HOUSEHOLD PORTFOLIOS AND RISK BEARING OVER AGE AND TIME*

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Abstract

We exploit the US Survey of Consumer Finances from 1998 to 2007 to study households' portfolio risk bearing. We compare alternative measures of risk, based on a financial portfolio or based on a broader portfolio also including human capital, real estate, business wealth and related debt. The measures provide a different ranking of household risk bearing, but they consistently show that risk bearing fell in the 2000s, and it positively correlates with wealth, good health status and financial sophistication. Furthermore, the time effect seems more relevant than the cohort effect, and the risk-age profile looks flat over the life-cycle.

Keywords: household finance, risk bearing, background risk, real estate, human capital.

JEL classification codes: D81, G11, D14.

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1. Introduction

Households face portfolio allocation problems over their entire life-cycle, across different stages of the business cycle and with different levels of background risk. Understanding how their portfolio risk varies over age and time is clearly important for academics, professionals and policy makers. In particular, policy makers are ultimately interested in household wellbeing. They may want to prevent households from bearing inefficiently low or high portfolio risks, to facilitate consumption smoothing (Cocco et al., 2005) or reduce wealth and income inequalities (Guvenen, 2006; Korniotis and Kumar, 2011).

In this paper we provide new insights on the evolution of the households' portfolio risk borne at a given point in time. We exploit data from the US Survey of Consumer Finances (SCF) from 1998 to 2007 to derive household portfolios, estimate various measures of risk and study the correlation between risk bearing, wealth, age, time, cohort, and the main household socio-demographic characteristics. A large body of literature already investigates household portfolio risk using micro data on portfolio choice (see Guiso *et al.*, 2001, for a review), but most of it focuses on specific types of risk (e.g., the stock share in financial portfolio), and relies on cross-sectional data for a single year, or on data regarding a specific part of the population (e.g. Agnew *et al.*, 2003; Ameriks and Zeldes, 2004; Lusardi and Mitchell, 2007).

Our analysis departs from the existing literature in three important directions. First, we make use of repeated cross sections of SCF data, which allows us to disentangle the age effects from time and cohort effects in a nationally representative and accurate dataset. Second, we consider comprehensive measures of risk. We indeed compare the financial stock share with the standard deviation of the financial portfolio (also including risk free deposits and risky bonds) and with the standard deviation of a portfolio including not only financial assets but also human capital, real estate, business wealth and related liabilities. Neglecting in particular non-financial assets may bias the analysis, because such assets usually account for most of household wealth, and they are more relevant in some groups of households (e.g., human capital for the youngest ones, business wealth for entrepreneurs). A standard deviation is a weighted sum of asset shares, which allows to summarize in one single statistic the multidimensional nature of the portfolio composition, also accounting for the different degree of risk the assets bring to household wealth. However, the various measures we consider do not necessarily provide the same ranking of risk bearing, as they

are based on a different set of assumptions and a different information set. Indeed, while for the stock share only the information on the total level of financial wealth is required, for the standard deviation we also exploit the portfolio composition and the risk characteristics of the asset categories. A final departure of our analysis is that we make a distinction in three sources of financial and non-financial risks. Specifically, we consider conditional, constrained and idiosyncratic risks. The distinction is due to the fact that non-financial assets are generally less liquid than financial ones, and can then be taken as exogenous at least in short-term portfolio choice, and the same assets also carry idiosyncratic risk that cannot be easily diversified. For each risk component we then study its contribution to total risk, and how it relates to observable household characteristics.

Our findings are the following. Our indicators are imperfectly correlated, and the correlation is particularly low when comparing measures based on the financial portfolio with those based on the complete portfolio made of financial and non-financial assets. This implies that, if one is interested in making a ranking of different household portfolios, the choice of the risk measure matters. The indicators, however, agree in indicating that many households bear only limited risk, and that risk bearing fell in the 2000s. In addition, after accounting for the main observable household characteristics, we find that the measures increase with wealth, good health status, and financial sophistication. We also find weak evidence of cohort effects, and stronger evidence of time effects. Finally, our analysis reveals a flat age-risk profile over the life-cycle, keeping all the other household variables constant.

The remainder of this paper is organized as follows. Section 2 surveys the literature on household portfolios, risk, age and time effects. Section 3 presents our measures of risk, while Section 4 describes our survey and time series data. Section 5 shows our main findings and discusses some robustness checks. Finally, Section 6 concludes. The Appendix provides technical details on the construction of human capital in household portfolios and on the complete risk components. A separate, Supplementary Appendix[1] reports the complete set of results for the robustness checks.

[1] Available at www.sites.google.com/site/abucciol/files/riskbearing_appendix.pdf.

2. Household risk bearing, age, cohort and time effects

Economists, professionals and policy makers look at data and theories on household portfolios from different perspectives and with different aims, but all of them are interested in an accurate description of what households actually do with their own money. In particular, attention is paid to the risk borne by the households, and on how it changes with age and over time. For most of the theoretical and empirical literature this means to investigate the fraction of household financial wealth invested in risky assets, usually stocks.

Models that examine optimal portfolio choice in the presence of non-tradable labor income, including Heaton and Lucas (1997, 2000) and Viceira (2001), find that equity shares ought to decline throughout the life-cycle. This is because households initially choose an optimal share of wealth to invest in the risky asset while considering their future labor income as a safe asset. As the life-cycle progresses future labor income is realized and it is substituted with bonds, which they consider a tradable form of safe assets. If permanent income risk is the most relevant source of income risk for the elderly, then the former prediction is consistent with Angerer and Lam's (2009) findings that an increase in permanent income risk is associated with a reduction in the risky asset share of the household portfolio. This intuitive result becomes weak when housing or non-homothetic preferences are considered. Cocco (2005) considers a life-cycle model with housing included in the utility function which predicts that younger households are highly invested in housing and thus have limited wealth to invest in stocks, which reduces the benefit of stock ownership. Wachter and Yogo (2010) consider the case of non-homethetic utility functions, with "basic" and "luxury" goods, which produces – together with an income profile increasing with age – an age profile for the risky asset share flatter than the one obtained with homothetic utility functions.

Empirical works are necessary to shed light on the relation between age and financial risk bearing, because there seems to be no agreement in the theoretical literature. Studies using a single cross section usually find that risk falls with age (for instance see McInish, 1982, Morin and Fernandez Suarez, 1983, and Pallson, 1996), but their informative power is limited for at least two reasons: (i) they cannot disentangle age, cohort and time effects, (ii) the ratio of financial risky assets to household (net) financial wealth is not a sufficient statistic for the financial risk borne by the households.

Some papers improve the evidence based on a single cross section by considering either repeated cross sections, or panel data. Poterba and Samwick (1997) use the Survey on Consumer Finance (SCF) from 1983 to 1995 to show how age and cohort effects interact in describing portfolio shares and they show, among other things, that younger cohorts have a higher attitude to accumulate housing debt. Jianakoplos and Bernasek (2006) use 1989, 1995 and 2001 SCF data to show that the risky asset share decreases with age and that younger cohorts invest a smaller fraction of their wealth in risky financial assets. Using panel data sets, as the Panel Survey of Income Dynamics, it is possible to directly investigate the determinants of the entry – exit decision in the stock markets and of the portfolio rebalancing. With this respect, Brunnermeier and Nagel (2008) prove that households rebalance very slowly; Alan (2006) assesses to what extent the participation to the stock market over the life cycle is affected by entry costs for first time investors; Bilias *et al.* (2010) document that portfolio rebalancing is not related to market movement. This evidence suggests that it might be the case that at least some of the risk is passively borne by the household due to their inability to react to the new market conditions.

3. Measures of risk bearing

We consider alternative indicators of risk bearing, based on observations on household portfolio holdings at market value, using different definitions of portfolio. For each indicator, a higher value means higher risk bearing. The indicators, however, are derived from different information sets and, for this reason, not necessarily they provide the same ranking of risk bearing.

3.1. Financial portfolio

Let us consider an economy with one risk free asset and a set of m risky financial assets. For each household $i, i = 1,...,N$ observed at time t, we know its portfolio shares, $w_{it} = \left[w_{it,1} \quad w_{it,2} \quad \dots \quad w_{it,m} \right]'$. In our application, $m = 2$ as we consider (corporate and government) bonds and stocks as risky assets. We call this "financial portfolio".

Following the standard literature on risk, our first indicator is the share of the financial portfolio held in stocks:

(1) $w_{it,2}$.

Although popular for its simplicity, this measure neglects that not only stocks, but also other assets contribute to household portfolio risk. For instance in a financial portfolio, corporate (government) bonds may be subject to firm- (country-) specific risk. In addition, the indicator ignores that in some years the same asset may be riskier than in other years. This issue is certainly important, as shown by the recent crisis of the financial markets.

Our second indicator acknowledges for this by computing the expected standard deviation of excess returns in the financial portfolio. This is a weighted combination of the asset shares, with weights given by the risk properties of each asset. This calculation requires to know, for all the risky asset categories, variances and covariances of their returns in excess from the return to the risk free asset. Let us call Σ_t^{ff} the matrix of variances and covariances at time *t*. For each household $i, i = 1,..., N$ observed at time *t*, we then compute the financial portfolio standard deviation as

(2) $$\sigma_{it}^{f} = \left(w_{it}' \Sigma_t^{ff} w_{it} \right)^{\frac{1}{2}}.$$

This indicator provides a thorough assessment of the household risk borne with a financial portfolio. The measure, however, does not describe total household portfolio risk; in fact, it ignores that other non-financial assets – which often account for a large amount of total wealth – also carry risky.

3.2. Complete portfolio

We then extend our definition of portfolio, and consider an economy with one risk free asset and a set of $n > m$ risky (financial and non-financial) assets. For each household $i, i = 1,..., N$ at time *t*, we observe its portfolio shares, $\omega_{it} = \left[\omega_{it,1} \quad \omega_{it,2} \quad \dots \quad \omega_{it,n} \right]'$. In our application, $n = 5$ and we consider as risky assets not only bonds and stocks, but also business wealth, real estate, and human capital. In addition we treat liabilities related to business wealth and real estate; for sake of simplicity we group them in the same category as bond, since they show similar risk characteristics. We call this “complete portfolio”.

Let us now call Σ_t the matrix of variances and covariances at time *t* of the excess returns for these asset categories. This allows us to compute the complete portfolio standard deviation:

$$\sigma_{it} = \left(\omega_{it}' \Sigma_t \omega_{it} \right)^{\frac{1}{2}}. \tag{3}$$

Non-financial assets are less liquid than financial assets. For instance, the real estate market is characterized by large transaction costs; in addition, most of the real estate share in household portfolios is held in is residential housing, and therefore constrained to satisfy consumption needs. Similar arguments can be made on the degree of liquidity in business wealth and human capital. In a short time horizon these assets may be seen as completely illiquid, which means that their holdings cannot be changed and are taken as exogenous input in a portfolio choice problem (Flavin and Yamashita, 2002).

