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Household Portfolio Risk

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HOUSEHOLD PORTFOLIO RISK

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Abstract

We exploit the US Survey of Consumer Finances from 1998 to 2010 to study households' portfolio risk. We compare alternative measures of ex-ante risk, based on a financial portfolio including deposits, bonds and stocks, or a broader portfolio also including real estate, business wealth and related debt. The measures provide different rankings of portfolio risk, but they all positively correlate with household wealth. Moreover, risk falls at the beginning of the sample period and rises at the end, together with the business cycle. Our findings are robust to different identification assumptions meant to disentangle the age, period and cohort effects.

JEL classification codes: D81, G11, D14.

Keywords: household finance, ex-ante portfolio risk, age-period-cohort effects, real estate, liquid wealth.

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1. Introduction

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. Particular attention is paid to the portfolio risk borne by the households. Finding regularities is interesting per se, but also useful from a policy perspective, 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 2010 to derive household portfolios, estimate various measures of ex-ante risk and study the distribution of portfolio risk in the population, and its correlation with observable household characteristics. Our measures of risk are the ex-ante standard deviation of the returns of different definitions of portfolio. A standard deviation is a weighted sum of asset share products, with weights given by the historical variance and covariance obtained from time series of past asset returns. This allows us to summarize in one single statistic the multidimensional nature of the portfolio composition, thus accounting for the different degree of risk the assets bring to household wealth. Our measures vary across observations for two main reasons: over time, for changes in the variance and covariance of asset returns; and in general, for changes in portfolio composition (i.e., the asset shares).

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 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 consider comprehensive measures of ex-ante risk. We indeed compare the standard deviation of the returns of the financial portfolio (including risk free deposits and risky bonds and stocks) with that of a complete portfolio including not only financial assets but also real estate, business wealth and related liabilities. The various measures we consider are based on a different set of assumptions and a different information set. 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 than in others (e.g., real estate for the youngest ones, business wealth for entrepreneurs).

A second departure of our analysis is that we make a distinction in two sources of complete portfolio risks: conditional and constrained risks. The distinction is due to the fact that non-financial assets (real estate, business wealth) are generally less liquid than financial ones, and can then be taken as exogenously given at least in short-run portfolio choice. For each risk component we then study its contribution to complete risk, and how it relates to observable household characteristics.

Finally, we make use of repeated cross sections of SCF data, which allows us to isolate the time trend of portfolio risk in a nationally representative and accurate dataset. This way we want to seek whether household portfolio risk is stable over the years, or rather it is exposed to the business cycle and the market conditions. During the years under our investigation, the US economy experienced periods of both expansion and recession. Specifically, the country had a prolonged period of economic growth until year 2000, interrupted by a bubble in the stock evaluation of the Internet companies (known as the “dot-com bubble”) and a mild recession until 2003, also fueled by the terroristic attacks in September 11 2001. The economy then recovered, but starting in September 2007 it underwent its most substantial downturn since the great depression, originated from the subprime mortgage crisis and the collapse of housing prices.

Our findings can be summarized as follows. 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 which assets to include in the risk measure matters. The indicators, however, agree in indicating that the distribution of risk is skewed to the left, and many households bear only limited risk. In addition, after accounting for the main observable household characteristics, all the measures increase with wealth. The estimation of age, period and cohort effect depends on the identification assumptions adopted, which are usually suggested by economic theory or empirical regularities. We instead try to exploit the information conveyed by the data. Repeated cross-sectional data sets allow to identify the second derivative of age, period and cohort effects without imposing any restriction (McKenzie, 2006). Our approach forces the regression parameters to satisfy the second-order period difference observed in the data. We find significant period effects: specifically we find that risk concerning the most liquid component of the portfolio fell at the beginning of the sample period and rose at the end, following the business cycle. These results are robust to changes in the identification assumptions, the regression specification, the sample composition and the calculation of the risk measures.

The remainder of this paper is organized as follows. Section 2 presents our risk indicators, while Section 3 describes our survey and time series data. The subsequent two sections show our main findings, on the distribution of the risk measures and the correlation among risk indicators (Section 4), and the correlation between risk, the main socio-demographic characteristics and the age, period and cohort effects (Section 5). Section 6 discusses some robustness checks. Finally, Section 7 concludes. Appendix A provides technical details on the link between portfolio shares and the risk components; Appendix B lists the full regression results for models with alternative identification assumptions of the age, period and cohort effects. A separate, Supplementary Appendix reports the output results for the robustness checks.

