# Who are the Value and Growth Investors?

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**ABSTRACT**

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

*JEL Classification: G11, G12.*

*Keywords:* Asset pricing, factor-based investing, household finance, human capital, portfolio allocation, value premium.

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A central question of modern finance is why value stocks consistently outperform growth stocks on average both in the U.S. and around the world (Basu (1977), Fama and French (1992, 1998), Graham and Dodd (1934)).[1] As Fama and French (1992, 1995) suggest, the value premium may be compensation for systematic risks other than market portfolio return risk, such as fluctuations in aggregate labor income and consumption (Cochrane (1999), Jagannathan and Wang (1996), Lettau and Ludvigson (2001), Lustig and van Nieuwerburgh (2005), Petkova and Zhang (2005), Yogo (2006)), cash-flow risk (Campbell and Vuolteenaho (2004)), costly reversibility of physical capital (Zhang (2005)), long-run consumption risk (Bansal, Dittmar, and Kiku (2009), Bansal, Dittmar, and Lundblad (2005), Bansal et al. (2014), Hansen, Heaton, and Li (2008)), and displacement risk (Garleanu, Kogan, and Panageas (2012)). Another possible explanation for the underperformance of growth stocks relative to value stocks is that investors are irrationally exuberant about the prospects of innovative glamour companies (DeBondt and Thaler (1985), Lakonishok, Shleifer, and Vishny (1994)).[2]

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

The paper makes several contributions to the literature. First, we show that the value tilt exhibits substantial heterogeneity across households. When we sort investors by the value tilt of their risky asset portfolios, the difference in expected returns between the top and bottom deciles is approximately equal to the value premium.

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

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

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

In robustness checks, we document that the equities most widely held by households are a mix of growth stocks and value stocks, and that the relationships between portfolio tilts and investor characteristics are not driven by these popular stocks. We further verify that our results are unlikely to be due to investor experience or stock characteristics other than the value loading, such as professional proximity, the dividend yield, taxes, firm age, skewness, and size. As in Calvet and

Sodini (2014), we use a subsample of Swedish twins to control for latent investor fixed effects, such as family background, upbringing, inheritance, or attitudes toward risk. The sensitivities of the value loading to socioeconomic characteristics are similar in the twin subsample as in the general household population, regardless of whether the twins communicate frequently with each other.[4]

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

The value ladder provides further validation of the hedging motive. Over the life cycle, the household becomes less dependent on human capital and its hedging demand should get progressively weaker, as the model of Lynch and Tan (2011) suggests. The value ladder should therefore be more pronounced in more cyclical industries. The empirical evidence confirms these predictions. Other types of hedging demand might also help explain the value ladder. For instance, to the extent that investment opportunities are time-varying, households should behave more myopically and have weaker hedging demand as their investment horizons shorten (Brennan, Schwartz, and Lagnado (1997), Campbell and Viceira (2002), Jurek and Viceira (2011), Larsen and Munk (2012), Lynch (2001)). The value ladder is therefore consistent with life-cycle variation in hedging demand.

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

These empirical regularities can be integrated into a unified equilibrium model. We develop a stylized model of the value tilt, based on a version of the intertemporal capital asset pricing model

(ICAPM) (Merton (1973)) that includes both labor income and discount rate risks. The analysis is qualitative but demonstrates that the relationships between the value tilt and variables such as age, wealth, human capital, and income risk can arise in a general equilibrium setting.

The Swedish data set provides highly detailed information on household finances and demographics but is somewhat less informative about psychological traits. With this caveat, we find that sentiment-based explanations of the value premium also help explain the portfolio evidence. Overconfidence, which is more prevalent among men than women (Barber and Odean (2001)), is consistent with the growth tilt of male investors. As attention theory predicts (Barber and Odean (2008)), a majority of direct stockholders hold a small number of popular stocks. Furthermore, some of the portfolio evidence can be explained by complementary risk-based and psychological stories. For instance, the growth tilt of entrepreneurs can be attributed both to exposure to private business risk (Heaton and Lucas (2000), Moskowitz and Vissing-Jørgensen (2002)) and to marked overconfidence in own decision-making skills (Busenitz and Barney (1997)). Our results therefore provide further evidence that retail investors favor assets with certain characteristics[5] and adjust their investment styles to news and past experience (Kumar (2009a), Campbell, Ramadorai, and Ranish (2014)).

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

The patterns we uncover contribute to the growing body of work showing the relevance of portfolio theory for explaining household financial behavior. Retail investors allocate a high share of liquid financial wealth to risky assets if they have high financial wealth and human capital (Calvet and Sodini (2014)), earn safe labor income (Betermier et al. (2012), Calvet and Sodini (2014), Guiso, Jappelli, and Terlizzese (1996)), and are not entrepreneurs (Heaton and Lucas (2000)).[6]

Households actively rebalance their financial portfolios in response to realized returns (Calvet, Campbell, and Sodini (2009a)). Furthermore, a majority of households incur small welfare losses from underdiversification (Calvet, Campbell, and Sodini (2007)). We document here that financial theory also accounts for the cross-sectional and time-series properties of household portfolio styles.

The rest of the paper is organized as follows. Section I presents the data and reports the cross-sectional distribution of the value loading. Section II empirically investigates how the value tilt relates to demographic and financial characteristics. Section III links the employment sector to the value tilt of the financial portfolio. Sections IV and V develop the equilibrium model and relate the evidence to risk- and sentiment-based explanations of the value premium. Section VI presents robustness checks and Section VII concludes. The Internet Appendix reviews the literature, discusses methodological details, reports additional empirical results, and fully derives the equilibrium model.[7]

# I. Data and Summary Statistics

## *A.* Local Fama and French Factors

Data on Nordic stock markets for the 1985 to 2009 period are available from FINBAS, a financial database maintained by the Swedish House of Finance. The data include monthly stock returns, market capitalizations at the semiannual frequency, and book values at the end of each year. Free-float-adjusted market shares are available from Datastream. We focus on stocks with at least two years of available data. We exclude stocks worth less than 1 krona, which filters out very small firms. For comparison, the Swedish krona traded at 0.1371 U.S. dollars on December 30, 2003. We end up with a universe of approximately 1,000 stocks, of which 743 are listed on one of the four major Nordic exchanges in 2003.[8]

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

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

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

where $r^e_{i,t}$ denotes the excess return of asset $i$ in month $t$ and $u_{i,t}$ is a residual that is uncorrelated with the factors. Estimated loadings are winsorized at -5 and +5. The value premium is substantial in Sweden: $HML_t$ averages to about 10% per year over the 1985 to 2009 period, which is consistent with the estimate for Sweden in Fama and French (1998) and is also in the range of country estimates reported in Liew and Vassalou (2000).