To this end, we distinguish the portfolio shares ω_{it} for household $i, i = 1, ..., N$ at time *t*, in two components, $\omega_{it} = \left[\omega_{it}^{f\prime} \quad \omega_{it}^{n\prime} \right]'$. Shares ω_{it}^{f} include all the holdings of financial risky assets (bonds and stocks), whereas shares ω_{it}^{n} include all the holdings of non-financial risky assets (business wealth, real estate, and human capital). We therefore partition the variance-covariance matrix Σ_t in four blocks:

$$\Sigma_t = \begin{bmatrix} \Sigma_t^{ff} & \Sigma_t^{fn} \\ \Sigma_t^{fn\prime} & \Sigma_t^{nn} \end{bmatrix}$$

where Σ_t^{ff} regards financial assets, Σ_t^{nn} non-financial assets, and Σ_t^{fn} the covariance between financial and non-financial assets.

Households face both market and idiosyncratic risk. One may assume that idiosyncratic risk is eliminated through diversification when investing in bonds and stocks; however, likely it is still present in the non-financial assets – whose investment cannot be properly diversified because of their large size. Therefore, the variance-covariance matrix of the non-financial assets, Σ_t^{nn}, should include a component reflecting the idiosyncratic risk of these assets. By definition, these risks are not correlated with the other sources of risk and we can decompose Σ_t^{nn} as:

$$\Sigma_t^{nn} = \overline{\Sigma}_t^{nn} + \tilde{\Sigma}_t^{nn}$$

where $\overline{\Sigma}_t^{nn}$ is the market variance-covariance matrix at time *t* of the excess returns for our non-financial assets and $\tilde{\Sigma}_t^{nn}$ is the diagonal matrix of idiosyncratic variances at time *t*, $\tilde{\Sigma}_t^{nn} = diag\left\{\left(\tilde{\sigma}_{t,k}^{nn}\right)^2\right\}$, with $k = 1,2,3$.

It can be shown (see Gourieroux and Jouneau, 1999, for details) that the complete portfolio variance is the sum of three components:

$$\sigma_{it}^2 = \omega_{it}'\Sigma_t\omega_{it} = \omega_{it}^{f|n\prime}\Sigma_t^{ff}\omega_{it}^{f|n} + \omega_{it}^{n\prime}\overline{\Sigma}_t^{nn|f}\omega_{it}^n + \omega_{it}^{n\prime}\tilde{\Sigma}_t^{nn}\omega_{it}^n$$

with $\omega_{it}^{f|n} = \omega_{it}^f + \left(\Sigma_t^{ff}\right)^{-1}\Sigma_t^{fn}\omega_{it}^n$ and $\overline{\Sigma}_t^{nn|f} = \overline{\Sigma}_t^{nn} - \Sigma_t^{fn\prime}\left(\Sigma_t^{ff}\right)^{-1}\Sigma_t^{fn}$. In our analysis we will consider these components separately.

Specifically, we take the conditional standard deviation:

(4) $$\sigma_{it}^{f|n} = \left(\omega_{it}^{f|n\prime}\Sigma_t^{ff}\omega_{it}^{f|n}\right)^{\frac{1}{2}}.$$

This measure differs from measure (2) based on the financial portfolio for three reasons. First, shares are expressed in terms of financial plus non-financial wealth, rather than just financial wealth; second, the bond share is reduced by any existing liabilities on business wealth and real estate; third, shares $\omega_{it}^{f|n}$ include a hedging component depending on the non-financial asset shares, $\left(\Sigma_t^{ff}\right)^{-1}\Sigma_t^{fn}\omega_{it}^n$, which reflects the covariance between financial and non-financial asset returns. Notice that the variance of the non-financial assets does not enter in the formula.

We also take the constrained standard deviation, which in contrast is considered fixed in the short run:

(5) $$\overline{\sigma}_{it}^{n|f} = \left(\omega_{it}^{n\prime}\overline{\Sigma}_t^{nn|f}\omega_{it}^n\right)^{\frac{1}{2}}.$$

We finally treat the idiosyncratic standard deviation:

(6) $$\tilde{\sigma}_{it}^n = \left(\omega_{it}^{n\prime}\tilde{\Sigma}_t^{nn}\omega_{it}^n\right)^{\frac{1}{2}}.$$

Furthermore, we also contrast the complete portfolio ("total") standard deviation, σ_{it}, with what we call the complete portfolio "market" standard deviation which neglects the idio-syncratic component:

(7) $$\overline{\sigma}_{it} = \left(\omega_{it}^{f|n\prime} \Sigma_t^{ff} \omega_{it}^{f|n} + \omega_{it}^{n\prime} \overline{\Sigma}_t^{nn|f} \omega_{it}^{n} \right)^{1/2}.$$

4. Data

4.1. Household portfolios

There are few surveys potentially useful to investigate how US households change their portfolio along the life-cycle. The Panel Study of Income Dynamics (PSID) is complemented by a Wealth Supplement run from 1984 to 1999 every five years, and every two years since 1999. The PSID is a longitudinal dataset, and thus it enjoys the typical advantages of panel data. However, with its information on assets holdings it is not possible to clearly separate the investment in risk free assets, such as deposits, from the investment in financial assets that entail some risk, such as government bonds. This limitation does not allow us to properly assess portfolio risk. Portfolio description is more detailed in the Health and Retirement Study, which is also a longitudinal study, but focuses on the population over the age of 50. An obvious candidate dataset for our purpose is therefore the US Survey of Consumer Finances (SCF).

The SCF is a repeated cross-sectional survey of households conducted every three years on behalf of the Federal Reserve Board. It collects detailed information on assets and liabilities, including home ownership and mortgages, together with the demographic characteristics of a sample of US households. The survey deliberately over-samples relatively wealthy households to produce more accurate statistics; in our analysis we then use the sampling weights provided by the SCF to obtain unbiased statistics for the US population. The SCF also handles the high rate of item non-response typical of wealth-related micro data by imputing a set of five values that represent a distribution of possibilities. Multiple imputations of missing data increase the efficiency of estimation, allowing the researcher to use all available information, and have the distinct advantage of providing information on uncertainty in the imputed values. We exploit this information as suggested in Rubin (1987); we develop our analysis independently for each of the five completed datasets and our final statistics are the average of the estimates derived for each dataset; standard errors account for the variability both within and between these five datasets.

Our data on household portfolio holdings are taken from the waves from 1998 to 2007 of the SCF.[2] Our final sample consists of 15,064 households with head aged between 25 and 80. We consider two definitions of portfolio. The "financial" definition includes the main financial assets, grouped in three categories: deposits (that we treat as risk free), bonds, and stocks. The "complete" definition also includes human capital, business wealth, real estate, and related liabilities. We include liabilities in the bond category, while the other three assets form new categories. Human capital is estimated conditional on age, gender, race and education of the household head using an approach similar to Jorgenson and Fraumeni (1989). In a nutshell, it is a discounted projection of the future realizations of gross income, for the head and the spouse (if any); see the Appendix for details.

Over the period we analyze, the size of household wealth (in 2007 USD) rose markedly using either definition. The median value of financial wealth moved from 22,000 USD in 1998 to 30,550 USD in 2007; the corresponding values for the complete definition of wealth were 1,246,594 USD in 1998 and 2,021,287 USD in 2007. Wealth was fueled by a rising stock market between 1998 and 2001, and by rising wages and house price markets between 2004 and 2007.

Each asset is classified as defined in Table 1, which also reports the composition of the aggregate complete portfolio, computed accounting for multiple imputations and sampling weights. The financial portfolio includes all the assets in the deposits, bonds, and stocks categories of the complete portfolio, therefore excluding mortgages and other liabilities. There is no exact correspondence in the questions of all the various SCF waves, as for instance before 2004 we have no information on the fraction of balanced composite assets (IRA-KEOGH accounts, retirement accounts, annuities, trust-managed accounts) invested in stocks. We then exploit information from a question on the prevalence of deposits, stocks and bonds in these composite investments to impute their value to the corresponding asset class. However, the trend shown by these assets in the imputations before 2004 (with more wealth held in deposits and less in stocks) is consistent with the trend observed in other as-

[2] We neglect waves prior to 1998 because portfolios happen to be largely different from those observed in later waves, as they are more highly concentrated in deposits (also for a change in the questionnaire). We believe that including these waves would bias our analysis as changes in portfolios would merely reflect institutional, regulatory and market changes in the set of investment possibilities. For instance, only recently 401(k) and similar retirement accounts became widely available, and new means of stock trading emerged, such as Internet-based brockerage services.

sets whose definition has remained constant across the waves (e.g., saving and money market accounts, directly held stocks, etc.).

Notice that the largest share in the aggregate portfolio is by far human capital (between 76% and 79%), which is roughly in line with simulation studies in Cocco (2005) and lower than in estimates from Jorgenson and Fraumeni (1989) who calculate a 90% human capital share for the US between 1948 and 1984. In our sample the aggregate share of human capital is lower, and keeps falling over the years, because of population ageing and because in the period under investigation its returns were lower than financial wealth (over the years 1998-2001) and real estate (2004-2007) ones.

Excluding human capital which is not accounted for, the size and time trend of the other aggregate assets is in line with official SCF statistics (Bucks et al., 2009). The second largest share of wealth is held in real estate (between 10% and 13%), mostly in owner-occupied residential housing; treatment of mortgages, especially on the primary residence, determines an aggregate short position in the bonds class.

From the table we see that most financial wealth is held in stocks.[3] Interestingly, we observe marked difference between portfolios in the 1998 and 2001 waves, and portfolios in the 2004 and 2007 waves. Indeed, the share of the financial portfolio invested in stocks was around 60% in waves 1998 and 2001 and smaller, around 50%, in waves 2004 and 2007. The decline between 2001 and 2004 was coupled with a corresponding increase in the holdings of deposits, from roughly 20% to 30%. In contrast, the holdings of bonds kept rather stable at 20% of the overall financial wealth. This pattern stopped an enduring trend showing the shift of financial wealth from safe and less risky financial assets (deposits, bonds) to more risky financial assets (stocks). It should be noticed that bond returns in excess from returns to risk free assets have been rather stable between 2001 and 2004 (see Section 4.2): other things being constant bond and deposit shares should have increased at the same pace. This evidence thus suggests that the time variation in the composition of the aggregate portfolio does not merely reflect changes in the value of the assets, but also some households' willingness to reshape their portfolios.

TABLE 1 ABOUT HERE

[3] For instance, the share of stocks in the aggregate financial portfolio of 2007 is roughly 4.74 /(2.69 +2.03 +4.74) = 50.32%, where 2.03 is the total amount of (directly and indirectly) owned bonds (excluding liabilities).

To better understand the evolution of portfolios over the life-cycle, we group our observations by cohorts. Specifically, we define cohorts within a range of 5 birth years. Our sample contains 13 such cohorts, born between 1920 and 1984. Since the oldest and the youngest cohorts are built from few observations, in the following figures we will show cohort-specific statistics based on at least 100 observations.

