thus, the value ladder of new entrants is parallel to and located below the value ladder of preexisting participants.

These results have a natural interpretation in a general equilibrium context. In an economy in which participants gradually sell their growth stocks and migrate toward value stocks, the growth stocks must be absorbed by another group of investors. The empirical evidence in this section shows that new entrants have a growth tilt compared to other households. 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. In future work, it would be interesting to construct a formal overlapping generations model with these features. Our results also suggest that demographic changes can affect the demand for value and growth stocks, which may have implications for the value premium.

6.3 Economic Significance of the Value Ladder

We have documented that a household's value tilt is related to its contemporaneous financial circumstances, and that a household migrates from growth stocks to value stocks over the life-cycle. These results suggest that the value ladder is driven both by (i) changes in financial conditions and (ii) pure investment horizon effects. We now quantify the respective roles of these two channels.

In Table XVI, Panel A, we consider a 30-year old investor, to which we assign the average financial wealth, real estate wealth, leverage, income and human capital in his age cohort in 2003. We also consider a 70-year old investor with the average characteristics of its age group. The estimates in Table III allow us to decompose the life-cycle variation in the value loading. Between 30 and 70, the value loading of the risky portfolio increases by 0.20, out of which 0.12 is due to age. For the stock portfolio, the value loading increases by 0.58 between 30 and 70, out of which 0.36 is attributed to age. For both portfolios, age therefore explains slightly more than 50% of the life-cycle variation in the value loading. Among financial characteristics, human capital and financial wealth are the most important variables. The reduction in human capital over the life-cycle accounts for 36% of the life-cycle variation of the risky portfolio loading, while the accumulation of financial wealth accounts for another 12% of the migration. Other characteristics, such as real estate, have a marginal impact.

In Table XVI, Panel B, we reestimate the decomposition when the interaction between real estate and leverage is taken into account. Age alone continues to explain half of the life-cycle variation in the value loading. The measured impact of real estate and leverage is now substantially stronger, which shows once again that is important to account for the interaction between debt and real estate wealth.

Overall, this section documents that households both actively rebalance the value loading at the yearly frequency and progressively shift to higher loadings over the life cycle. As in the portfolio-choice models of Jurek and Viceira (2011) and Lynch (2001), households seem to have a slow-moving target loading, and actively undo the higher frequency passive changes that move them away from the target. Furthermore, changes in age account for half of the value ladder, while changes in human capital and financial wealth account for the most of the remainder. Life-cycle variation in human capital and financial wealth are important determinants of value and growth investing, which deserve to be incorporated in future portfolio-choice models.

7 Conclusion

This paper documents strong empirical patterns in the holdings of value and growth stocks by households. The average value investor is substantially older, and has higher financial wealth, higher real estate wealth, lower leverage, lower income risk, and lower human capital than the average growth investor. Moreover, males, entrepreneurs, and immigrants tend to have a growth tilt. These baseline results hold regardless of whether or not one excludes popular or professionally close stocks, and are unlikely to be explained away by latent preferences, genes, communication, or financial market experience.

Our study provides empirical support for a number of key theoretical explanations of the value premium. Consistent with risk-based theories, value stocks are held by investors who are in the best position to take financial risk, for instance because they hold substantial liquid wealth, earn safe incomes, and have low debt. Our paper is the first to document portfolio evidence in favor of rational theories of the value premium. Furthermore, the relationships between growth investing and variables such as gender or entrepreneurship seem consistent with the representativeness heuristic and overconfidence biases documented in the psychology literature. Thus the panel is explained by a mix of psychological and risk-based explanations of the value premium.

We provide evidence that households actively manage their holdings of growth and value stocks. At yearly frequencies, households dynamically rebalance their exposure to the value factor in response to passive variation in the portfolio tilt. Quite strikingly, the relationships between the value tilt and household characteristics hold just as strongly for new entrants as they do for preexisting participants. At longer life-cycle horizons, households climb the “value ladder” and gradually shift from growth to value investing as they become older, wealthier, less levered, and less dependent on their human capital. We estimate that pure horizon effects, captured by age, account for at least 50% of the life-cycle variation of the value tilt, which provides strong empirical support for intertemporal hedging (Lynch 2001).