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

## *B.* Household Panel Data

The Swedish Income and Wealth Registry is an administrative data set compiled by Statistics Sweden that has previously been used in studies of household finance (Calvet, Campbell, and Sodini (2007, 2009a, 2009b)). Until 2007, Statistics Sweden and the tax authority had 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 for each year from 1983 to 2007. The disaggregated wealth data include the worldwide assets owned by the resident at year-end from 1999 to 2007. Real estate, debt, bank accounts, stockholdings, and mutual fund investments are observed at the level of each property, account, or security.

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

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

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

## *C.* Definitions of Main Variables

### *C.1.* Financial Assets and Real Estate

We use the following definitions throughout the paper. Cash consists of bank account balances and Swedish money market funds.[9] Risky mutual funds refer to all funds other than Swedish money market funds. Risky financial assets consist of directly held stocks and risky mutual funds. We exclude assets with less than three months of return data from the portfolio analysis.

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

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

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

where $w_{h,i,t}$ denotes the weight of asset $i$ in household $h$'s risky portfolio at time $t$. We occasionally call $v_{h,t}$ the HML loading or the value tilt. The value loadings of the fund and stock portfolios are defined similarly. The estimation methodology takes advantage of (i) the detailed yearly data available for household portfolios, which permit the calculation of $w_{h,i,t}$, and (ii) the long monthly series available for individual assets, which permit the precise estimation of $v_i$.

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

We measure the household's financial wealth at date $t$ as the total value of its cash holdings, risky financial assets, directly held bonds, capital insurance, and derivatives, excluding from consideration illiquid assets such as real estate, consumer durables, and defined contribution retirement accounts. Also, our measure of wealth is gross financial wealth and does not subtract mortgage or other household debt. Residential real estate consists of primary and secondary residences, while commercial real estate consists of rental, industrial, and agricultural property. The leverage ratio is defined as total debt divided by financial and real estate wealth.

### *C.2.* **Human Capital**

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

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

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

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

where $\xi_{h,t} \sim \mathcal{N}(0, \sigma^2_{\xi,h})$ is the persistent shock to income in period $t$. The Gaussian innovations $\varepsilon_{h,t}$ and $\xi_{h,t}$ are white noise and are uncorrelated with each other at all leads and lags. We conduct the estimation separately on household bins sorted by (i) immigration status, (ii) gender, and (iii) educational attainment. We compute the fixed effects estimators of $a_h$ and $b$ in each bin, and then estimate $\rho_h$, $\sigma^2_{\xi,h}$, and $\sigma^2_{\varepsilon,h}$ by maximum likelihood on each household income series.

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

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

and conditional variance

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

We call $\sigma_h$ the conditional volatility of income and use it as a measure of income risk.

We define expected human capital as

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

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

## *D.* Summary Statistics on Participating Households

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

**– Table ?? here –**

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

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

By contrast, almost 30% of direct stockholders own at least five different stocks. This subgroup is important for the following reasons. Households with at least five stocks have high education levels and exhibit no bias toward popular stocks. They have substantially higher financial wealth ($\$125,000$) and select a higher risky share (61%) than the average investor, and correspondingly own the bulk of aggregate equity. In the bottom rows of Table **??**, Panel B, we report the fraction of the aggregate portfolio held by specific subsets of investors. The aggregate portfolio is constructed by summing the stock and fund holdings of all participants. Households that own five stocks or more, which represent only 17% of all participants, own 36% of aggregate mutual fund holdings and 80% of aggregate direct stockholdings. They therefore account for a substantial fraction of the household demand for risky assets. Polkovnichenko (2005) similarly shows that a minority of diversified wealthy households hold the bulk of aggregate equity in the U.S.

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

**– Figure ?? here –**

Swedish households own a sizable fraction of Swedish firms, as Figure **??** illustrates. We sort firms by market capitalization, and for each size bucket we report the fraction of firms in the size bucket (solid line) and the fraction of equity owned directly by Swedish households (solid bars). Households directly own 30% to 50% of firms with a market capitalization up to 100 million U.S. dollars and directly own a smaller fraction of larger firms.[11] For the majority of Swedish companies, the aggregate demand from the household sector is therefore substantial and can potentially have a sizable impact on stock prices.

## *E.* The Cross-Section of Value Tilts

*Individual Stocks.* Table **??** reports the value loadings of stocks listed on the Stockholm Stock Exchange at the end of 2003. The loadings range from -3.22 (10th percentile) to 0.94 (90th percentile), with a median of -0.37. The distribution of the value loading across individual stocks is therefore highly heterogenous and negatively skewed. The value-weighted (VW) portfolio of Swedish stocks, which by construction coincides with the SIXRX market index, has a value loading of -0.15 in 2003.[12] We therefore view a value loading of -0.15 in 2003 as being neutral. The equal-weighted (EW) average stock loading is more negative than its VW counterpart, which stems from the large number of small growth stocks.

**– Table ?? here –**

*Household Portfolios.* Like individual stocks, household portfolios exhibit substantial heterogeneity in the value loading. Among participants, the loading of the risky portfolio ranges from -0.94 (10th percentile) to 0.10 (90th percentile); the implied expected return differential is therefore approximately equal to the value premium.[13] The median loading is nearly neutral at -0.18, so the distribution of the risky portfolio loading is negatively skewed. Cross-sectional heterogeneity is slightly more pronounced for the stock portfolio tilt, as intuition suggests.