We start with the cohort-specific age profile of wealth. For each cohort and for each wave we compute aggregate wealth as the average wealth holdings in the sample, weighted using the SCF sampling weights. Figure 1 shows the resulting age profile for the financial definition (left panel) and for the complete definition (right panel) of wealth. Values are reported in 2007 USD using the Consumer Price Index for all urban consumers (source: US Bureau of Labor Statistics). In the figure, lines placed more toward the left describe younger cohorts than lines toward the right. The figure shows for financial wealth the typical inverted U-shape profile, with remarkable cohort and time effects, with younger cohorts systematically richer than older ones. In contrast, complete wealth falls monotonically with age, because human capital progressively decreases.

FIGURE 1 ABOUT HERE

We then turn our attention to the single asset holdings. Figure 2 reports the age profile of the asset shares for our complete definition of portfolio. Cohort portfolios are constructed as the aggregate portfolios from the (weighted) observations in our sample and conditional on cohorts and age. Financial portfolio shares do not seem to vary remarkably over the life-cycle. In contrast, complete portfolio shares vary largely. Most of the variation is driven by human capital, which accounts for nearly 100% of wealth at the beginning of economic life and then markedly falls with age, leaving all the other asset shares rise. The remaining age variation in portfolio allocation seems driven by the timing of housing investment. With volatile house prices, the insurance motive makes young households purchase their house early in life (see Sinai and Souleles, 2005 and Banks *et al.*, 2010a). In order to increase their housing consumption they resort to debt.[4] From the comparison across cohorts, it emerges that younger cohorts have larger positions in human capital and real estate, and smaller positions in stocks. It is worth noticing that the stock share is increasing more mar-

[4] The percentage of households with a mortgage peaks at around the age of 45.

kedly only when the negative bond position is decreasing. That is, debt positions primarily due to real estate investment make stock investment less attractive. This evidence is consistent with Becker and Shabani (2010) who find that households with mortgage debt are 10 percent less likely to own stocks and 37 percent less likely to own bonds compared to similar households with no outstanding mortgage debt.

Later in the life cycle, households are expected to downsize their housing investment. However, older households do not switch from homeownership to renting. Thus, if they reduce their position in primary residence, they do so by moving to a smaller, but still owned, house. This finding is consistent with Banks *et al.* (2010b), who show that the housing transition rate from owner to renter in a five-year range is a mere 4.3% for the US homeowners over 50 years old.

FIGURE 2 ABOUT HERE

4.2. Asset time series

Information on asset market returns is essential to estimate our standard deviation measures. We take annual financial returns (bonds and stocks) from the "Merrill Lynch US Corporate & Government Master Index" and "MSCI USA Stock Index" time series of US asset total return indices (downloaded from Datastream). We consider as risk free annual return for deposits the yield of 3-month T-bills. Annual returns for business wealth are derived from proprietor's income from Bureau of Economic Analysis (BEA). To measure annual returns on human capital we construct from BEA data a time series of labor income consistent with the definition we used in the SCF.[5]

It is more problematic to find a time series of real estate returns valid for our purpose. From the perspective of a household, we need a series that accounts for not only capital gains, but also earnings due to (imputed) rents. The longest time series suitable for our purpose is the repeat-sale, purchase-only index calculated for the whole of the US from the Federal Housing Finance Agency (FHFA). We combine this index with an estimate of imputed rents-price ratios for the US market calculated in Davis *et al.* (2008). The rent-price

[5] See the Appendix. We take the difference between personal income and earnings from rents, dividends, and capital gains. The resulting time series incorporates wage and salary disbursements, supplements to wages and salaries, proprietors' income with inventory valuation and capital consumption adjustments, and personal current transfer receipts, less contributions for public social insurance. BEA data refer to the whole US population, and thus they already incorporate unemployment spells and job-to-job mobility.

ratio decreased between 1979 and the second quarter of 2006 from 4.85% to 3.64%, and started rising again in the following years. The average ratio in our sample period is 4.76%, in line with estimates in Flavin and Yamashita (2002) and Pelizzon and Weber (2008).

We construct time series of annual returns covering the years from 1979 to 2007 at a quarterly frequency (the FHFA index is not available at higher frequency). We derive excess returns of risky assets as the difference with risk free returns. In the benchmark analysis, we construct moments using a moving 20-year window (80 observations) for excess returns. Specifically, for the survey data collected in year *X* we assume that portfolio decisions are based on excess returns observed between year *X-19* and year *X*. As a result, households interviewed in different years have different expectations about future market movements.

Figure 3 informs on the outcome of this estimation exercise. The two top panels report the rolling expected excess return (top-left panel) and rolling standard deviation (top-right panel) for each asset from 1998 to 2007. The vertical lines show the data points we use in each wave, which are summarized in Table 2.

TABLE 2 ABOUT HERE

We see that expected excess returns on stocks rose largely in the first part of the period, together with a prolonged period of economic expansion, and showed large fluctuations afterwards, following the mild recession of year 2001. The stock market decline reversed gains posted earlier, and by the end of 2001 it had brought the stock index close to its 1998 levels. It subsequently recovered, beginning in late 2007 a decline with the current economic crisis. Expected excess returns on bonds grew until 2001, while expected excess returns on real estate kept growing from 1999 to 2006, outperforming bonds since 2004. This is reflected in Figure 2, where stock shares systematically show a marked growth between the first and the second point of the curve for each cohort. The fall we instead observe in the age profile of stock shares between the second and third point of the curve for each cohort (that is, between 2001 and 2004) describes the shift of savings toward real estate, following the increase in the returns over this period. Standard deviations are – unsurprisingly – more stable over time, but nevertheless, bond risk witnesses a remarkable reduction since year 2000. In order to assess the riskiness of household portfolios we also need to evaluate the

pairwise correlations of excess returns. The two bottom panels of Figure 3 show the rolling estimates of the correlation between bonds (bottom-right panel) and the other excess returns (bottom-left panel), and between stocks and the other excess returns. The two panels suggest a marked change over the years, consistent with the change we observe in portfolio composition by wave, especially when going from 1998 to 2001; in particular the correlation between bonds and stocks fell from a very high level (around 50%) at the beginning of our sample period, consistently with the literature (e.g., Baele *et al.*, 2010). As a consequence, although the standard deviations of the asset excess returns are quite stable over time, the standard deviation of a portfolio may vary considerably due to the fluctuations of the correlations.

FIGURE 3 ABOUT HERE

Measuring idiosyncratic risk would require time series of the asset returns on firm sectors, regional real estate, and job category. This would allow us to compute different sets of variance-covariance matrices, and associate the relevant one to each household. Unfortunately, we do not have such information. Previous studies, mainly focused on the distinction between permanent and transitory income shocks, find that idiosyncratic risk can be very large compared to market risk, and the total variance can be even ten times as large as the market one (e.g., Meghir and Pistaferri, 2004; Cocco *et al*., 2005). For this reason, in the analysis we set the idiosyncratic variance-covariance matrix $\tilde{\Sigma}_t^{nn} = \theta diag\left\{\overline{\Sigma}_t^{nn}\right\}$, i.e., as a diagonal matrix including the market variance of business wealth, real estate and human capital, multiplied by a factor θ. In the benchmark analysis we set $\theta = 9$. In our intention, this choice should represent an upper bound for idiosyncratic variance. Choosing a different constant value of θ would not alter our conclusions.

5. Results

5.1. Distribution of risk bearing

We start our analysis by showing summary statistics on the evolution of risk bearing over time. Table 3 reports the median levels of risk we derive from the household portfolios in

each SCF wave. All the measures agree in indicating higher risk bearing in the years 1998 and 2001 rather than in the years 2004 and 2007, in correspondence to high stock shares, high volatility of bonds and stocks and high correlation between bonds and stocks. Notice the wide drop in the median stock share between 2001 and 2004. This drop reflects two facts: i) a marked fall in the number of stock holders (from 63.58% of 2001 to 53.98% of 2004), and ii) a large reduction in the stock holding of those who invest in stocks (the median stock share in the financial portfolio goes from 58.21% of 2001 to 42.24% of 2004). We want to point out that we are not interested in the absolute size of risk (which depends on the measure chosen, and the assumptions on the variances and covariances), but rather on its size relative to each other measure. From the table we then learn that, in the complete portfolio, market standard deviation is driven mainly by constrained risk, whereas total standard deviation is driven mainly by idiosyncratic risk. [6] This depends on the large portfolio shares held in human capital. Hence, there seems to be little freedom of adjusting portfolio risk in a short-term investment horizon.

TABLE 3 ABOUT HERE

Before going further, we compare our risk indicators with the answers to two SCF questions on self-assessed risk aversion and investment horizon. The question on risk aversion is the following:

> *«Which of the following comes closest to describing the amount of financial risk that [you/ you and your (husband/ wife/ partner)] are willing to take when you save or make investments?»*

which allows the four answers listed below:

> *1. Take substantial financial risks expecting to earn substantial returns*
>
> *2. Take above average financial risks expecting to earn above average returns*
>
> *3. Take average financial risks expecting to earn average returns*
>
> *4. Not willing to take any financial risks*

[6] Conditional standard deviation is between 72.22 and 87.37 percent of market standard deviation, depending on the wave; idiosyncratic standard deviation, after including the rescaling factor θ, is between 94.32 and 94.85 percent of total standard deviation.

In the sample households more frequently report the more risk averse answers, 3 and 4 (respectively in 41.73 and 34.34 percent of the cases). Given the small response rate of the first two answers (especially the first one), in our analysis we group together answers 1 and 2.

The question on the time horizon reads as follows:

> *«In planning [your/ your family's] saving and spending, which of the following is most important to [you/ you and your (husband/ wife/ partner)]?»*

and admits five possible answers:

1. *Next few months*
2. *Next year*
3. *Next few years*
4. *Next 5-10 years*
5. *Longer than 10 years*

In the sample we observe higher frequency of answers 3 and 4 – 2-10 years – (respectively in 27.88 and 27.25 percent of the observations), while the remaining three categories are roughly equally distributed.

Table 4 shows median statistics of our risk indicators, separately for groups of households divided by their response to the self-assessed risk aversion question (panel a) and the self-assessed time horizon question (panel b). One should expect our risk indicators to decrease with the self-assessed risk aversion (obviously), and increase with the self-assessed investment horizon (because investors have more time to recover from any loss). From the table it emerges that our hypothesis is indeed confirmed, at least for the measures based on the financial portfolio (financial stock share, financial standard deviation) and for the conditional standard deviation. This is due to the fact that the SCF questions explicitly refer to financial rather than total wealth, or households have in mind financial wealth regarding their investment horizon.