2. Measures of Portfolio Risk

We consider alternative indicators of risk, based on observations on household portfolio holdings at market value, and using different definitions of portfolio. Specifically, we consider a financial portfolio in Subsection 2.1 and a financial plus non-financial portfolio in Subsection 2.2; finally, in Subsection 2.3 we split the risk of this latter portfolio in two components, one drawn from liquid assets and one from illiquid assets. Investment in the two asset components is likely driven by different time horizon goals.

The indicators exploit information on household portfolio shares, market volatility and correlations between asset categories. For each indicator, a higher value means higher risk; different values arise when there are different market volatilities and correlations, or different portfolio shares (due to different allocation or different market prices). It is worth pointing out, however, that not necessarily the indicators provide the same ranking of portfolio risk, because they are derived from different information sets.

2.1. 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, $w_{it} = \begin{bmatrix} w_{it,1} & w_{it,2} & \dots & w_{it,m} \end{bmatrix}'$. In our application, $m = 2$ as we consider (corporate and government) bonds and stocks as two separate risky assets. We call this "financial portfolio". The literature on portfolio risk commonly uses the share of the financial portfolio held in stocks, $w_{it,2}$, as indicator. Although popular for its simplicity, this measure neglects that other assets contribute to household portfolio risk, different assets carry different levels of (possibly correlated) risk, and the amount of risk involved with an asset may be higher in some periods than in others.

Our first indicator computes 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 characteristics 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

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

This indicator, that we label *financial standard deviation*, provides a thorough assessment of the household financial portfolio risk. The measure, however, ignores that other non-financial assets – noticeably owner-occupied housing, which often accounts for a large amount of total wealth – also carry risky.

2.2. 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 benchmark application, $n = 4$ and we consider as risky assets not only bonds and stocks, but also business wealth, real estate, and related liabilities; for sake of simplicity we group liabilities in the bond category. 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, that we label *complete standard deviation*:

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

2.3. LIQUID AND ILLIQUID ASSETS

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 residential housing, and therefore constrained to satisfy consumption needs. Similar arguments can be made on the degree of liquidity in business wealth. In a short time horizon these assets may be seen as completely illiquid, which means that they cannot be traded and are taken as exogenous input in a portfolio choice problem (Flavin and Yamashita, 2002). In our framework, this implies that in a short-run perspective complete portfolio risk can be split in two components, where one cannot be modified and is therefore taken as given.

To this end, we distinguish the portfolio shares ω_{it} for household $i, i = 1, ..., N$ at time t in two components, $\omega_{it} = \begin{bmatrix} \omega_{it}^{f\prime} & \omega_{it}^{n\prime} \end{bmatrix}'$. Shares ω_{it}^{f} include all the holdings of financial (i.e., liquid) risky assets, whereas shares ω_{it}^{n} include all the holdings of non-financial (i.e., illiquid) risky assets. We partition the variance-covariance matrix Σ_t accordingly in four blocks:

$$\Sigma_t = \begin{bmatrix} \Sigma_t^{ff} & \Sigma_t^{fn} \\ \Sigma_t^{fn\prime} & \Sigma_t^{nn} \end{bmatrix} \tag{3}$$

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

It can be shown (for details see Gourieroux and Jouneau, 1999) that the complete portfolio variance is the sum of two components, where the second component measures risk involving only illiquid assets and cannot be modified in the short run:

$$\sigma_{it}^2 = \omega_{it}{}'\Sigma_t \omega_{it} = \omega_{it}^{f|n\prime}\Sigma_t^{ff}\omega_{it}^{f|n} + \omega_{it}^{n\prime}\overline{\Sigma}_t^{nn|f}\omega_{it}^{n} \tag{4}$$

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

Specifically, we look at the *conditional standard deviation*:

$$\sigma_{it}^{f|n} = \left(\omega_{it}^{f|n\prime}\Sigma_t^{ff}\omega_{it}^{f|n}\right)^{\frac{1}{2}}. \tag{5}$$

This measure differs from the measure in Equation (1) based on the financial portfolio for three reasons. First, financial asset shares are computed relative to financial plus non-financial wealth $\left(\omega_{it}^{f}\right)$, rather than just financial wealth $\left(w_{it}\right)$; 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 Equation (5).

We also look at the *constrained standard deviation*, which in contrast to the conditional standard deviation is considered fixed in the short run because households cannot easily modify it:

$$\sigma_{it}^{n|f} = \left(\omega_{it}^{n\prime}\Sigma_t^{nn|f}\omega_{it}^{n}\right)^{\frac{1}{2}}. \tag{6}$$

3. Data and Summary Statistics

Our analysis makes use of two sources of data: composition of household portfolios, and standard deviations and covariances of the market excess returns in the asset categories of bonds, stocks, business wealth and real estate. We describe these two sources of data, in Subsection 3.1 and in Subsection 3.2 respectively.