Our results provides new directions for portfolio-choice and asset-pricing theories of the value factor. The household panel reveals that growth investing is tightly linked to human capital, income risk, and psychological biases, which would deserve formal investigation in calibrated portfolio-choice models. Furthermore, our empirical findings suggest that powerful general equilibrium effects are at play in the cross-sectional distribution and the dynamics of portfolio tilts. The development of overlapping generations models matching these features would be natural extensions of the present paper. Last but not least, the empirical patterns in the demand for value and growth stocks uncovered in this paper may have major implications for equity valuation, 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 3.2. 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 families of assets and household portfolios used in the paper. The columns report (i) the value loading of the aggregate portfolio, (ii) the cross-sectional distribution of the value loading, and (iii) the expected return 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. Household aggregate portfolios are constructed by adding up the market values of individual household holdings.

	Value Loading							Expected Return Spread Between Top and Bottom Deciles
	Aggregate Portfolio	Cross-Sectional Distribution						
		Mean	10th	25th	50th	75th	90th	
Assets								
Stocks listed on Stockholm Stock Exch.	-0.15	-0.87	-3.22	-1.57	-0.37	0.09	0.94	0.42
Funds	-0.10	-0.15	-0.41	-0.26	-0.10	0.01	0.20	0.06
Households								
All participants								
- Risky portfolio	-0.26	-0.30	-0.94	-0.46	-0.18	0.00	0.10	0.11
- Stock portfolio	-0.36	-0.58	-1.20	-1.09	-0.53	0.11	0.39	0.16
- Fund portfolio	-0.18	-0.20	-0.57	-0.30	-0.14	0.00	0.08	0.07
Fundholders								
- Risky portfolio	-0.25	-0.25	-0.71	-0.40	-0.17	-0.01	0.09	0.08
- Stock portfolio	-0.35	-0.57	-1.17	-1.06	-0.52	0.10	0.38	0.16
- Fund portfolio	-0.18	-0.20	-0.57	-0.30	-0.14	0.00	0.08	0.07
Direct stockholders								
- Risky portfolio	-0.28	-0.38	-1.07	-0.61	-0.24	-0.02	0.11	0.12
- Stock portfolio	-0.36	-0.58	-1.20	-1.09	-0.53	0.11	0.39	0.16
- Fund portfolio	-0.19	-0.22	-0.58	-0.33	-0.16	-0.03	0.07	0.07
Direct stockholders with 1 or 2 stocks								
- Risky portfolio	-0.27	-0.38	-1.11	-0.65	-0.23	0.01	0.11	0.12
- Stock portfolio	-0.64	-0.62	-1.14	-1.14	-1.00	0.11	0.44	0.16
- Fund portfolio	-0.17	-0.21	-0.58	-0.31	-0.14	-0.01	0.07	0.07
Direct stockholders with 3 or 4 stocks								
- Risky portfolio	-0.29	-0.41	-1.05	-0.62	-0.28	-0.05	0.10	0.12
- Stock portfolio	-0.49	-0.59	-1.37	-1.07	-0.54	0.03	0.36	0.18
- Fund portfolio	-0.18	-0.22	-0.57	-0.33	-0.16	-0.04	0.06	0.06
Direct stockholders with 5+ stocks								
- Risky portfolio	-0.28	-0.38	-0.98	-0.56	-0.25	-0.05	0.10	0.11
- Stock portfolio	-0.32	-0.48	-1.30	-0.83	-0.33	0.02	0.25	0.16
- Fund portfolio	-0.21	-0.24	-0.60	-0.35	-0.18	-0.06	0.03	0.06

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 3.2. 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
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 real estate wealth interacted with leverage. We conduct the estimation on the representative panel of households over the 1999 to 2007 period defined in Section 3.2. 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 sample of households that includes all 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	0.96	0.002	3.25	0.000	-0.55
Log commercial real estate	0.000	1.13	0.006	8.42	0.000	-1.11
Log residential real estate × Leverage ratio	-0.001	-3.81	-0.004	-4.75	0.000	-1.25
Log commercial real estate × Leverage ratio	-0.002	-5.23	-0.003	-3.10	-0.001	-3.76
Leverage ratio	-0.011	-3.91	-0.040	-5.25	-0.004	-2.11