TABLE 4 ABOUT HERE

We then turn our attention to the empirical distribution of the measures of risk. Figure 4 plots the cumulative distribution function (cdf) of our indicators. All the measures report

wide heterogeneity, reflecting different portfolio allocation, and inform that a large part of the population has very little (if any) propensity to risk bearing. This is particularly evident for the stock share, that is set to 0 for a number of households between 40% and 50% of the sample in a given year. The financial standard deviation is also equal to zero for a large number, between 20% and 30%, of the households.[7] In all the other cases, risk bearing is always larger than zero because households hold at least risk free deposits and risky human capital (which happens in 8.98% of the sample). Notice that the cdfs referring to the waves 2004 and 2007 are typically drawn above the cdfs for the waves 1998 and 2001, which means that over those years the distributions are shifted toward lower levels of risk bearing. This difference over the years is consistent with the findings discussed above regarding Table 3, namely, that households shifted their portfolios toward safer assets. The contrast across waves is more evident when looking at the non-financial asset returns, that show a reduction in their historical standard deviation during the latest two waves under investigation (see Figure 3).

FIGURE 4 ABOUT HERE

The indicators then show a similar time trend and wide heterogeneity of risk bearing. However, they may provide different results at the single household level. Table 5 reports the correlation for each pair of indicators, taken as average over the four waves. The correlation is very high (0.922) between the two indicators based on the financial portfolio (stock share and standard deviation), and smaller (0.581) between the two indicators based on the complete portfolio (market and total standard deviation). The correlation is rather small (between 0.061 and 0.311) when we compare indicators based on the financial portfolio with indicators based on the complete portfolio. This suggests that focusing on the complete portfolio rather than the financial one may lead to different conclusions. A household appearing to bear marked risk according to one indicator, may bear less risk using a different indicator.

TABLE 5 ABOUT HERE

[7] It is smaller than before because many households hold only risk free and bond assets in their financial portfolio.

Still from Table 5 we learn that, among the risk components, constrained and idiosyncratic risk – both a function of non-financial asset shares – have correlation near one,[8] and are both negatively correlated with the conditional standard deviation. Intuitively, the larger the non-financial asset shares, the smaller the financial asset shares. Constrained and idiosyncratic risks correlate negatively also with all the other risk measures, apart from total standard deviation – where the non-financial asset shares play a dominant role. Figure 5 graphically compares the estimates of the households' specific indicators, pooling all the four waves together. For comparability purpose we add in the figure the financial stock share, and the risky financial wealth share (bonds plus stocks) in the complete portfolio. We observe clear (positive) patterns only when comparing constrained and idiosyncratic standard deviations, or the financial wealth share and the conditional standard deviation. In all the other cases, there is wide dispersion suggesting that the various measures capture different definitions of risk.

FIGURE 5 ABOUT HERE

5.2. Age profile

In this subsection we investigate the correlations between our measures of risk bearing, age and other household characteristics, time and cohort effects. To this end we run quantile regression analyses, one for each measure, where the dependent variable is our risk bearing indicator. We opt for quantile regression, rather than OLS regression, since this method is less sensitive to large outliers. The specification includes five sets of explanatory variables, on wealth, demographics, financial sophistication, self-assessed measures, age, cohort, and time effects. As wealth variable we consider the logarithm of "tangible" wealth from financial, business and real assets. In the set of demographic variables we treat variables for race, gender, education, marital status, number of household members, children (yes or no), and

[8] Notice that $\left(\overline{\sigma}_{it}^{f|n}\right)^2 = \frac{1}{\theta}\left(\widetilde{\sigma}_{it}^{n}\right)^2 - \omega_{it}^{n\prime}\Sigma_t^{fn\prime}\left(\Sigma_t^{ff}\right)^{-1}\Sigma_t^{fn}\omega_{it}^{n}$, that is, the (square of) constrained standard deviation is a linear function of the (square of) idiosyncratic standard deviation and a household- and time-specific component. Also recall that we compute the correlation separately in each wave, and in the table we report the average across waves. This means that any difference between constrained and idiosyncratic standard deviations is attributable only to household portfolio composition. However, the difference is negligible because i) household portfolios are usually concentrated mostly in human capital, and ii) the correlation between financial and non-financial assets is generally low.

occupational status of the household head. In the same vein as Guiso and Jappelli (2005), we further include in the specification some proxies for financial sophistication: the number of financial institutions the household is involved with, and two dummy variables. The dummies are worth one respectively if there is regular consulting of a professional financial advisor, or the head works in the finance sector. Following Rosen and Wu (2004), we also include one dummy variable for the self-perceived good or excellent health status of the head.

We finally add variables meant to disentangle time and cohort effects from age effects. After trying alternative specifications, we choose one where age effects are captured with dummy variables covering a five-year age range (the baseline is age 25-29), time effects are measured with the average excess return of the stock market in the three years prior to the wave[9], and cohort effects are measured with the average excess return of the stock market when the head was between 20 and 24 years old.[10] This specification mimics one in Ameriks and Zeldes (2004), where in particular the variable on the cohort effect is meant to describe a "learning" process of the market behavior when young.

Previous literature, mainly analyzing the stock share in the financial portfolio, finds for risk positive correlation with wealth (e.g., Siegel and Hoban, 1982; Morin and Suarez, 1983), and higher education (Halek and Eisenhauer, 2001). Our analysis is comparable to these works because, in all the cases, we take as dependent variable a combination of the portfolio shares with weights varying over time, but common to all the households in a given year.

Table 6 shows the results of our analysis, separately for each of the seven indicators rescaled by their median in the sample (to have comparable estimates). Overall we have 14,553 observations with full information on the variables in the specification. We first focus on the two measures based on the financial portfolio definition. The stock share and the standard deviation of financial portfolio returns correlate positively with wealth, college education, self-assessed good health status, the number of financial institutions where doing business, and with the dummy variable for individuals working in the finance sector; they

[9] Based on our time series of stock excess returns. For instance, for year 2007 we take the average from the 12 quarterly observations between 2005 and 2007.

[10] Our time series of stock excess returns does not allow to retrieve this information from the oldest cohorts. For this reason we refer to data available in Kenneth French's website. Specifically, we consider as excess market return the value-weight return on all NYSE, AMEX, and NASDAQ stocks (from CRSP) minus the one-month Treasury bill rate (from Ibbotson Associates).

correlate negatively with the dummy variables for non-white and self-employed individuals. In addition, we find no cohort effect but a strongly positive time effect. This means that the risk indicator rises when the stock excess return in the previous three years is high, such as in the first two waves of our sample.

When we look at the two measures based on the complete portfolio definition, only some of our previous findings are confirmed. We still find positive correlations with wealth, good health status, the number of financial institutions where doing business, and with the dummy for individuals working in the finance sector. This time we also find significant evidence of not only time effects but also cohort effects, which indicates that people who experience high market returns when aged 20-24 are more likely to bear market risk. However, the size of this effect is tiny – especially if compared with the size of time effects. Finally, we find significantly positive effects for self-employed and female heads. This may be surprising if compared with the results in the first two columns of Table 6.

We believe the case of self-employed workers is paradigmatic. These individuals hold most of their wealth in a business. Ignoring this, and focusing on just their financial portfolio, would suggest that they are less risk tolerant than employees. Actually, they choose their financial portfolio having in mind that they already bear substantial business risk. In fact, when we consider a complete definition of portfolio, the effect of being a self-employed worker is reverted. This evidence is in line, for instance, with Heaton and Lucas (2000).

More difficult to accept is the finding of a positive effect for females. This has to do with the proportion between financial and total wealth. In fact females in the sample have relatively little human capital, and hold most of their wealth in financial assets. Having their wealth more highly concentrated in riskier assets, this implies that females appear more risk tolerant than males. We would find the same conclusions if we took the financial /total wealth share as dependent variable. Females would appear less risk tolerant only if they made large investment in risk free deposits – but they do not.

We conclude our regression analysis by looking at the three risk components. We expect them to capture different effects. In particular, compared with the financial measures of columns (1)-(2), we expect an inversion of sign when studying the risk components of equations (4)-(6). It can indeed be shown that an increase in the financial share affects negatively the constrained and idiosyncratic standard deviations, and is likely to positively af-

fect the conditional standard deviation. In the appendix we discuss the special case with one financial asset and one non-financial asset. This implies that all the variables positively affecting the financial shares also affect positively the conditional standard deviation, but affect negatively the constrained and idiosyncratic standard deviations.

Looking at conditional standard deviation, the significant effects found for the measures based on the complete portfolios are obtained also here. In addition, there are significantly positive effects of college education, retirement status, and female gender. As expected, some of the effects change sign when looking at the constrained and idiosyncratic standard deviations: we indeed find negative effects of wealth and college education, and positive effects of self-employment, time and cohort.

Finally, notice that the size of the minimum degrees of freedom, reported in the bottom of Table 6, is higher under the complete portfolio measures than under the financial portfolio measures. Multiple imputations use for the t-statistics a number of degrees of freedom that depends on the ratio of the variance within imputations to the variance between imputations. The value indicated in the table is the minimum number of degrees of freedom among all the parameters. In general one should prefer a higher number, as it means that estimates vary little across imputations. We find this to happen under our complete portfolio measures, which are then less heavily affected by missing information.

TABLE 6 ABOUT HERE

We conclude the analysis with a graphical representation of the age effects estimated for our indicators. In Figure 6 we depict the estimated age profile conditional on the median values of wealth, demographic and other household characteristics; for comparability reason, the profile is divided by the median risk bearing indicator observed in the sample. Each age profile is coupled with a 95% confidence interval derived from the covariance matrix of the coefficient estimates.

There is marked difference between the measures based on the financial portfolio and the measures based on the complete portfolio. The former show an age profile that is essentially flat up to age 60, and then falls – especially as concerns the stock share, which is halved for the elderly. This evidence is somewhat more complex than some common rules of thumb adopted by practitioners, e.g., to invest in stocks a fraction $(100-age)\%$ of the

financial wealth, and closer to others, e.g., to decrease the proportion of a portfolio devoted to stocks as one approaches retirement (Malkiel, 1996). In contrast, the two measures based on the complete portfolio show an age profile that is constantly flat and associated to a narrow confidence interval. This profile is driven by the constrained and idiosyncratic risk components, which show an age profile that is also flat. In contrast, we observe for the conditional standard deviation an age profile increasing up to age 50; this profile is less influent in the complete portfolio standard deviation, apart from old age, because household portfolios are made mainly of constrained (human capital) assets. Young people have large human capital but limited financial resources. Since human capital cannot be used to pay bills and debts, they find it hard to endure any short-term investment losses. Evidence of a rising age profile with the conditional standard deviation is not surprising given wealth size (Figure 1) and the complete portfolio shares (Figure 2). In fact, evidence of portfolio risk rising with age is not new and is found, for instance, also in Wang and Hanna (1997) analyzing from SCF data the ratio of risky assets over an extended definition of portfolio, to include financial, real and human wealth. The complete portfolio is largely dependent on human capital, which naturally falls with age. As individuals get older, their portfolios exhibit higher investment in assets that carry relatively more risk than human capital. Our indicators capture this life-cycle effect in the change of the conditional portfolio weights $\omega_{it}^{f|n} = \omega_{it}^{f} + \left(\Sigma_t^{ff}\right)^{-1} \Sigma_t^{fn} \omega_{it}^{n}$. These weights rise with age following the financial portfolio shares ω_{it}^{f} (see Figure 2).