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

# II. Life-Cycle Variation in the Value Tilt

## *A.* The Value Ladder

In Figure **??**, we illustrate that households progressively switch from growth to value investments over the life cycle, a phenomenon that we call the value ladder. The figure is based on the risky portfolio (Panel A) and the stock portfolio (Panel B) of all Swedish households owning, respectively, risky assets and equities during the period. We sort households by birthyear into nine cohorts, and for each cohort we plot in the solid line the average VW value loading between 1999 and 2007.[14] Cohort loadings are demeaned each year to control for variation in the average loading of individual stocks due to new listings and delistings. The dotted lines plot the predicted cohort loadings based on pooled panel regressions, as is discussed in Section II.C.

**– Figure ?? here –**

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

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

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

## *B.* Demographic and Financial Determinants

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

**– Table ?? here –**

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

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

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

*Investor Subgroups.* In Table **??**, we reestimate the baseline regression on five separate groups of investors: (1) mutual fund owners, (2) direct stockholders, and (3) to (5) direct stockholders sorted by the number of firms that they own. The baseline results remain valid in all groups. Furthermore, the explanatory power of the regression is twice as high for households with at least three stocks as for households with one or two stocks. Thus, diversified stockholders, who own the bulk of aggregate equity, tend to select value tilts that are best explained by their financial and demographic characteristics.

**– Table ?? here –**

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

**– Table ?? here –**

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

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

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

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

## *C.* Economic Significance

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

**– Table ?? here –**

The table reveals that life-cycle changes in age, human capital, and financial characteristics tend to increase the value loading and account for almost all of the amplitude of the value ladder. For both the risky and the stock portfolios, age captures about 60% of the life-cycle variation in the value loading. The decumulation of human capital between 30 and 70 drives 20% of the life-cycle variation of the loading, while the accumulation of financial wealth accounts for the remaining 20%. Other characteristics, such as real estate, have more marginal impacts.[15] In the Internet Appendix, we show that the impact of real estate and leverage is substantially stronger when their interaction is taken into account.

**– Figure ?? here –**

In Figure **??**, we illustrate the predicted average loading (dotted lined) and observed average loading (solid lines) of cohorts between 1999 and 2007. Each line plots the average loading of households in a given cohort, weighted by financial wealth. We compute the predicted values by using the linear coefficients of the baseline regression applied to the set of characteristics used in Table **??**: age, financial characteristics, and human capital. Consistent with Table **??**, these variables explain the ladder with good accuracy, both for the risky and for the stock portfolios. In the Internet Appendix, we regress the predicted loading on the actual loading for each cohort. The $R^2$ is substantial, averaging 66% for the risky portfolio and 74% for the stock portfolio. Socioeconomic characteristics, which have only limited explanatory power at the household level, have strong implications for the value loading at the cohort level and may therefore substantially impact asset prices.

## *D.* New Entrants and Active Rebalancing

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

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

*Active Rebalancing at the Yearly Frequency.* To climb the value ladder over the life cycle, households presumably need to rebalance their portfolios at shorter horizons to mitigate the impact of realized returns and revert to their slow-moving target. For this reason, we now investigate passive and active variation in the value tilt of household portfolios.[16] Consider household $h$ with portfolio weights $w_{h,i,t-1}$ $(i = 1, \ldots, I)$ at the end of year $t-1$. If the household did not trade during the following year, the share of each asset $i$ at the end of year $t$ would be

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

and the portfolio value loading would then be $v^P_{h,t} = \sum_{i=1}^{I} w^P_{h,i,t} v_i$. We can therefore decompose the actual change in the portfolio value loading as

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

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

**– Table ?? here –**

In Table **??**, we regress the active change, $a_{h,t}$, on the passive change, $p_{h,t}$, the lagged value loading, $v_{h,t-1}$, and either no characteristics or all lagged characteristics. The passive change has a negative and highly significant coefficient for all portfolios, regardless of whether 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. Households actively fight the passive variation generated by realized returns, which confirms that the value ladder is not driven purely by inertia.

# III. Systematic Labor Income Risk and the Value Tilt

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

## *A.* Industry Sensitivities

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

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

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

**– Table ?? here –**

Table **??**, Panel A, documents that income growth is strongly correlated across sectors.[17] We estimate the linear specification

$$\ell_{s,t} = \alpha_s + \varphi_s \bar{\ell}_t + \varepsilon_{s,t} \tag{6}$$

for each of the 70 sectors, and report the distribution of the sensitivity, $\varphi_s$, and the coefficient of determination, $R^2$, across regressions. The $R^2$s of the 70 regressions are generally high and average 0.88. Thus, per-capita national income growth, $\bar{\ell}_t$, is an important factor explaining the panel of sectoral growth rates. The sensitivity, $\varphi_s$, is heterogeneous across sectors, ranging from 0.81 (10th percentile) to 1.22 (90th percentile).

## *B.* Industry Variation in the Value Loading

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

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

We make several observations about these results. First, we impute household sensitivities from industry data because household income growth has a large idiosyncratic component and the direct measurement of household sensitivity entails large estimation error, as is further explained in the Internet Appendix. Second, our approach is motivated by earlier research showing that the value factor correlates positively with future economic growth and labor income in U.S. and international data (Liew and Vassalou (2000)). In the Internet Appendix, we replicate these earlier results on Swedish data, even though the available time series are relatively short. We also consider a direct measure of risk, the sensitivity of labor income to the lagged value factor itself, and similarly find that the portfolio value loading is negatively related to the labor income sensitivity to HML.

## *C.* The Value Ladder Across Industries

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

**– Table ?? here –**

These results suggest that the shape of the value ladder should vary across industries. To confirm this prediction, in Figure **??**, we plot the average value loading of the risky portfolio in the most cyclical and least cyclical industries for the nine cohorts observed over the nine-year sample period. The figure is based on wealth-weighted estimates over the full sample period. We find that the value ladder is indeed steeper in cyclical industries. Furthermore, the value ladders join up for older households, consistent with the intuition that older households have weak hedging needs regardless of their employment sector.