Panel B: Family Size Variables

	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 V
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 3.2. 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		Stockholders		One or Two Stocks		Three or Four Stocks		Five or More Stocks	
	(1)		(2)		(3)		(4)		(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 VI
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 in aggregate household financial wealth (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 3.2. The aggregate household financial wealth used in the second column is the total amount of wealth owned by risky asset market participants. In the last row we consider the aggregate portfolio of the top ten popular stocks. The value loadings and book-to-market ratio percentiles are based on stock averages, where stocks are weighted by their shares of aggregate household portfolio reported in 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 VII
Value Loadings of Portfolios of Popular and Professionally Close Stocks

This table reports pooled regressions of the value loading of household subportfolios on household characteristics in the presence of year, industry, and county fixed effects. Every subportfolio in the table is a subset of the stock portfolio. We consider the portfolio of popular stocks in column (1), the portfolio of stocks other than popular stocks in column (2), the portfolio of professionally close stocks in column (3), and the portfolio of stocks other than professionally close stocks in column (4). The computations are based on the representative panel of households over the 1999 to 2007 period defined in Section 3.2. All variables are described in Table A. Standard errors are clustered at the household level.

	Dependent Variable: Value Loading of Stock Subportfolio							
	Popular (1)		Not Popular (2)		Profess. Close (3)		Not Profess. Close (4)	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Financial Characteristics								
Log financial wealth	0.019	8.39	0.144	22.01	0.073	12.87	0.053	16.48
Log residential real estate	0.002	4.08	0.004	2.45	0.003	1.90	0.004	5.01
Log commercial real estate	0.007	15.30	0.002	1.81	0.003	2.29	0.007	11.70
Leverage ratio	0.005	1.79	-0.029	-3.01	-0.033	-3.70	-0.002	-0.49
Human capital and Income Risk								
Log human capital	-0.085	-10.53	-0.101	-4.38	-0.109	-5.20	-0.115	-9.47
Log income	-0.021	-3.86	-0.077	-4.89	-0.040	-2.61	-0.034	-3.85
Self-employment dummy	-0.020	-1.95	-0.139	-4.29	-0.098	-3.52	-0.023	-1.52
Unemployment dummy	-0.009	-1.25	-0.069	-2.84	-0.020	-0.97	-0.017	-1.45
Conditional income volatility	-0.047	-2.21	-0.704	-11.01	-0.335	-6.35	-0.312	-9.54
Demographic Characteristics								
Age	0.005	17.20	0.016	19.21	0.008	10.33	0.008	17.80
Male household head dummy	-0.061	-10.21	-0.169	-9.74	-0.080	-5.49	-0.113	-13.77
High school dummy	-0.029	-3.79	-0.032	-1.33	-0.035	-1.85	-0.025	-2.37
Post-high school dummy	0.017	2.81	0.061	3.55	0.032	2.17	0.022	2.65
Economics education dummy	-0.010	-1.28	-0.004	-0.18	0.028	1.70	-0.021	-1.95
Immigration dummy	-0.086	-9.20	-0.321	-10.59	-0.148	-5.86	-0.126	-9.09
Family size	0.017	7.14	0.021	3.03	0.015	2.54	0.022	6.58
Adjusted R^2	2.95%		5.35%		3.08%		3.33%	
Number of observations	287,574		188,449		98,916		288,409	

Table VIII
Financial Market Experience

This table reports pooled regressions of the value loading in 2007 on (i) the number of years in the panel when the household participates in risky asset markets, (ii) the earliest value loading in the panel, and (iii) all the other household characteristics, and year, industry, and county fixed effects. The computations are based on the representative panel of households over the 1999 to 2007 period defined in Section 3.2. All variables are described in Table A.