FIGURE 6 ABOUT HERE

5.3. Sensitivity analysis

Our findings lie on assumptions on the computation of human capital and the variances and covariances of asset returns. To assess the importance of these assumptions, here we report the outcome of some robustness checks of our analysis, performed along these two dimensions. In addition, we repeat our benchmark analysis in significant subsamples of our data. Methodological details and complete results can be found in the Supplementary Appendix; here we just comment on the relevant findings. Overall, the robustness checks confirm our benchmark results.

5.3.1. Human capital

Different human capital discount rate

Our benchmark results are driven by the large size of human capital shares. We then repeat the analysis by reducing this share. We do so by setting a higher discount rate to future income realizations. Specifically, we set it to the real average stock rate of return over the 20 years before each wave; the discount rate is then between 5 and 7 percent higher than the one based on the sole risk free rate of return. In aggregate, the resulting portfolio share in human capital is between 65.03 percent (2007) and 68.23 percent (1998), about 10 percent lower than in the benchmark analysis. The shift of portfolio risk from human capital to (riskier) asset categories leads to a generalized increase in our risk indicator. This notwithstanding, our results are confirmed.

Riskless human capital at retirement

In the benchmark analysis we treat human capital from pension income exactly the same way as human capital from labor income. However, pension income is usually less risky than labor income. We then replicate the analysis under the extreme situation where pension human capital is riskless.

This implies a reduction in the size of the risky human capital share in the household portfolio, compared to the benchmark case (in aggregate, around 60 percent rather than 80 percent). This share also falls more markedly with age, and in completely null after retirement age 65. Only in this extreme case the age profile of household portfolios differs from the benchmark analysis. Specifically, it falls under the complete portfolio standard deviation, driven by the reduction in the constrained and idiosyncratic standard deviations.

5.3.2. Asset return moments

No hedging

There is no consensus in the literature on the size of the covariance between financial and non-financial asset returns. However, this affects our estimates through the hedging component of conditional standard deviation. Some works find these covariances to be null (for instance see Flavin and Yamashita, 2002, for real estate, and Table 3 in Cocco *et al.*, 2005, for human capital), which implies no hedging at all. We therefore repeat our analysis by

imposing null covariance between the excess returns of financial assets (bond, stock) and non-financial assets (business wealth, real estate, human capital). Imposing null correlation alters neither the estimates, nor the ranking of the households. The benchmark results are confirmed.

Fixed moments

The variations we observe in risk bearing arise from changes in portfolio composition and the moments of the asset excess returns. It may be interesting to see which change is the main driver of these variations. To investigate this issue, we repeat our analysis by keeping the moments of the asset returns fixed in all the waves, and equal to those we associate to wave 1998 in the benchmark analysis. In this environment, variation reflects only changes in household portfolios.

Our findings are again preserved. Even if asset variances and covariances are now kept fixed, in the regressions we still find significantly positive time effects. This suggests that households who face changes in asset return moments adjust their complete portfolios to offset such changes, in an effort to bear a risk relatively stable with age.

Alternative moment estimates

In our exercise we estimate the historical variance-covariance matrix of excess returns using a 20-year backward time horizon. Different estimates would associate different weights to the asset shares, and might give rise to different results. We provide new estimates in which the moments of the asset returns are derived from a time series of 15 years instead of 20 years; similar conclusions arise using a 10-year window. Compared to the benchmark estimates, asset return moments computed this way exhibit lower variance in waves 1998 and 2001, and correlations more volatile over time. Also in this case, the multivariate analysis on household portfolios does confirm our main results, and gives rise to an age profile in line with our previous findings.

5.3.3. Sample composition

Wealthy households

What we interpreted as heterogeneity in risk borne by the households might in fact be due to heterogeneity in entry barriers or transaction costs. That is, some households may had

chosen not to invest in some assets (e.g., a business) because of high costs of investing. Other households may had chosen their portfolio composition in earlier years, and then just kept it with no adjustment to avoid market transaction costs. It is reasonable to expect that, the wealthier the household, the less relevant entry barriers and transaction costs are for portfolio choice (see, e.g. Vissing-Jorgensen, 2002). We then repeat our analysis on a restricted subsample made of the top 20% wealthiest households. Compared to the full sample, on average the subsample of the wealthiest households is more highly educated and financially sophisticated, earns a higher income, has more financial wealth, and invests more heavily in risky assets.

Due to the reduction in the sample size, in this case our estimates are less precise. However, the main results of our multivariate analysis still hold: in particular there is a positive relation between risk bearing and wealth, and age and time effects are close to those of the benchmark case.

Long time horizon for investment

Non-financial assets are less liquid than financial assets in a short-term time horizon. However, households may take a long-term investment horizon. Indeed in our sample, 43.90% of the households declare to have an investment time horizon equal to 5 years or longer. We then repeat our analysis on these households who, compared to the full sample, on average earn higher income, have more wealth, are more highly educated, and invest more in risky assets. Even though we expect these people to see non-financial assets as more liquid than investors with shorter-time horizon, we confirm our benchmark findings. In particular, we find no difference when decomposing risk in its conditional, constrained and idiosyncratic parts.

6. Conclusions

In this paper we use data from the waves 1998-2007 of the US Survey of Consumer Finances (SCF) to shed light on the evolution of US households' portfolio risk, and the correlation between risk bearing, wealth, age and the main household socio-demographic characteristics. The use of repeated cross sections allows us to disentangle age effects from time and cohort effects.

In our analysis we consider different indicators of risk bearing, based on two different definitions of portfolio (financial and complete, with the latter also including human capital, business wealth, real estate, and related debt). The indicators show a similar time trend with risk bearing falling in the 2000s, and inform that the distribution of household risk bearing is skewed to the left, with many households bearing little risk. Moreover, in all the cases we find our measures of risk bearing to correlate positively with wealth, good health, and some proxies for financial sophistication. However, the indicators are imperfectly correlated, and the correlation is particularly low when comparing measures based on the financial portfolio with ones based on the complete portfolio.

Our data show weak evidence of cohort effects, while time effects seem more relevant. In particular, we find that risk bearing tends to increase following high stock market returns. We generally find a flat age profile of risk bearing, under the assumption that the other household characteristics remain fixed over the life-cycle. This is mainly driven by the age profile of the non-financial components of the portfolio.

There are several avenues for future research. On an exploratory side, it seems interesting to compare risk bearing among individuals of different countries having similar characteristics, and over an extended time period to include the financial crisis. On a theoretical side, we will develop a fully multi-period framework, closer to a life-cycle model of asset allocation, from which to infer risk attitude from observed portfolio holdings, separately from time discounting.

Appendix

A1. Human capital calculation

We construct human capital using an approach similar to Jorgenson and Fraumeni (1989). The approach computes human capital as the net present value of the income flow that will be produced over an assumed lifetime, in the presence of survival probabilities. Expected future incomes are predicted from the observed incomes of the cross section of individuals. An advantage of this method is that it allows to estimate human capital even for those households who report no income (0.91% of the sample).

For this purpose we use the waves 1995-2007 of the SCF (19,165 observations in total), taking into account imputations and sampling weights. Notice that we also include one

wave (1995) not treated in our portfolio analysis. This wave shows largely different portfolios from the subsequent waves; however, there is no reason to exclude it as long as the focus is on income.

We assume income arises from a process depending on several characteristics of the head, in particular gender (male, female), race (white, non-white) and education (high school or lower, college). We denote the realization of these three variables by group $x \in X$. The combination of the three variables gives rise to eight possible groups.

We describe human capital for household *i* at time *t*, whose head is aged *a* and belongs to group *x*, as follows:

$$HC_{it}^{a}(x) = y_{it}^{a}(x) + LI_{it}^{a}(x)$$

where $y_{it}^{a}(x)$ is the gross income obtained from the survey for the household head and spouse (if any), and $LI_{it}^{a}(x)$ is imputed household lifetime gross income. Gross income is calculated as the sum of (before taxes) family income from wages and salaries, from business, unemployment compensation, worker's compensation, social security, supplemental social security, child support, other welfare and assistance programs, and total transfers (mainly help from relatives). On average in our data, income is between 4 and 5% of human capital. Lifetime income is imputed from predictions of future income realizations, and is defined as follows:

$$LI_{it}^{a}(x) = \sum_{b=a+1}^{T} \pi_{it}^{a,b}(x)\, \hat{y}_{it}^{b}(x) \left(\frac{1}{1+r_t}\right)^{b-a}.$$

That is, lifetime income is the sum of the predicted income levels, $\hat{y}_{it}^{b}(x)$, conditional on age *b* and group *x*, weighted by a survival probability $\pi_{it}^{a,b}(x)$ of being alive at age *b* conditional of being alive at age *a* and time *t*, for individual *i* belonging to group *x*[11], and corrected by a discount rate $(1+r_t)$, computed as average over the 20 years before *t* of real risk free returns (3-month T-bill yields net of CPI growth).[12]

Income predictions up to age 64 are derived, separately for each education group, from the OLS regression of the logarithm of one plus income over a third-order polynomial on

[11] Actually, in our calculation survival probabilities differ by gender and not also by race or education, because no such data are available.
[12] This shows a decline from 5.96% of 1995 to 3.62% of 2007.

age, gender and race dummies, cohort dummies and time dummies respecting the Deaton-Paxson orthogonality constraints. As one may expect, projected income is higher for households with a male, white and more highly educated head. Income predictions since age 65 are the income prediction at age 64 times a replacement rate. The rate is given by the ratio of average observed income between 65 and 69 to average observed income between 60 and 64, and it is computed separately by education groups: we estimate an average replacement rate of 88.88% for high school graduates, and 71.95% for college graduates.