 

**– Figure ?? here –**

# IV. Relation to Risk-Based Theories

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

## *A.* Hedging Demand

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

To the best of our knowledge, our paper is the first to provide direct evidence of hedging demand of any kind in the risky portfolios of households. It also lends support to the link between the value premium and income risk, which has been the subject of a vast asset pricing literature.[18] In his Presidential Address to the American Finance Association, Cochrane (2011) develops the following interpretation of the value factor: “If a mass of investors has jobs or businesses that will be hurt especially hard by a recession, they avoid stocks that fall more than average in a recession.” Our results confirm Cochrane’s prediction.

*Age Effects.* The relationship between portfolio tilts and age is a natural implication of the hedging motive. Since long-term investors are less myopic than short-term investors, the hedging motive is theoretically stronger for younger than for older households, as the portfolio literature emphasizes (Brennan, Schwartz, and Lagnado (1997), Campbell and Viceira (2002)). A ladder of portfolio tilts can hence arise in a wide class of environments.

Given the direct evidence in Section III, we can naturally relate the value ladder to aggregate income risk. This view is further reinforced by the evidence in Figure **??** that the value ladder is steeper in industries with a high sensitivity to the macro factor. Indeed, in a life-cycle setting, a young agent facing high state risk has a strong hedging motive, which progressively weakens as the agent ages and becomes more myopic. This suggests that the slope of the value ladder is primarily driven by the hedging motive of the young and is therefore steeper in more cyclical industries.[19] The data confirm this theoretical prediction.

Other forms of state risk may also contribute to the value ladder. The asset pricing literature documents that growth stocks provide a hedge against adverse variation in investment opportunities. Since young investors face higher reinvestment risk than old investors, the young should be tilted toward growth and the old toward value. Jurek and Viceira (2011), Larsen and Munk (2012), and Lynch (2001) develop this logic in calibrated portfolio choice settings. Put slightly differently, since value stocks have a shorter duration than growth stocks (Cornell (1999), Dechow, Sloan, and Soliman (2004), Lettau and Wachter (2007)), young investors should hold long-duration growth stocks while old investors should select short-duration value stocks.[20] The value ladder is consistent with these mechanisms.

*Human Capital.* In addition to these results, we uncover that high expected human capital is associated with a growth tilt in the financial portfolio. This relationship is strong in all of the specifications considered in this paper and the Internet Appendix. Intuition suggests that human capital is a form of both wealth, which in principle might induce a value tilt, and risk, which in the data induces a growth tilt. We can offer several possible explanations for the dominance of the risk channel that build on the extensive literature relating the value premium to the production process.[21] Since human capital is a key complement of physical capital in production, households with a high level of human capital should tilt away from the physical capital in value firms and instead invest in growth firms.[22] A complementary explanation is that human capital is highly risky because it is exposed to tail risks and innovation shocks that are difficult to anticipate and measure ex ante, as in the theoretical models of Garleanu, Kogan, and Panageas (2012) and Kogan, Papanikolaou, and Stoffman (2013). The strong empirical link between human capital and growth investing is a novel empirical fact that deserves further theoretical research.

## *B.* Risk Aversion, Wealth, and Background Risk

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

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

Expected utility theory implies a link between effective risk tolerance and the level of background risk. The regression results on family size, income risk, self-employment, and immigration status all give empirical support to this prediction. The unexpected birth of a child induces a growth tilt, consistent with the view that the arrival of a newborn entails lower resources per-capita and higher idiosyncratic needs. High income volatility also creates a growth tilt. Indeed, the volatility of real disposable income at the household level is substantial in Sweden, with an average of 16% per year (Table **??**), and is primarily idiosyncratic, as we show in the Internet Appendix. Similarly, entrepreneurs and immigrants exhibit a growth tilt, presumably because of substantial idiosyncratic risk in business assets and income.[23]

## *C.* Intergenerational Effects

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

## *D.* Household Tilts in Partial and General Equilibrium

We now show that all the empirical results can be integrated into a unified equilibrium model in the style of Merton (1974), Long (1974), and Breeden (1979). The economy, which we fully specify in the Internet Appendix, consists of $K$ state variables, $I$ risky assets, and a set of investors with finite horizons and heterogeneous lifespans. The model accommodates a wide range of overlapping generations structures. We do not attempt to calibrate it but note that when the state variables consist of aggregate labor income and the market price of risk, the model can relate the HML portfolio to labor income risk, as in Jagannathan and Wang (1996), and to time-varying returns, as in Campbell and Vuolteenaho (2004).[24] In both cases, value stocks are more exposed to state risk than growth stocks.

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

The optimal portfolio of an individual investor $h$ is determined by diversification and hedging.

The shares of risky wealth held in each risky asset, $\boldsymbol{\omega_t^h} \in \mathbb{R}^I$, satisfy

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

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

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

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

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

In the context of HML, equation (8) illustrates why young investors with risky incomes and weak balance sheets should tilt their financial portfolios away from value. As is discussed in Section IV.A, young investors generally have higher sensitivities $\eta_{k,t}^h$ than old investors. When aggregate income is a state variable, the sensitivity $\eta_{k,t}^h$ is strong if the household is exposed to high systematic risk in labor income or has a large stock of human capital. Moreover, investors with weak balance sheets and high levels of background risk typically have low risky shares,[25] which means that their relative sensitivity to all state variables, $\eta_{k,t}^h/w_t^h$, is high. Young investors with risky incomes and weak balance sheets should select risky portfolios that are dominated by hedging demand and are therefore tilted toward growth, as is evident in the data.

## V. Relation to Sentiment-Based Theories

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

Cognitive biases have a number of potential implications for portfolio choice. Men and entrepreneurs are known to be especially prone to overconfidence (Barber and Odean (2001), Busenitz and Barney (1997), Cooper, Woo, and Dunkelberg (1988)) and should therefore favor growth stocks. The evidence in Section II.B confirms these predictions. Women tend to select low risky shares and invest in value stocks, while men tend to select aggressive risky shares and go growth. These gender patterns cannot be easily explained by differences in risk aversion alone, since a risk-tolerant investor should choose both a high risky share and a value tilt. Similarly, the positive empirical link between entrepreneurship and growth investing might be explained by overconfidence.