	Dependent Variable: Value Loading					
	Risky Portfolio (1)		Stock Portfolio (2)		Fund Portfolio (3)	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Initial value loading	0.351	35.77	0.470	34.01	0.126	29.09
Experience						
Number of participation years	-0.006	-4.07	-0.015	-2.46	-0.011	-11.42
Financial Characteristics						
Log financial wealth	0.018	7.24	0.075	12.57	0.002	1.29
Log residential real estate wealth	0.000	-0.24	0.003	2.07	-0.001	-4.79
Log commercial real estate wealth	0.001	1.73	0.007	7.11	0.000	0.10
Leverage ratio	0.004	1.23	0.010	0.93	0.000	0.23
Human Capital and Income Risk						
Log human capital	-0.079	-6.96	-0.140	-6.18	-0.021	-3.98
Log income	-0.004	-0.46	0.018	1.00	-0.014	-3.40
Self-employment dummy	-0.052	-3.93	-0.064	-2.45	-0.007	-1.18
Unemployment dummy	-0.026	-2.27	-0.032	-1.13	-0.001	-0.16
Conditional income volatility	-0.172	-6.09	-0.046	-0.83	-0.023	-1.75
Demographic Characteristics						
Age	0.001	1.49	0.005	5.90	0.001	4.13
Male household head dummy	-0.037	-7.36	-0.055	-4.45	-0.003	-0.91
High school dummy	-0.022	-3.50	-0.077	-4.63	-0.003	-0.78
Post-high school dummy	-0.010	-2.02	0.037	3.00	-0.015	-5.27
Economics education dummy	-0.036	-5.04	-0.009	-0.55	-0.019	-4.80
Immigration dummy	-0.073	-7.63	-0.133	-6.17	0.007	1.55
Family size	0.029	11.72	0.005	0.89	0.012	9.17
Adjusted R^2	15.15%		13.25%		6.12%	
Number of observations	50,818		27,701		45,257	

Table IX
Twins

This table reports pooled regressions of the value loading on household characteristics and yearly twin-pair fixed effects estimated on the 1999 to 2007 panel of participating households with an adult twin. 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). All variables are described in Table A. Standard errors are clustered at the household level.

	Yearly Twin Pair Fixed Effects					
	Dependent Variable: Value Loading					
	Risky Portfolio (1)		Stock Portfolio (2)		Fund Portfolio (3)	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Financial Characteristics						
Log financial wealth	0.009	2.00	0.030	2.79	0.010	3.32
Log residential real estate wealth	0.002	1.59	0.005	1.58	0.000	0.14
Log commercial real estate wealth	0.001	0.72	0.006	2.69	0.000	0.31
Leverage ratio	-0.001	-0.18	0.033	1.55	0.000	0.08
Human Capital and Income risk						
Log human capital	-0.070	-4.00	-0.083	-1.93	-0.025	-1.87
Log income	-0.060	-4.53	-0.087	-3.02	-0.023	-2.41
Self-employment dummy	-0.001	-0.05	0.022	0.55	-0.019	-1.44
Unemployment dummy	-0.038	-2.71	-0.017	-0.47	-0.021	-2.25
Conditional income volatility	-0.365	-7.75	-0.459	-3.81	-0.126	-3.69
Demographic Characteristics						
Male household head dummy	-0.027	-2.69	-0.025	-0.97	-0.019	-2.88
High school dummy	-0.035	-2.27	-0.071	-1.83	-0.005	-0.50
Post-high school dummy	0.004	0.30	0.040	1.33	-0.012	-1.47
Economics education dummy	-0.010	-0.73	0.019	0.55	-0.008	-0.75
Family size	0.040	8.26	0.035	2.76	0.015	4.75
Adjusted R^2	12.56%		22.79%		10.71%	
Number of observations	104,522		43,906		87,972	

Table X
Communication

This table reports pooled regressions of the value loading on yearly twin-pair fixed effects and characteristics, estimated on (a) households with twins communicating frequently with each other ("High Communication"), and (b) households with twins communicating infrequently with each other ("Low Communication"). The value loading is computed 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). A twin pair is classified as "High Communication" if the frequency of mediated communication and the frequency of unmediated communication are both above the median, and as "Low Communication" otherwise. The communication subsamples are obtained from the 1999 to 2007 panel of participating households with an adult twin. All variables are described in Table A of the main text. Standard errors are clustered at the household level.