A2. Risk components and portfolio shares

Consider a simplified framework with one risk free asset with portfolio share ω_{it}^0, one financial asset with portfolio share ω_{it}^f, and one non-financial asset with portfolio share $\omega_{it}^n = 1 - \omega_{it}^0 - \omega_{it}^f$. In this case, the formula for the conditional standard deviation simplifies to

$$\sigma_{it}^{f|n} = \omega_{it}^{f|n}\sigma_t^f = \left(\omega_{it}^f + \frac{\sigma_t^{fn}}{\left(\sigma_t^f\right)^2}\omega_{it}^n \right)\sigma_t^f \tag{A1}$$

while the formula for the constrained standard deviation simplifies to

$$\sigma_{it}^{n|f} = \omega_{it}^n\sigma_t^{n|f} = \omega_{it}^n\left(\left(\sigma_t^n\right)^2 - \left(\frac{\sigma_t^{fn}}{\sigma_t^f} \right)^2 \right)^{\frac{1}{2}} \tag{A2}$$

and the formula for the idiosyncratic risk becomes

$$\tilde{\sigma}_{it}^n = \omega_{it}^n\sigma_t^n . \tag{A3}$$

The derivatives of (A1)-(A3) with respect to ω_{it}^f are:

$$\frac{\partial\sigma_{it}^{f|n}}{\partial\omega_{it}^f} = -\frac{\partial\sigma_{it}^{f|n}}{\partial\omega_{it}^n} = \sigma_t^f\left(1 - \frac{\sigma_t^{fn}}{\left(\sigma_t^f\right)^2} \right)$$

$$\frac{\partial\sigma_{it}^{n|f}}{\partial\omega_{it}^f} = -\frac{\partial\sigma_{it}^{n|f}}{\partial\omega_{it}^n} = -\left(\left(\sigma_t^n\right)^2 - \left(\frac{\sigma_t^{fn}}{\sigma_t^f} \right)^2 \right)^{\frac{1}{2}} < 0$$

$$\frac{\partial\tilde{\sigma}_{it}^n}{\partial\omega_{it}^f} = -\frac{\partial\tilde{\sigma}_{it}^n}{\partial\omega_{it}^n} = -\sigma_t^n < 0.$$

The first derivative is positive if the correlation between financial and non-financial assets is lower than the ratio between their standard deviations. This is granted, in particular, in the plausible situation where the market risk of financial assets is higher than the market risk of non-financial assets. This implies that an increase in the financial asset share ω_{it}^{f} (or a reduction in the non-financial asset share ω_{it}^{n}) affects

- positively: conditional standard deviation
- negatively: constrained and idiosyncratic standard deviations

The overall effect of the financial asset share on the complete portfolio measures is unclear. The derivative of the total variance with respect to ω_{it}^{f} is

$$\frac{\partial\left(\sigma_{it}\right)^{2}}{\partial\omega_{it}^{f}}=2\omega_{it}^{f}\left(\left(\sigma_{t}^{f}\right)^{2}-2\left(\sigma_{t}^{n}\right)^{2}\right)-2\left(2\left(\sigma_{t}^{n}\right)^{2}-\sigma_{t}^{fn}\right). \tag{A4}$$

Given the time series data discussed in Section 4.2, we expect the variance of financial assets to be much higher than the variance of non-financial assets, which in turn is higher than the covariance between financial and non-financial asset returns. The derivative in (A4) is positive if

$$\omega_{it}^{f}>\frac{2\left(\sigma_{t}^{n}\right)^{2}-\sigma_{t}^{fn}}{\left(\sigma_{t}^{f}\right)^{2}-2\left(\sigma_{t}^{n}\right)^{2}}$$

which is more likely at higher ages.

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Table 1. Portfolio weights and portfolio composition (%)

Category	SCF 1998	SCF 2001	SCF 2004	SCF 2007
Checking accounts	0.454	0.475	0.441	0.363
Savings and money market accounts	0.256	0.377	0.653	0.617
Call accounts at brokerages	0.116	0.138	0.093	0.076
IRA-KEOGH accounts	*0.212*	*0.232*	*0.175*	*0.186*
Retirement accounts	*0.449*	*0.463*	*1.130*	*1.202*
Annuities	*0.042*	*0.065*	*0.176*	*0.105*
Trust-managed accounts	*0.114*	*0.311*	*0.418*	*0.138*
DEPOSITS	**1.642**	**2.061**	**3.086**	**2.689**
Directly held govt. bonds	0.362	0.441	0.386	0.316
Directly held corp. bonds	0.136	0.080	0.106	0.055
Certificates of deposit	0.395	0.302	0.289	0.331
Savings bonds	0.071	0.069	0.052	0.039
Tax free mutual funds	0.179	0.198	0.128	0.212
Govt. bond mutual funds	0.050	0.036	0.038	0.063
Other bond mutual funds	0.118	0.041	0.087	0.067
½ Balanced mutual funds	0.048	0.065	0.051	0.063
½ Other mutual funds	0.001	0.000	0.051	0.071
Life insurances (cash value)	0.704	0.599	0.285	0.309
Loans on primary residence (-)	-2.567	-2.286	-2.704	-2.863
Loans on other real estate (-)	-0.650	-0.451	-0.785	-0.822
Loans on business (-)	-0.115	-0.118	-0.133	-0.147
IRA-KEOGH accounts	*0.274*	*0.371*	*0.477*	*0.490*
Retirement accounts	*0*	*0.000*	*0.002*	*0.000*
Annuities	*0.072*	*0.016*	*0.001*	*0.002*
Trust-managed accounts	*0.173*	*0.003*	*0.006*	*0.007*
BONDS	**-0.749**	**-0.634**	**-1.664**	**-1.807**
Directly held stocks	2.388	2.334	1.703	1.685
Stock mutual funds	0.916	0.929	0.948	0.976
½ Balanced mutual funds	0.048	0.065	0.051	0.063
½ Other mutual funds	0.001	0.000	0.051	0.071
IRA-KEOGH accounts	*1.175*	*1.285*	*0.934*	*0.957*
Retirement accounts	*0.994*	*1.163*	*0.644*	*0.669*
Annuities	*0.094*	*0.139*	*0.102*	*0.121*
Trust-managed accounts	*0.318*	*0.629*	*0.249*	*0.202*
STOCKS	**5.936**	**6.545**	**4.678**	**4.743**
BUSINESS WEALTH	**4.372**	**4.364**	**4.431**	**5.372**
Owner-occupied primary residence	7.415	7.417	8.774	9.341
Other real estate	2.683	2.704	3.301	3.395
IRA-KEOGH accounts	*0.028*	*0*	*0*	*0*
Retirement accounts	*0.015*	*0.005*	*0*	*0*
Annuities	*0*	*0*	*0*	*0*
Trust-managed accounts	*0.066*	*0.041*	*0*	*0*
REAL ESTATE	**10.206**	**10.167**	**12.075**	**12.736**
Labor human capital	63.870	61.412	59.256	57.301
Pension human capital	14.723	16.085	18.138	18.966
HUMAN CAPITAL	**78.593**	**77.497**	**77.394**	**76.267**
Genuine observations	3607	3768	3906	3783

Note. The definition of financial portfolio considers only the assets in the deposits, bonds and stocks categories; all liabilities (mortgages, lines of credit and loans) are excluded.

Table 2. Risk and expected asset returns (%)

Wave	1998	2001	2004	2007
Risk free return	7.046	5.964	4.736	4.398
Bond excess return	3.223	4.905	4.742	3.237
	(9.584)	(7.966)	(6.687)	(5.308)
Stock excess return	6.830	6.985	6.987	5.470
	(16.170)	(17.075)	(16.800)	(16.035)
Business wealth excess return	0.034	1.710	2.152	2.092
	(7.907)	(6.441)	(4.671)	(4.593)
Real estate excess return	2.731	3.363	5.006	5.181
	(3.057)	(2.759)	(3.072)	(3.522)
Human capital excess return	-0.144	0.299	1.075	1.266
	(2.420)	(2.207)	(1.954)	(1.914)

Note. Standard deviation of excess returns in parentheses.

Table 3. Median values of the risk indicators (× 100)

Wave	1998	2001	2004	2007	ALL
Financial stock share	22.642	32.434	5.350	4.025	12.572
Financial SD	8.385	7.784	3.550	2.941	5.729
Complete market SD	2.448	2.238	1.986	1.971	2.205
Complete total SD	7.628	6.931	6.177	6.126	6.648
Conditional SD	0.680	0.532	0.261	0.249	0.476
Constrained SD	2.341	2.161	1.952	1.912	2.037
Idiosyncratic SD	2.407	2.179	1.953	1.926	2.054
Genuine observations	*3504*	*3625*	*3814*	*3687*	*14631*

Note. SD= Standard Deviation.

Table 4. Risk (× 100) and self-assessed measures

a. Self-assessed risk aversion

Risk attitude scale *	**1-2**	**3**	**4**
Financial stock share	46.189	26.605	0
Financial SD	8.517	6.604	1.166
Complete market SD	2.310	2.226	2.141
Complete total SD	6.786	6.612	6.582
Conditional SD	0.589	0.539	0.299
Constrained SD	2.059	2.020	2.049
Idiosyncratic SD	2.078	2.035	2.063
Frequency (%)	*23.93*	*41.73*	*34.34*

*Note. SD= Standard Deviation. * 1-2= high risk tolerance; 3= moderate risk tolerance; 4= no risk tolerance*

b. Self-assessed time horizon for investment

Time horizon scale *	**1**	**2**	**3**	**4**	**5**
Financial stock share	0	0	8.351	22.857	39.216
Financial SD	2.589	3.723	5.282	6.611	7.772
Complete market SD	2.160	2.182	2.202	2.233	2.281
Complete total SD	6.575	6.697	6.636	6.626	6.738
Conditional SD	0.309	0.388	0.469	0.539	0.589
Constrained SD	2.039	2.073	2.027	2.022	2.049
Idiosyncratic SD	2.053	2.089	2.043	2.039	2.068
Frequency (%)	*16.56*	*11.66*	*27.88*	*27.25*	*16.65*

*Note. SD= Standard Deviation. * 1= next few months; 2= next year; 3= next few years; 4= next 5-10 years; 5= more than 10 years*

Table 5. Correlation among risk bearing indicators

	Average across waves	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1	Financial stock share	1						
2	Financial SD	0.922	1					
3	Complete market SD	0.311	0.304	1				
4	Complete total SD	0.082	0.061	0.581	1			
5	Conditional SD	0.394	0.396	0.943	0.324	1		
6	Constrained SD	-0.102	-0.119	-0.020	0.766	-0.261	1	
7	Idiosyncratic SD	-0.101	-0.118	-0.016	0.767	-0.257	0.999	1

Note. SD= Standard Deviation. The table reports the average of wave-specific correlations.