3.1. 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 a longitudinal dataset representative of the US population, meant to record the evolution of income over the years. The survey is complemented by a Wealth Supplement run every five years from 1984 to 1999, and every two years since 1999. The PSID 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 on the US population, but focuses on individuals 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 of Governors. 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 therefore 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. We develop our analysis on the average of these imputations.

Our data on household portfolio holdings are taken from the five waves from 1998 to 2010 of the SCF. Our final sample consists of 18,372 households with head aged between 25 and 80 and for whom we have full information on the main demographic characteristics (e.g., age, race, education) and portfolio composition, and with financial wealth not below one thousand USD. 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 business wealth, real estate, and related liabilities; we include liabilities in the bond category, while the other two assets form new categories. Composite assets are allocated in the asset categories according to their composition declared in the survey.

Panel c) of Table I reports the asset composition of the aggregate complete portfolio separately by wave, computed accounting for sampling weights. For composite assets we know how they are invested; we allocate them accordingly.[1] The financial portfolio includes all the assets in the deposits, bonds, and stocks categories of the complete portfolio, excluding loans. Over the period we analyze, the size of household financial wealth (converted in 2010 USD using the Consumer Price Index for all urban consumers, computed from the Federal Reserve Bank of St. Louis) showed no clear trend (see panel a) of Table I), with the median peaking in 2001 and 2007 (45,151 and 42,263 USD, respectively) but the average growing also in 2010 – suggesting an increased inequality in the distribution of wealth. In contrast, complete wealth kept growing up to 2007, with both the median and average indicators reaching the largest values in the sample period (190,319 and 672,392 USD, respectively). Wealth was fueled by a rising stock market between 1998 and 2001, and by rising house price markets between 2004 and 2007; both markets fell abruptly between 2007 and 2010.

TABLE I ABOUT HERE

[1] 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 composite assets 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 is consistent with the trend observed in other assets whose definition has remained constant across the waves (e.g., saving and money market accounts, directly held stocks, etc.). Only for "balanced" and "other" mutual funds we do not know their composition, and we arbitrarily choose to equally split them in the "bonds" and "stocks" categories. This assumption, however, is not crucial because holdings of the two assets are uncommon and, when present, generally weight little in the household portfolios.

In general, holdings are widespread for each asset category apart from business wealth, which regards only 13-15 percent of the sample (see panel b) of Table I). We observe a progressive reduction in the holders of bonds and stocks, that in 2010 were respectively 65 and 53 percent as opposed to 73 and 61 percent as of 1998.

The size and time trend of the aggregate asset categories is in line with official SCF statistics (see, e.g., Bricker et al., 2012). The largest share of aggregate wealth is held in real estate (between 43 and 52 percent; see panel c) of Table I), 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 also see that most financial wealth is held in stocks[2], while the investment in bonds is more limited. Investment in business wealth, although concentrated in few households, is large in aggregate.

Over time our data show a general decrease in the holdings of stocks in favor of deposits and real estate. Changes in portfolio shares are affected by household decisions (whether and how much trade) and the different realizations of the asset prices. The table accounts for three phases:

- *The stock market boom*, including waves 1998 and 2001. This period is characterized by relatively high stock shares.
- *The housing market boom*, including waves 2004 and 2007. This period is characterized by low stock shares and high deposit and real estate shares. Changes in the shares are

[2] For instance, the share of stocks in the aggregate financial portfolio of 2010 is roughly 19.474/(16.894+9.013+19.474) =42.91 percent, where 9.013 percent is the share of (directly and indirectly) owned bonds, excluding loans.

mostly due to exit from the stock market and entry in the housing market, often financed through debt.

- *The downturn*, including wave 2010. This period is characterized by a reduction in the real estate share, and an increase in the share of deposits. This period also features a generalized reduction of wealth.

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 3 birth years. Our sample contains 23 such cohorts, born between 1918 and 1985. We start with the cohort-specific age profile of wealth. We compute the average wealth holdings for each cohort and for each wave 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. In the figure, lines placed more toward the left describe younger cohorts than lines toward the right. The figure shows for both financial and complete wealth the typical inverted U-shape profile, with remarkable cohort and time effects, and younger cohorts systematically richer than older ones.

FIGURE 1 ABOUT HERE

We then turn our attention to the single asset holdings. Figure 2 reports the age profile of the average asset shares, computed as in Figure 1 for our financial and complete definitions of portfolio. Financial portfolio shares look roughly constant over a large portion of life. This evidence is in contrast with some common rules of thumb suggested 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).