	Dependent Variable: Value Loading											
	Risky Portfolio				Stock Portfolio				Fund Portfolio			
	High Communication (1)		Low Communication (2)		High Communication (3)		Low Communication (4)		High Communication (5)		Low Communication (6)	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Financial Characteristics												
Log financial wealth	0.012	2.32	0.010	2.15	0.039	2.81	0.038	2.97	0.014	4.39	0.010	2.94
Log residential real estate wealth	0.000	-0.01	0.002	1.46	0.000	-0.01	0.010	2.71	-0.001	-0.65	-0.001	-1.80
Log commercial real estate wealth	0.003	3.11	0.002	1.83	0.013	5.55	0.009	3.88	0.001	0.84	0.001	0.71
Leverage ratio	0.002	0.25	-0.003	-0.37	-0.002	-0.11	0.018	0.89	0.005	1.11	-0.005	-1.08
Human Capital and Income Risk												
Log human capital	-0.097	-4.56	-0.094	-4.79	-0.186	-3.72	-0.167	-3.39	-0.037	-2.49	-0.035	-2.38
Log income	-0.051	-3.20	-0.047	-3.12	-0.064	-1.88	-0.053	-1.51	-0.033	-3.15	-0.033	-2.91
Self-employment dummy	-0.016	-0.58	-0.011	-0.49	-0.006	-0.09	0.009	0.18	-0.033	-1.86	0.000	0.02
Unemployment dummy	-0.033	-1.97	-0.035	-2.11	-0.026	-0.56	-0.053	-1.00	-0.023	-2.12	-0.013	-1.25
Conditional income volatility	-0.423	-7.05	-0.375	-6.46	-0.385	-2.86	-0.435	-3.41	-0.161	-4.03	-0.163	-4.52
Demographic Characteristics												
Age	0.002	2.58	0.002	1.64	0.009	3.37	0.006	2.63	0.000	0.36	0.000	0.49
Male household head dummy	-0.026	-2.21	-0.020	-1.96	-0.018	-0.56	-0.054	-2.07	0.007	1.01	-0.011	-1.62
High school dummy	-0.025	-1.69	-0.001	-0.07	0.005	0.12	0.026	0.63	-0.007	-0.70	0.004	0.34
Post-high school dummy	-0.004	-0.38	0.005	0.45	0.041	1.11	0.099	3.42	-0.022	-2.59	-0.018	-2.42
Economics education dummy	-0.047	-2.83	-0.019	-1.11	-0.037	-0.83	0.029	0.77	-0.034	-2.62	-0.011	-1.03
Family size	0.046	8.59	0.038	7.27	0.052	3.36	0.055	3.91	0.021	6.14	0.017	4.89
Adjusted R^2	3.15%		2.13%		5.64%		4.08%		2.28%		1.64%	
Number of observations	36,230		42,588		15,462		17,448		30,572		36,008	

Table XI
ACE Decomposition

This table reports an ACE decomposition of the value loading of households with twins over the 1999 to 2007 period. We report the results for (i) all twins, (ii) twins who communicate frequently with each other (“High Communication”), and (iii) twins who communicate infrequently with each other (“Low Communication”). The set of columns labeled “No Controls” presents the ACE decomposition for the value loading itself. The set of columns labeled “With Controls” presents the ACE decomposition for the value loading residual from the regression in Table IX. Panel A conducts the analysis at the level of the risky portfolio, Panel B at the level of the stock portfolio, and Panel C at the level of the fund portfolio. A twin pair is classified as “High Communication” if the frequency of mediated communication and the frequency of unmediated communication are both above the median, and as “Low Communication” otherwise.

Panel A: Value Loading of Risky Portfolio

	No Controls		With Controls	
	Genetic Component	Common Component	Genetic Component	Common Component
All twin pairs	17.0%	0.1%	16.1%	-0.6%
High-communication pairs	35.39%	-6.13%	33.05%	-6.27%
Low-communication pairs	0.87%	4.74%	-0.23%	4.87%

Panel B: Value Loading of Stock Portfolio

	No Controls		With Controls	
	Genetic Component	Common Component	Genetic Component	Common Component
All twin pairs	12.3%	13.7%	10.8%	11.4%
High-communication pairs	37.58%	7.55%	37.64%	3.74%
Low-communication pairs	-0.24%	11.65%	-3.91%	11.15%