Table 6. Heterogeneity of risk bearing

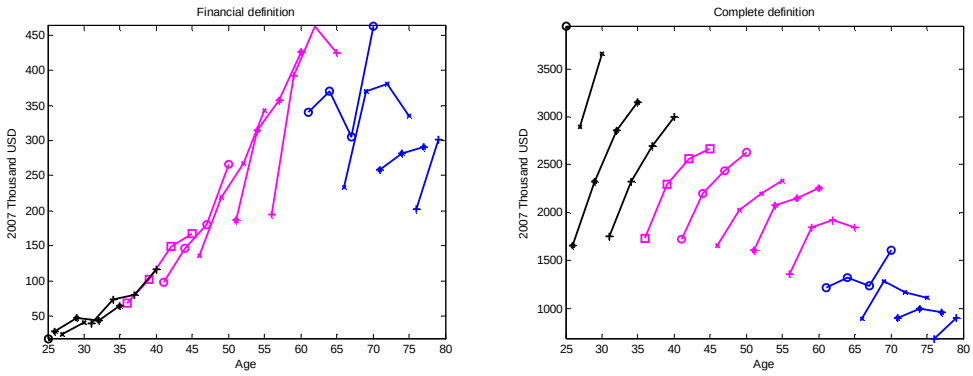
Quantile regression	Financial portfolio		Complete portfolio		Complete portfolio components		
	Stock share	SD	SD Market	SD Total	SD Conditional	SD Constrained	SD Idiosyncratic
Ln(wealth)	0.166***	0.141***	0.014***	0.001**	0.096***	-0.004***	-0.003***
	(0.012)	(0.006)	(0.001)	(0.001)	(0.005)	(0.001)	(0.001)
Non-white	-0.259***	-0.145***	0.001	0.004	-0.028	0.005	0.005
	(0.069)	(0.033)	(0.004)	(0.003)	(0.024)	(0.003)	(0.003)
Female	-0.072	0.006	0.019***	0.010**	0.133***	0.006	0.006
	(0.091)	(0.039)	(0.005)	(0.004)	(0.031)	(0.004)	(0.004)
College graduate	1.068***	0.145***	0.017***	-0.004	0.172***	-0.014***	-0.014***
	(0.063)	(0.025)	(0.003)	(0.003)	(0.021)	(0.003)	(0.003)
Married	-0.042	-0.019	0.003	0.006*	-0.003	0.006	0.006
	(0.078)	(0.037)	(0.004)	(0.004)	(0.029)	(0.004)	(0.004)
N. household members	-0.034	-0.022	0.002	0.003**	0.004	0.002	0.002
	(0.030)	(0.016)	(0.002)	(0.001)	(0.011)	(0.001)	(0.002)
With children	-0.099	-0.012	-0.009*	-0.001	-0.043	0.005	0.004
	(0.080)	(0.040)	(0.005)	(0.003)	(0.031)	(0.004)	(0.004)
Self-employed	-0.423***	-0.205***	0.068***	0.065***	0.011	0.061***	0.061***
	(0.070)	(0.037)	(0.004)	(0.004)	(0.029)	(0.003)	(0.003)
Retired	-0.033	-0.027	0.007	-0.004	0.128***	-0.007	-0.006
	(0.094)	(0.048)	(0.006)	(0.005)	(0.039)	(0.005)	(0.005)
N. financial institutions where doing business	0.245***	0.045***	0.007***	0.001**	0.071***	-0.001	-0.001
	(0.016)	(0.007)	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)
With financial advisor	0.161**	0.044	0.008***	-0.005	0.097***	-0.008***	-0.008***
	(0.058)	(0.026)	(0.003)	(0.003)	(0.021)	(0.003)	(0.003)
Works in finance sector	0.423***	0.151***	0.020***	0.019***	0.107***	0.014***	0.014***
	(0.115)	(0.037)	(0.004)	(0.004)	(0.030)	(0.004)	(0.004)
Self-assessed good health	0.340***	0.074**	0.015***	0.007**	0.120***	0.004	0.004
	(0.055)	(0.029)	(0.003)	(0.003)	(0.022)	(0.003)	(0.003)
Time effect	0.800**	1.593***	0.740***	0.786***	2.932***	0.667***	0.808***
	(0.258)	(0.120)	(0.015)	(0.012)	(0.100)	(0.014)	(0.013)
Cohort effect	0.009	0.006**	0.001***	0.002***	0.008***	0.002***	0.002***
	(0.005)	(0.003)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)

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Age 30-34	0.125	0.081	-0.004	-0.000	-0.033	0.007	0.007
	(0.118)	(0.058)	(0.007)	(0.006)	(0.044)	(0.006)	(0.006)
Age 35-39	0.290**	0.154**	0.001	0.002	0.055	0.010*	0.009*
	(0.115)	(0.056)	(0.006)	(0.005)	(0.043)	(0.005)	(0.005)
Age 40-44	0.360***	0.159**	0.012*	0.013**	0.150***	0.013**	0.013**
	(0.108)	(0.056)	(0.006)	(0.005)	(0.041)	(0.006)	(0.005)
Age 45-49	0.242*	0.127**	0.013*	0.001	0.233***	0.005	0.006
	(0.107)	(0.056)	(0.007)	(0.006)	(0.043)	(0.006)	(0.006)
Age 50-54	0.166	0.084	0.021***	0.003	0.256***	-0.001	0.000
	(0.122)	(0.058)	(0.008)	(0.006)	(0.046)	(0.006)	(0.006)
Age 55-59	0.350**	0.089	0.021***	-0.015**	0.353***	-0.020***	-0.018***
	(0.126)	(0.057)	(0.008)	(0.006)	(0.048)	(0.006)	(0.006)
Age 60-64	-0.201	-0.029	0.020**	-0.026***	0.334***	-0.043***	-0.040***
	(0.127)	(0.069)	(0.009)	(0.006)	(0.059)	(0.006)	(0.006)
Age 65-69	-0.170	-0.038	0.042***	-0.023***	0.365***	-0.047***	-0.044***
	(0.138)	(0.070)	(0.009)	(0.007)	(0.064)	(0.007)	(0.007)
Age 70-74	-0.625***	-0.150*	0.018*	-0.022***	0.361***	-0.047***	-0.044***
	(0.152)	(0.082)	(0.010)	(0.007)	(0.079)	(0.008)	(0.007)
Age 75-79	-0.450**	-0.024	0.039***	-0.015*	0.412***	-0.039***	-0.033***
	(0.167)	(0.084)	(0.010)	(0.008)	(0.069)	(0.008)	(0.008)
Constant	-1.684***	-0.995***	0.733***	0.910***	-0.843***	1.004***	0.988***
	(0.141)	(0.070)	(0.009)	(0.007)	(0.057)	(0.008)	(0.007)
Genuine observations	14,553	14,553	14,553	14,553	14,553	14,553	14,553
Minimum degrees of freedom	9.3	16.6	51.5	32.6	18.5	20.2	45.7
Median dep. var. (x 100)	12.572	5.729	2.205	6.648	0.476	2.037	2.054

*Note. SD= Standard Deviation. The dependent variable is rescaled by its median in the sample. Time effect: average market excess return in the three years prior to the wave. Cohort effect: average market excess return when 20-24 years old. Age effects: dummy variables covering a five-year age range. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

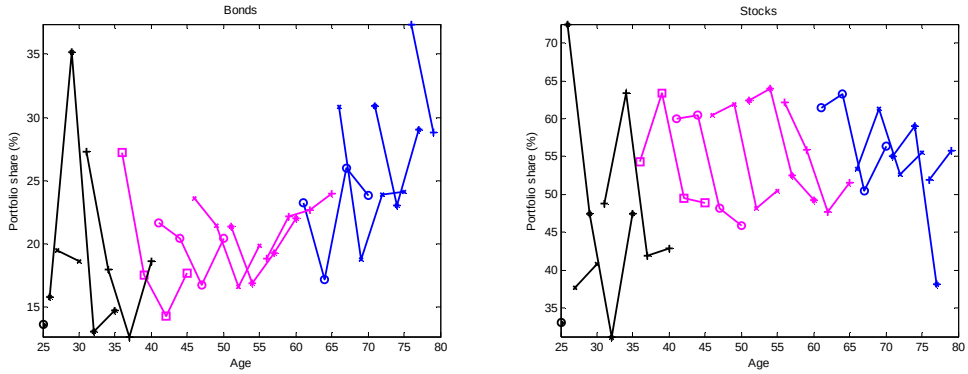
Figure 1. Cohort wealth size by age



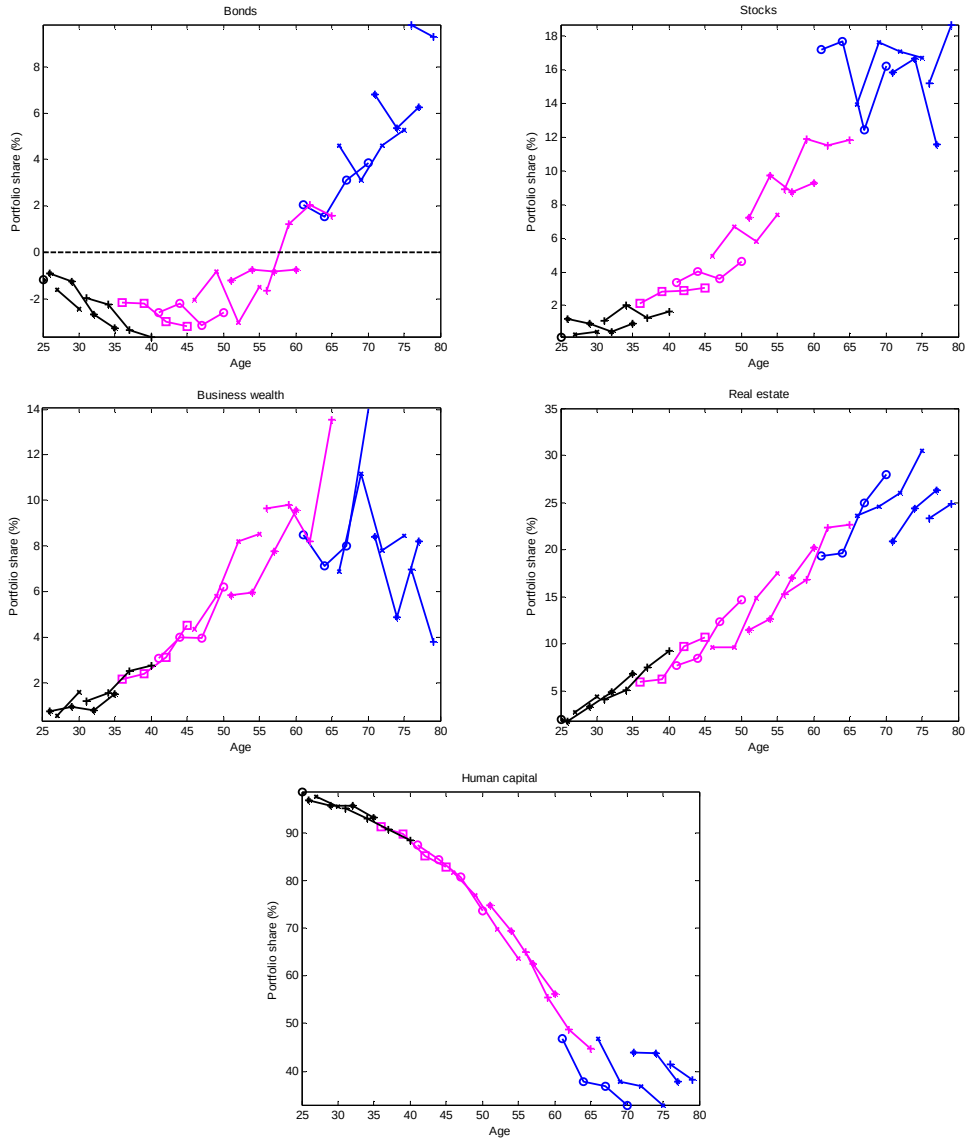
Note. The definition of cohort includes all those born in a 5-year range.

Figure 2. Cohort portfolio holdings by age

a. Financial portfolio



b. Complete portfolio



Note. The definition of cohort includes all those born in a 5-year range.