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

 

# VI. Identification and Robustness Checks

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

## *A.* Stock Characteristics

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

**– Table ?? here –**

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

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

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

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

## *B.* Investor Characteristics

*Financial Market Experience.* A possible explanation of the value ladder is that new investors naively purchase overpriced growth stocks, learn that they are bad deals, and then progressively migrate toward value stocks as time goes by.[26] We show that a measure of experience – the number of years since entry – has a significantly *negative* impact on the value loading and cannot explain away the effect of other characteristics, which is inconsistent with the simple learning story. In a recent study, Campbell, Ramadorai, and Ranish (2014) consider an Indian brokerage data set containing highly detailed information on individual trades but no socioeconomic characteristics. They show that the returns experienced by a household drive its future portfolio style. Our results indicate that the number of years spent in financial markets cannot explain away the relationship between age and value investing.

*Latent Heterogeneity.* The twin panel allows us to check that the characteristics do not merely proxy for latent traits or cohort effects. To do so, we estimate the specification

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

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

where $v_{k,j,t}$ denotes the value loading of sibling $j \in \{1,2\}$ in pair $k$ at date $t$, $\alpha_{k,t}$ is a yearly pair fixed effect, $x_{k,j,t}$ denotes the vector of yearly characteristics of sibling $j$, and $e_{k,j,t}$ is an orthogonal error. Yearly twin-pair fixed effects capture the impact of time, such as age or stock market performance, as well as similarities between the twins, such as common genetic makeup, family background, upbringing, and expected inheritance.[27] Consistent with the intuition that latent heterogeneity is quantitatively important, the twin regressions have substantially higher adjusted $R^2$s than the baseline regression, reaching 27% for the stock portfolio of identical twins (compared to 4% in Table **??**). The coefficients on characteristics are nonetheless fully consistent with the baseline regressions, which shows that latent heterogeneity does not drive our results.

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

*Genes.* We use the twin communication data to reject the claim that value investing is driven largely by genes. Cronqvist, Siegel, and Yu (2015) consider a model in which the value loading of twin $s$ in pair $k$ is the sum of three *independent* components: a so-called "genetic" component, $a_{k,s}$, a common component, $c_k$, and an idiosyncratic component $\varepsilon_{k,s}$.[28] On this basis, they attribute 30% of the cross-sectional variation of the value loading to the component $a_{k,s}$. We show that this estimate is highly sensitive and drops to less than 1% among infrequent communicators. The model used by Cronqvist, Siegel, and Yu (2015) is therefore severely misspecified, because a purely genetic component should not depend fully on communication. “Genetic” models of the *risky share* are similarly flawed, as Calvet and Sodini (2014) explain.

### *C.* Other Robustness Checks

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

## VII. Conclusion

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

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

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# Appendix

## Table A.I

## Definition of Household Variables

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

| Variable | Description |
|---|---|
| Cash | Bank account balances and Swedish money market funds. |
| Fund portfolio | Portfolio of mutual funds other than Swedish money market funds. |
| Stock portfolio | Portfolio of directly held stocks. |
| Risky portfolio | Combination of stock and fund portfolios. |
| Risky share | Proportion of risky assets in the portfolio of cash and risky financial assets. |
| Financial wealth | Value of holdings in cash, risky financial assets, capital insurance products, derivatives, and directly held bonds, excluding defined-contribution retirement accounts. |
| Share of popular stocks | Fraction of the stock portfolio invested in public firms that were one of the 10 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 one-digit industry code as an adult household member's 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 nonfinancial disposable real income. |
| Income | Total household disposable income. |
| Self-employment dummy | Dummy variable equal to one if the household head is self-employed. |
| Unemployment dummy | Dummy variable equal to one if the household head is unemployed. |
| Conditional income volatility | Standard deviation of the total income shock, defined as the sum of the persistent and transitory income shocks in a given year. |
| Loading of sectoral income on national income | Sensitivity of a sector's per-capita income growth to the growth rate of per-capita income in the overall economy. |
| Age | Age of the household head. |
| Male household head dummy | Dummy variable equal to one if the household head is male. |
| High school dummy | Dummy variable equal to one if the household head has a high school degree. |
| Post-high school dummy | Dummy variable equal to one if the household head has had some post-high school education. |
| Economics education dummy | Dummy variable equal to one if the household head received education in a field related to economics and management. |
| Family size | Number of adults and children living in the household. |

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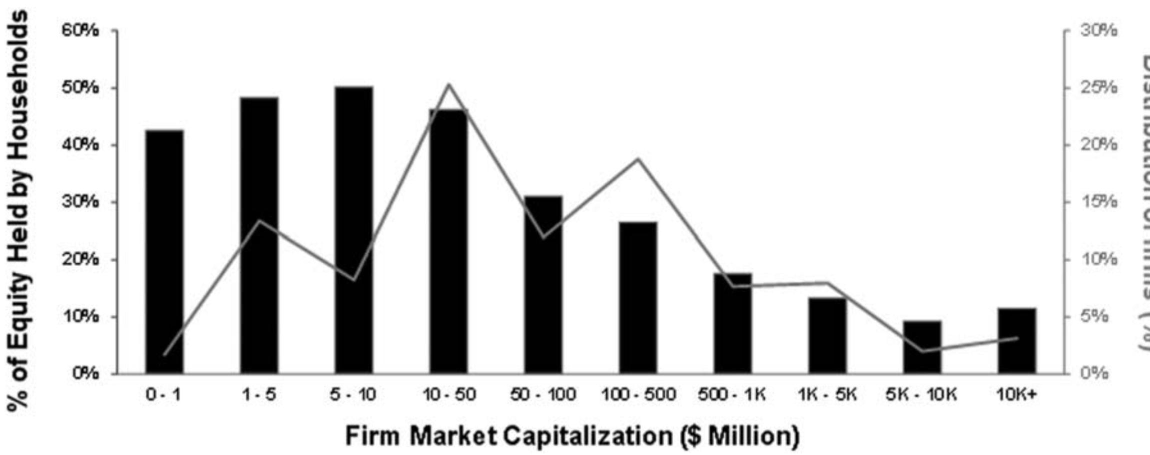