Panel C: Value Loading of Fund Portfolio

	No Controls		With Controls	
	Genetic Component	Common Component	Genetic Component	Common Component
All twin pairs	8.7%	4.4%	7.3%	3.8%
High-communication pairs	33.80%	-10.21%	32.24%	-10.75%
Low-communication pairs	-8.25%	12.74%	-9.50%	12.69%

Table XII
Decomposition of Income Risk

This table analyzes the systematic and idiosyncratic components of income risk, and their relationships to the value tilt. For every household, we regress the stochastic component of labor income defined in Section 3.3 on the four Fama-French-Cahart factors, and refer to the explained component as the systematic component and to the residual as idiosyncratic risk. Panel A reports the standard deviation of labor income risk, the persistence parameter of the labor income process, and the share of idiosyncratic risk in the standard deviation of labor income risk. Panel B reports a pooled regression of the value loading on (i) the systematic and idiosyncratic components of income, and (ii) other characteristics, and year, industry, and county fixed effects. 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 3.2. Standard errors are clustered at the household level.

Panel A: Decomposition of Income Risk

	Dependent Variable: Income Shock		
	Total Volatility	Persistence Parameter	Idiosyncratic Share
Active Households			
Cross-sectional average	16.26%	46.75%	80.99%
Cross-sectional standard deviation	9.89%	40.60%	13.80%
Retired Households			
Cross-sectional average	11.82%	65.76%	78.67%
Cross-sectional standard deviation	9.37%	34.74%	16.59%

Panel B. Impact of Income Risk on Portfolio Tilt

	Dependent Variable: Value Loading					
	Risky Portfolio (1)		Stock Portfolio (2)		Fund Portfolio (3)	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Components of Income Risk						
- Market beta	0.042	4.17	0.062	3.09	0.016	2.81
- Value loading	0.021	1.84	0.038	1.70	0.015	2.21
- Size loading	0.027	2.34	0.070	3.04	0.007	0.99
- Momentum loading	-0.005	-0.35	-0.034	-1.22	0.003	0.42
- Idiosyncratic volatility	-0.329	-21.09	-0.314	-10.49	-0.116	-13.57

Table XIII
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 3.2. 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 XIV
Value Loadings of New Participants

This table reports pooled regressions of a new participant's value loading on socioeconomic characteristics and year, industry, and county fixed effects. We conduct the estimation on households that enter the stock market between 1999 to 2007 in the representative sample defined in Section 3.2. The analysis is based on data in the year of entry. All variables are described in Table A.

	Dependent Variable: Value Loading					
	Risky Portfolio (1)		Stock Portfolio (2)		Fund Portfolio (3)	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Financial Characteristics						
Log financial wealth	0.015	2.25	0.106	6.82	0.014	3.78
Log residential real estate	-0.002	-1.46	-0.001	-0.43	-0.001	-0.99
Log commercial real estate	0.000	0.13	0.009	2.27	0.000	0.39
Leverage ratio	0.015	4.98	0.037	3.79	0.000	-0.22
Human Capital and Income Risk						
Log human capital	-0.036	-1.49	-0.059	-1.26	-0.005	-0.38
Log income	-0.048	-2.12	-0.041	-0.87	-0.018	-1.95
Self-employment dummy	-0.189	-4.51	-0.243	-3.43	0.001	0.08
Unemployment dummy	-0.029	-1.42	-0.126	-2.20	0.012	1.10
Conditional income volatility	-0.328	-5.99	-0.253	-2.21	-0.065	-2.11
Demographic Characteristics						
Age	0.001	2.08	0.007	4.38	0.000	1.08
Male household head dummy	-0.109	-7.88	-0.126	-3.57	-0.020	-2.37
High school dummy	0.005	0.30	0.021	0.49	0.007	0.74
Post-high school dummy	-0.058	-3.72	-0.089	-2.46	-0.012	-1.33
Economics education dummy	-0.036	-1.87	0.000	0.00	-0.016	-1.33
Immigration dummy	-0.043	-2.31	-0.061	-1.37	0.017	1.64
Family size	0.030	5.07	0.010	0.69	0.006	1.88
Adjusted R^2	2.06%		3.73%		0.44%	
Number of observations	13,927		4,779		10,472	

Table XV
Existing vs. New Participants

This table reports a pooled regression of the value loading on (i) age dummies for participating households, (ii) age dummies for households that enter risky asset markets during the year, and (iii) all the other characteristics of the baseline regression, and year, industry, and county fixed effects. Age dummies are cumulative. The computations are based on the representative sample of households over the 1999 to 2007 period defined in Section 3.2. All variables are discussed in Table A of the main text. Standard errors are clustered at the household level. The full results are available in the Internet Appendix.