Figure 3. Rolling excess return

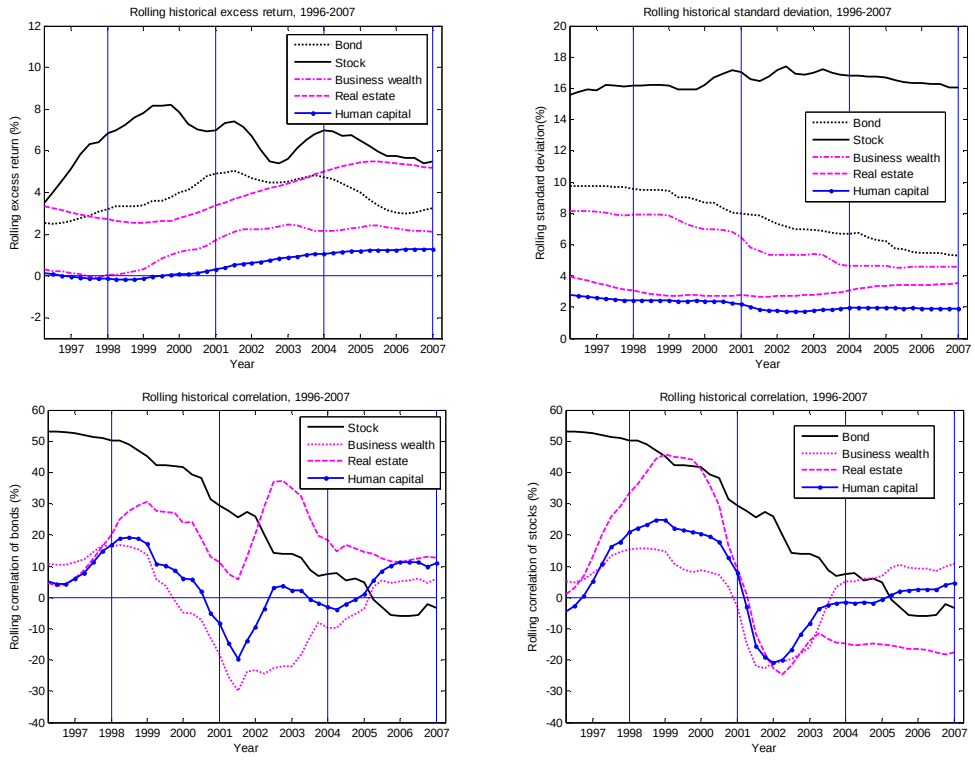
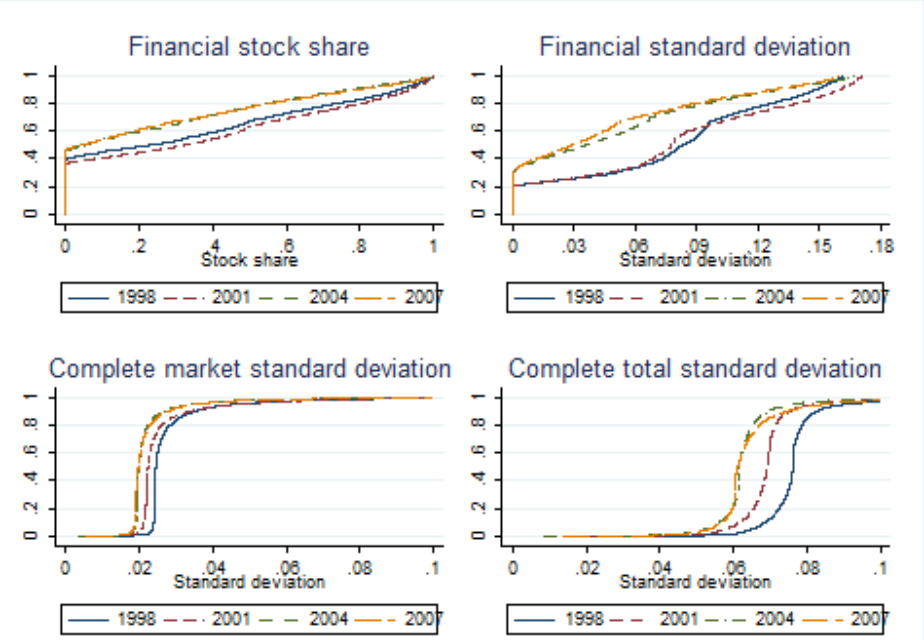


Figure 4. Empirical cdf of risk bearing

a. Financial and complete portfolios



b. Complete portfolio risk components

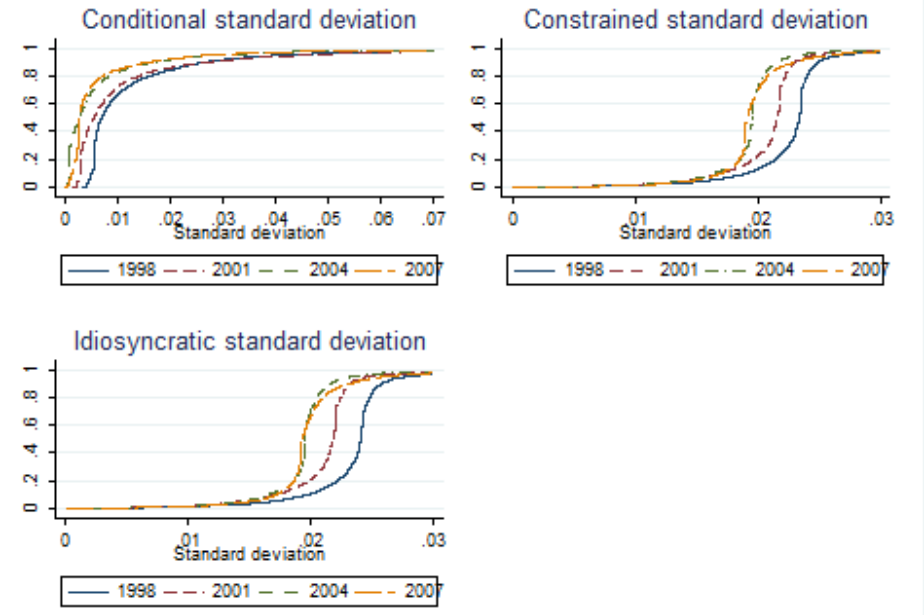


Figure 5. Correlations among risk bearing indicators

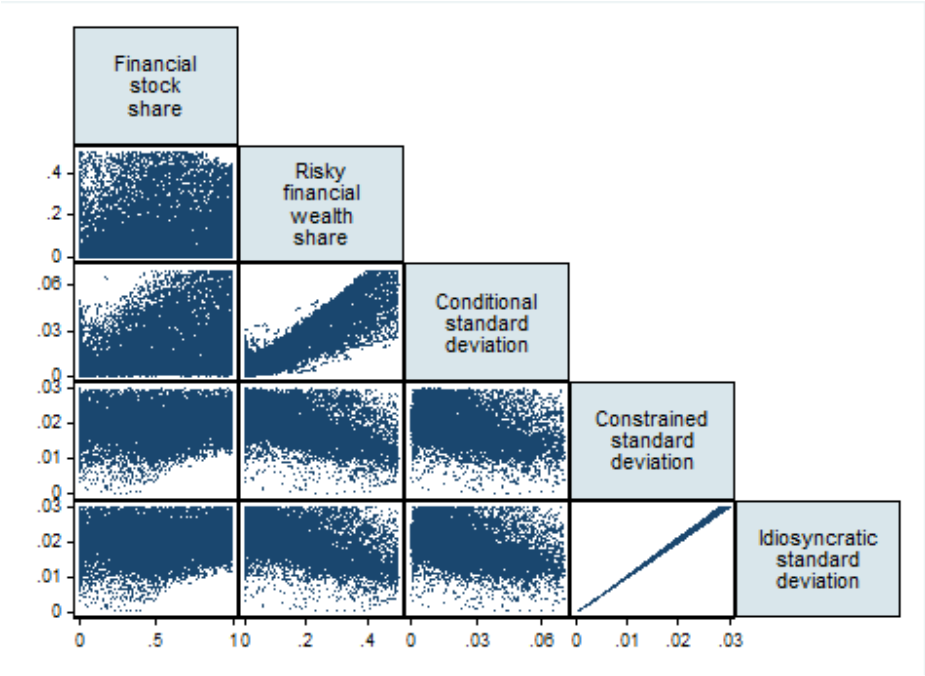
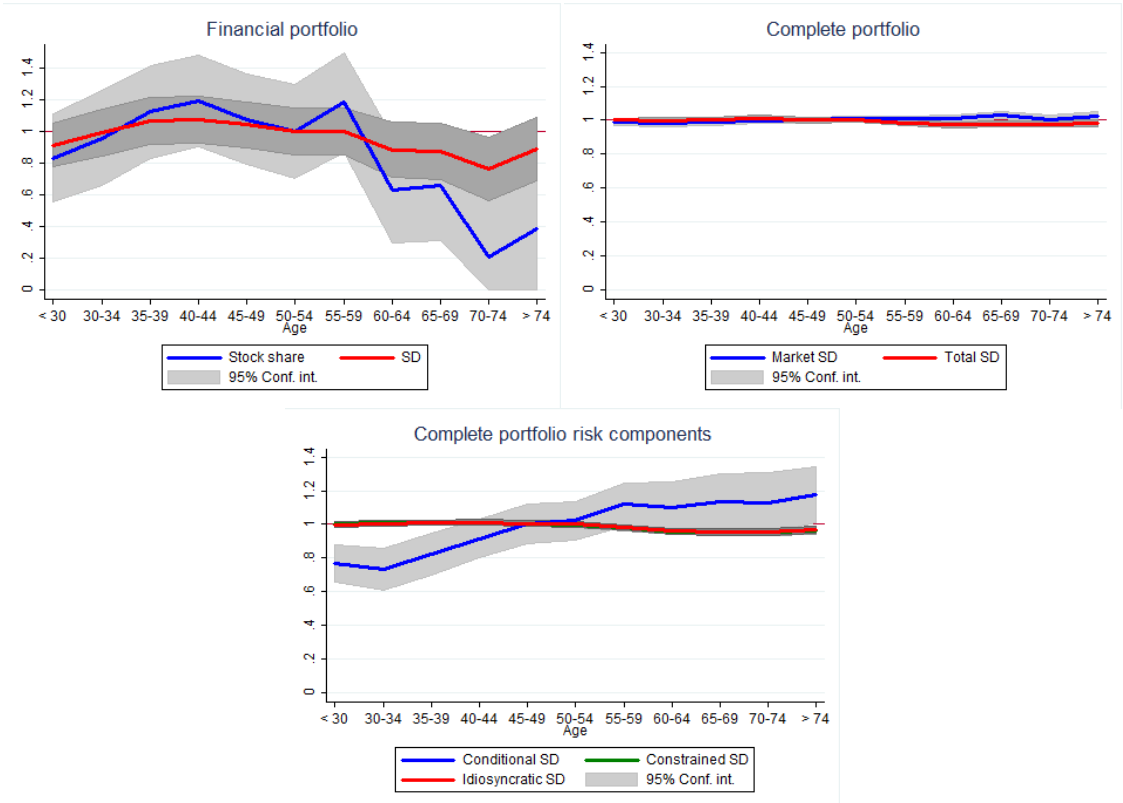


Figure 6. Age profile of risk bearing



Note. In each curve, the age profile is reported as a ratio to the median risk bearing indicator in the sample.