**Figure 1**

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

(a)

(b)

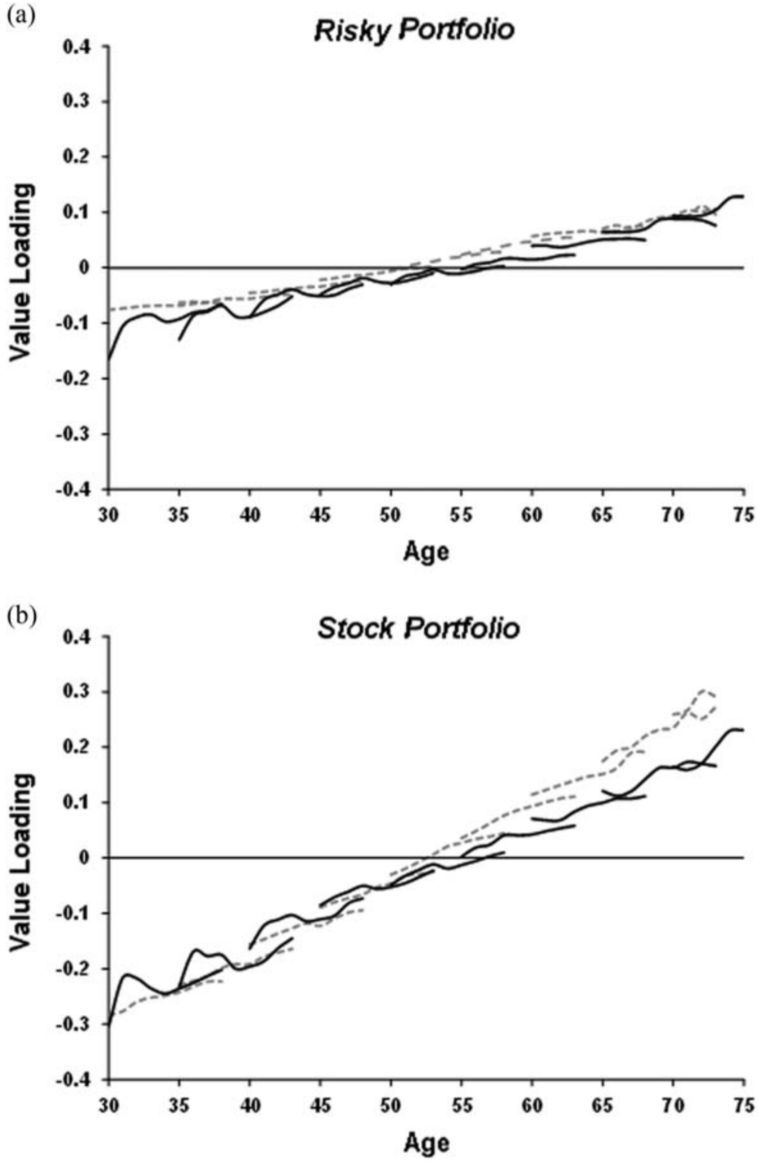


**Figure 2**
**The value ladder. The figure plots the value loading of the risky portfolio (Panel A) and the stock portfolio (Panel B) for different cohorts of households. Each solid line corresponds to the average loadings of households in a given cohort, weighted by financial wealth. Each dotted line is the corresponding predicted value loading, obtained by using age, wealth variables, and human capital multiplied by the household-level baseline regression coefficients in Table III. A cohort is defined as a five-year age bin. The first cohort contains households with a head aged between 30 and 34 in 1999, while the oldest cohort has a head aged between 70 and 74 in 1999. The loadings of all households in year *t* are demeaned to control for changes in the composition of the Swedish stock market. Panel A is based on the panel of all Swedish risky asset market participants and Panel B on the panel of all Swedish direct stockholders over the 1999 to 2007 period.**