	Dependent Variable: Value Loading					
	Risky Portfolio (1)		Stock Portfolio (2)		Fund Portfolio (3)	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Age Dummies						
30 and above	0.003	0.45	0.052	3.29	0.000	-0.07
35 and above	0.005	1.23	0.047	4.28	0.000	-0.05
40 and above	0.010	2.87	0.039	4.14	0.005	2.11
45 and above	0.012	3.55	0.058	6.62	0.002	0.91
50 and above	0.015	4.49	0.040	5.17	0.000	0.15
55 and above	0.019	5.98	0.037	5.60	0.002	1.07
60 and above	0.011	3.49	0.022	3.36	0.003	1.59
65 and above	0.019	3.52	0.021	1.92	0.006	1.66
70 and above	0.058	5.62	0.139	6.47	0.023	3.46
New Entrant Dummies						
New entrant aged 30+	-0.091	-5.99	-0.252	-6.14	-0.007	-0.83
New entrant aged 35+	-0.007	-0.35	-0.007	-0.12	-0.008	-0.62
New entrant aged 40+	-0.032	-1.42	-0.090	-1.48	0.004	0.29
New entrant aged 45+	-0.007	-0.28	-0.025	-0.41	0.000	-0.02
New entrant aged 50+	0.001	0.07	0.037	0.69	0.005	0.40
New entrant aged 55+	-0.020	-0.93	-0.029	-0.61	-0.009	-0.65
New entrant aged 60+	-0.001	-0.04	-0.068	-1.23	-0.002	-0.12
New entrant aged 65+	-0.119	-2.96	-0.028	-0.39	-0.010	-0.43
New entrant aged 70+	-0.010	-0.45	-0.013	-0.26	0.032	2.58

Table XVI
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 and a 70-year old household, to which we assign the average characteristics of households in their respective cohorts in 2003. In Panel A, the impact of changes in characteristics is assessed using the baseline regression coefficients in Table III. Panel B is based on the specification estimated in Table IV, Panel A, in which real estate is interacted with leverage. All variables are described in Table A.

Panel A: Economic Impact Computed from Baseline Regression

Variable	Demographic Group		Marginal Effect on Value Loading		
	30-Year Old	70-Year Old	Risky Portfolio	Stock Portfolio	Fund Portfolio
Age	30	70	0.109	0.353	0.023
Financial wealth ($)	30,247	126,547	0.024	0.071	0.017
Residential real estate ($)	126,329	175,897	0.000	0.001	0.000
Commercial real estate ($)	12,957	48,668	0.001	0.010	0.000
Leverage	0.91	0.06	0.000	0.006	0.001
Income ($)	45,255	60,367	-0.013	-0.013	-0.008
Human capital ($)	1,237,705	305,171	0.073	0.145	0.030
Total effect			**0.195**	**0.574**	**0.062**
Fraction due to age			**56.0%**	**61.6%**	**36.9%**

Panel B: Economic Impact with Real Estate-Leverage Interaction

Variable	Demographic Group		Marginal Effect on Value Loading		
	30-Year Old	70-Year Old	Risky Portfolio	Stock Portfolio	Fund Portfolio
Age	30	70	0.105	0.341	0.023
Financial wealth ($)	30,247	126,547	0.021	0.067	0.015
Residential real estate ($)	126,329	175,897	0.012	0.035	0.004
Commercial real estate ($)	12,957	48,668	0.016	0.029	0.006
Leverage	0.91	0.06	0.010	0.033	0.004
Income ($)	45,255	60,367	-0.013	-0.012	-0.008
Human capital ($)	1,237,705	305,171	0.069	0.142	0.027
Total effect			**0.220**	**0.636**	**0.071**
Fraction due to age			**47.76%**	**53.59%**	**32.89%**