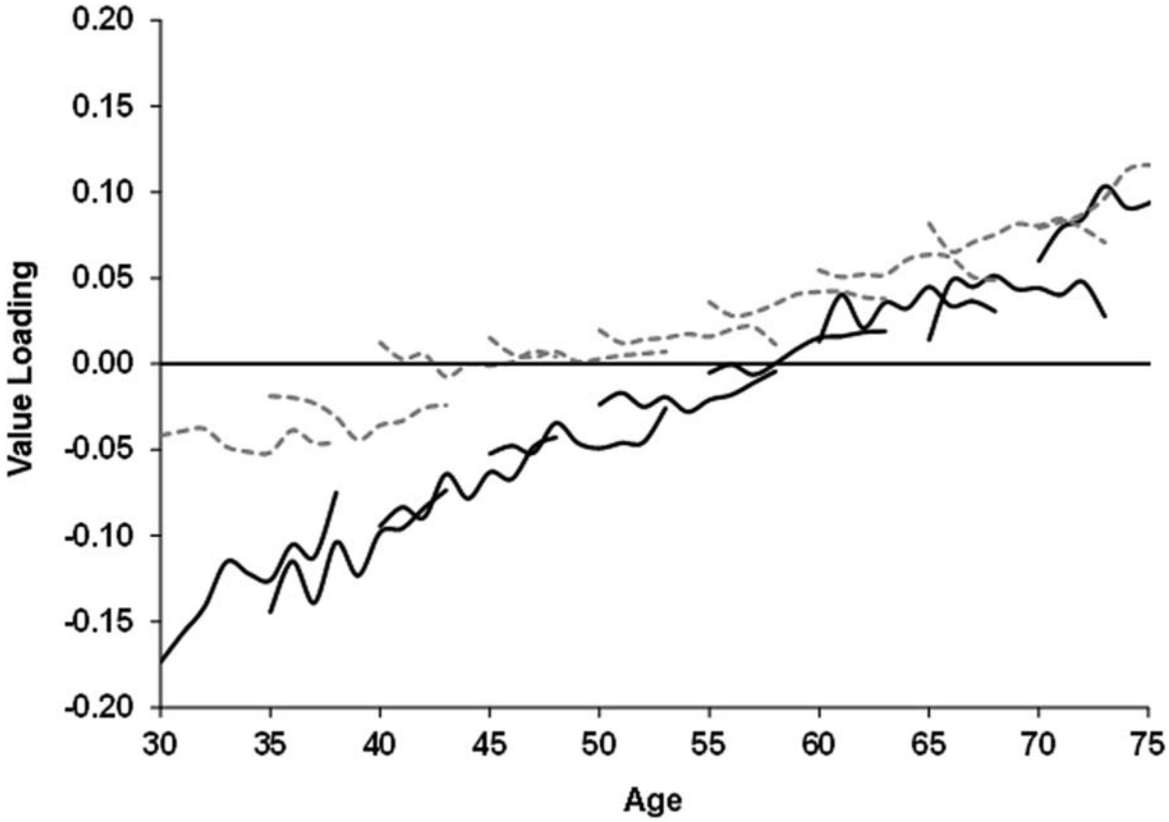


**Figure 3**

**The value ladder across industries. The figure plots the value loading of the risky portfolio for cohorts of households in the top 25% (solid lines) and the bottom 25% (dotted lines) of industry sensitivity. We measure industry sensitivity by regressing per-capita income growth in the industry on per-capita income growth in the economy. Each line corresponds to a given cohort, defined as a fiveyear 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 cohortŠs loading in year *t* is the wealth-weighted average year t loading of households in the cohort. The figure is based on the panel of all Swedish risky asset market participants over the 1999 to 2007 period.**

**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 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 I.B. All variables are described in Table A.I.

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

**Table II**

**Cross-Sectional Distribution of the Value Loading**

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

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

**Table III**

**Panel Regression of the Value Loading on Characteristics**

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

| | Dependent Variable: Value Loading | | | | | | Dependent Variable: | |
|---|---|---|---|---|---|---|---|---|
| | Risky Portfolio | | Stock Portfolio | | Fund Portfolio | | Risky Share | |
| | (1) | | (2) | | (3) | | (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 | |

This table reports results from the pooled regressions of the risky share and the HML portfolio betas on household characteristics in the presence of year, industry, and county fixed effects. The data includes years 1999 to 2007.

**Table IV**

**Value Loadings of Investor Subgroups**

This table reports pooled regressions of the value loading of the risky portfolio on household characteristics and year, industry, and county fixed effects estimated over different investor subgroups. The regressions are similar to the baseline regressions in Table III, but are estimated on subsamples of: fund holders in column (1), direct stockholders in column (2), and direct stockholders sorted by the number of stocks owned in columns (3) to (5). The investor subsamples are obtained from the representative panel of househ

| | 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 V**
**Alternative Risk Measures**

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

| Panel A: Real Estate Interacted with Leverage | | | | | | |
|---|---|---|---|---|---|---|
| | Dependent Variable: Value Loading | | | | | |
| | Risky Portfolio | | Stock Portfolio | | Fund Portfolio | |
| | (1) | | (2) | | (3) | |
| | Estimate | *t*-stat | Estimate | *t*-stat | Estimate | *t*-stat |
| Log residential real estate | 0.000 | 1.37 | 0.003 | 3.79 | 0.000 | -0.44 |
| Log commercial real estate | 0.001 | 2.01 | 0.007 | 9.87 | 0.000 | -0.88 |
| Log residential real estate | | | | | | |
| × Leverage ratio | -0.001 | -4.28 | -0.004 | -4.88 | 0.000 | -1.40 |
| Log commercial real estate | | | | | | |
| × Leverage ratio | -0.001 | -3.13 | 0.000 | -0.45 | -0.001 | -3.48 |
| Leverage ratio | -0.012 | -4.11 | -0.040 | -5.10 | -0.004 | -2.29 |
| Panel B: Children | | | | | | |
| | Dependent Variable: Value Loading | | | | | |
| | Risky Portfolio | | Stock Portfolio | | Fund Portfolio | |
| | (1) | | (2) | | (3) | |
| | Estimate | *t*-stat | Estimate | *t*-stat | Estimate | *t*-stat |
| Dummy for having children | 0.087 | 17.21 | 0.028 | 2.17 | 0.03 | 8.20 |
| Dummy for having twins | -0.020 | -2.63 | -0.039 | -1.83 | -0.01 | -1.15 |

**Table VI**
**Economic Significance**

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

| | Risky Portfolio | | Stock Portfolio | | Fund Portfolio | |
|---|---|---|---|---|---|---|
| | 30→50 | 50→70 | 30→50 | 50→70 | 30→50 | 50→70 |
| Observed change in value loading | 0.087 | 0.136 | 0.226 | 0.249 | 0.017 | 0.042 |
| Predicted change due to: | | | | | | |
| *Financial Characteristics* | | | | | | |
| - Log financial wealth | 0.015 | 0.008 | 0.042 | 0.022 | 0.010 | 0.005 |
| - Log residential real estate | 0.001 | 0.000 | 0.005 | -0.003 | 0.000 | 0.000 |
| - Log commercial real estate | 0.001 | 0.004 | 0.010 | 0.025 | 0.000 | 0.000 |
| - Leverage ratio | 0.000 | 0.000 | 0.002 | 0.001 | 0.000 | 0.000 |
| *Human Capital and Income Risk* | | | | | | |
| - Log human capital | 0.024 | 0.037 | 0.048 | 0.073 | 0.010 | 0.015 |
| - Log income | -0.006 | -0.009 | -0.006 | -0.008 | -0.004 | -0.006 |
| - Self-employment dummy | 0.000 | -0.009 | 0.000 | -0.009 | 0.000 | -0.003 |
| - Unemployment dummy | 0.000 | 0.001 | 0.000 | 0.001 | 0.000 | 0.000 |
| - Conditional income volatility - | -0.004 | 0.000 | -0.003 | 0.000 | -0.001 | 0.000 |
| *Demographic Characteristics* | | | | | | |
| - Age | 0.055 | 0.055 | 0.177 | 0.177 | 0.012 | 0.012 |
| - Male household head dummy | -0.001 | -0.018 | -0.001 | -0.031 | 0.000 | -0.004 |
| - High school dummy | 0.001 | 0.002 | 0.003 | 0.006 | 0.001 | 0.001 |
| - Post-high school dummy | 0.001 | 0.007 | -0.001 | -0.007 | 0.001 | 0.006 |
| - Economics education dummy | 0.002 | -0.001 | 0.001 | 0.000 | 0.001 | -0.001 |
| - Immigration dummy | 0.000 | 0.003 | 0.000 | 0.007 | 0.000 | 0.000 |
| - Family size | -0.035 | -0.015 | -0.024 | -0.011 | -0.016 | -0.007 |
| Change due to age and wealth characteristics | 0.090 | 0.094 | 0.278 | 0.287 | 0.028 | 0.027 |
| Proportion of change due to: | | | | | | |
| - age | 61.1% | 58.1% | 63.6% | 61.5% | 41.1% | 42.9% |
| - financial characteristics | 18.6% | 11.6% | 21.3% | 15.8% | 37.7% | 21.9% |
| - human capital and income | 20.3% | 30.3% | 15.0% | 22.6% | 21.2% | 35.2% |

**Table VII**
**Active Rebalancing of the Value Loading**

This table reports pooled regressions of the active change in the value loading on (i) the passive change in the value loading and (ii) the lagged value loading. We conduct the analysis at the level of the risky portfolio in columns (1) and (2), the stock portfolio in columns (3) and (4), and the fund portfolio in columns (5) and (6). For each portfolio, we report the regression with and without lagged household 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 I.B. Standard errors are clustered at the household level.

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

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Adjusted $R^2$ | 6.85 % | | 0.070 | | 5.27 % | | 0.054 | | 7.06 % | | 0.071 | |
| Number of observations | 406,561 | | 406,561 | | 221,143 | | 221,143 | | 355,443 | | 355,443 | |

**Table VIII**

**Systematic Labor Income Risk**

This table investigates the factor structure of industry-level income growth and its implications for household financial portfolios. For each of the 70 two-digit industries, we regress sectoral per-capita income growth on national per-capita income growth and report in Panel A the distribution of the corresponding slopes and R2 coefficients. Panel B reports pooled regressions of a household's portfolio value loading on (i) the loading of the household's sectoral income on national income, (ii) conditional income volatility, and (iii) other standard characteristics as well as year, industry, and county fixed effects. The household income loading is defined as the weighted average loading of the sectors in which the adults in the household are employed. The full results are reported in the Internet Appendix. The computations are based on the representative panel of households over the 1999 to 2007 period defined in Section I.B. Standard errors are clustered at the household level.

| Panel A: Cross-Sectional Distribution of Sectoral Exposure to National Income Shocks | | | | | | |
|---|---|---|---|---|---|---|
| | Mean | 10th | 25th | 50th | 75th | 90th |
| Loading of sectoral income on national income | 1.03 | 0.81 | 0.95 | 1.05 | 1.15 | 1.22 |
| $R^2$ | 0.88 | 0.74 | 0.83 | 0.92 | 0.95 | 0.96 |
| Panel B: Income Exposure to National Income Shocks | | | | | | |
| | Dependent Variable: Value Loading | | | | | |
| | Risky Portfolio | | Stock Portfolio | | Fund Portfolio | |
| | (1) | | (2) | | (3) | |
| | Estimate | *t*-stat | Estimate | *t*-stat | Estimate | *t*-stat |
| Loading of sectoral income on national income | -0.205 | -10.05 | -0.200 | -3.86 | -0.077 | -5.54 |
| Conditional income volatility | -0.342 | -20.45 | -0.330 | -10.30 | -0.111 | -12.23 |

**Table IX**

**Value Loadings of Households Sorted by Age and Industry Exposure**

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

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

**Table X**
**Stocks Most Widely Held by Swedish Households**

The table reports the 10 stocks that are most widely held by Swedish households at the end of 2003. In column (1), stocks are sorted by the proportion of households that hold them directly. We also report: (2) the stock's percentage of aggregate household direct stockholdings, (3) the stock's percentage of the total market capitalization of all firms listed on Swedish exchanges, (4) the stock's percentage of the free-float-adjusted market capitalization of all firms listed on Swedish exchanges, (5) the stock's value loading, and (6) the percentile of the stock's book-to-market ratio. The analysis is conducted on the representative panel defined in Section I.B. In the bottom row, we consider the aggregate household portfolio of popular stocks and report its share of aggregate household stock wealth, its share of the Swedish stock market, its value loading, and the average book-to-market ratio percentile of popular stocks weighted by their shares of the aggregate household stock wealth (imputed from column (2)).

| | % of Stockholders Owning Company | % of Household Stock Wealth | % of Swedish Stockmarket | % of Swedish Free Float | Value Loading | B/M Quantile |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Ericsson | 60.5% | 21.7% | 7.5% | 8.7% | -1.22 | 25.4% |
| Telia | 46.5% | 4.0% | 6.5% | 4.2% | -1.00 | 44.2% |
| Swedbank | 24.5% | 3.8% | 2.7% | 2.7% | 0.11 | 46.8% |
| SEB | 23.6% | 5.5% | 2.7% | 3.1% | 0.74 | 56.2% |
| Volvo | 14.6% | 5.0% | 3.2% | 3.4% | 0.41 | 68.9% |
| H&M | 11.4% | 4.8% | 5.2% | 3.8% | -0.07 | 4.3% |
| Billerud | 10.8% | 1.1% | 0.2% | 0.2% | -0.06 | 46.3% |
| AstraZeneca | 9.7% | 5.4% | 4.8% | 3.8% | 0.09 | 68.2% |
| Nokia | 8.7% | 3.8% | 23.8% | 31.1% | -0.08 | 14.7% |
| Investor | 8.6% | 2.5% | 2.0% | 1.6% | 0.27 | 80.8% |
| Aggregate portfolio of popular stocks of popular stocks | | 57.5% | 58.5% | 62.6% | -0.41 | 39.2% |