Table A
Definition of Household Variables

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

Variable	Description
Cash	Bank account balances and money market funds.
Fund portfolio	Portfolio of mutual funds other than money market funds.
Stock portfolio	Portfolio of directly held stocks.
Risky portfolio	Portfolio of risky mutual funds and directly held stocks.
Risky share	Proportion of risky assets in the portfolio of cash and risky financial assets.
Financial wealth	Value of holdings in cash, risky financial assets, capital insurance products, derivatives, and directly held bonds, excluding illiquid assets and defined contribution retirement accounts.
Share of popular stocks	Fraction of the household 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.
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 an 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 all the 352 firms listed on Swedish exchanges (SSE, ATO, NGM, INO) and all Swedish households that own stocks at the end of 2003.

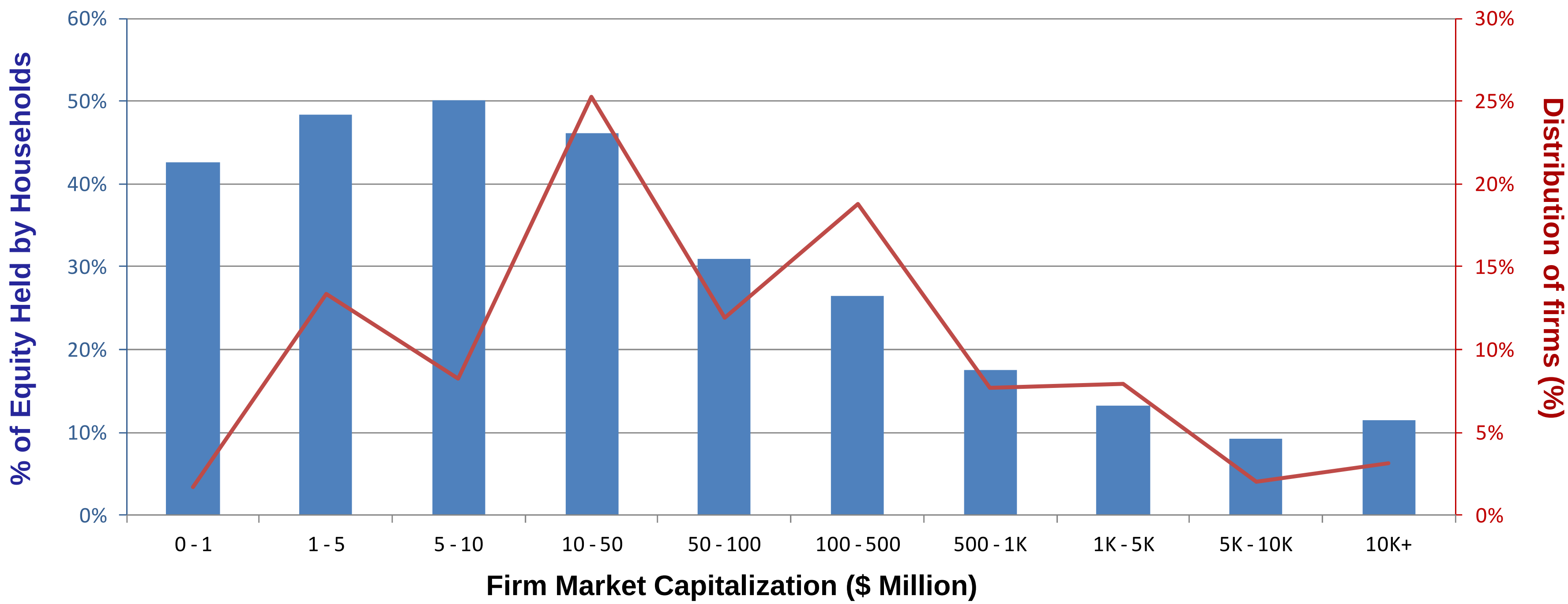

Figure 2
The Value Ladder

This figure illustrates the value loading of the stock portfolio for different cohorts of households. Each solid 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 direct stockholders over the 1999 to 2007 period.