Only complete portfolio shares seem to vary markedly over the life-cycle, possibly because of the timing of housing investment. With volatile house prices, the insurance motive makes young households purchase their house early in life (Sinai and Souleles, 2005; Banks et al., 2010a). In order to increase their housing consumption they resort to debt.[3] From the comparison across cohorts for a given age, it emerges that younger cohorts have smaller positions in bonds, and larger positions in real estate – especially between the ages of 30 and 40. 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

3.2. ASSET TIME SERIES

Historical information on asset market returns is essential to estimate our ex-ante risk measures. We take annual bond returns from the "Merrill Lynch US Corporate & Government Master Index" (downloaded from Datastream) and annual stock returns from prices and dividends of the S&P 500 index (downloaded from Robert Shiller's website[4]). We con-

[3] In our sample the percentage of households with a mortgage peaks at age 42 (58.84%).

[4] www.econ.yale.edu/~shiller/data/

sider as risk free annual return for deposits the yield of 3-month T-bills (source: Federal Reserve Bank of St. Louis). Annual returns for business wealth are derived in such a way to measure both earnings and capital gains, according to the formula

$$r_t^{BW} = \frac{P_t - P_{t-1} + E_t}{P_{t-1}} = \frac{E_t}{E_{t-1}} \frac{1}{PE_{t-1}} \left(1 + PE_t\right) - 1. \tag{7}$$

Earnings E_t are taken from the time series on proprietor's income of the National Income and Product Accounts (NIPA) table computed by the Bureau of Economic Analysis (BEA), while the price-earnings ratio PE_t is constructed as the average annual price over the average annual earnings from data on the S&P 500 index; see Shiller (2005) for details on these data.

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 all-transaction index calculated for the whole of the US from the Federal Housing Finance Agency (FHFA). We add to returns from this index an estimate of imputed rents-price ratios for the US market calculated in Davis et al. (2008). The rent-price ratio decreased between 1979 and the first quarter of 2006 from 4.85% to 3.49%, and started rising again in the following years, reaching a level of 4.55% at the end of 2010. The average ratio in our sample period is 4.69%, 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 2010 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 *t* we assume that moments arise from excess returns observed between year *t-19* and year *t*. As a result, households interviewed in different years face different risks on the returns to their assets.

Figure 3 plots the rolling moments of excess returns estimated this way. From panel a) of the figure we see that – unsurprisingly – business wealth features the highest excess returns and the highest standard deviation. Excess returns on stocks, bonds and business wealth rose largely in the first years of the sample up to year 2000, and showed large fluctuations afterwards, with phases of prolonged falls and rises. By the end of 2001 the stock market index was close to its 1998 levels. It subsequently recovered, but between September 2007 and March 2009 it had a further major fall, partly reflected in our rolling excess returns. The index recouped about one half of the losses in the remaining period of our sample. After peaking in 2002, returns in business wealth progressively fell up to 2007. They then started rising again, although with larger volatility since 2009. In contrast, excess returns on real estate kept growing from 1999 to 2006, showing a decline since 2007. 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, representing years 1998 and 2001 respectively. 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 house prices over this period. Standard deviations are more stable over time but, nevertheless, bond risk witnesses a remarkable reduction since year 2000, while stock risk and especially business risk are much higher in the latest part of our sample – the one characterized by the economic crisis.

In order to assess the riskiness of household portfolios we also need to evaluate the pairwise correlations of excess returns. Panel b) of Figure 3 shows the rolling estimates of the correlation between bonds and the other excess returns (left), and between stocks and the other excess returns (right). The panel suggests 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 around 50% to near 0, 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

4. Distribution of Portfolio Risk

Column 1 of Table II reports the average levels of the four risk indicators. On average, the standard deviation of the household financial portfolio in the 1998 - 2010 period is estimated to be 5.19%, a value well below the corresponding indicator for the stock market and comparable to the volatility of bonds (see Figure 3). The average standard deviation for the complete portfolios is 6.43%, almost 25% higher than the indicator for the pure financial portfolio. This result reveals that, on average, the risk borne by the households is higher when we consider also the illiquid assets and their related liabilities. The decomposition of the complete standard deviation shows that on average the constrained component is the least risky (3.53% as opposed to 4.51 of the conditional standard deviation).

It is interesting to study the distribution of the risk indicators conditional on the answers to one SCF question on self-assessed risk aversion. The question 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 four answers:

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

In the sample households more frequently report the more risk averse options, 3 and 4 (respectively in 41.16 and 36.16 percent of the cases). Given the small response rate of the first two answers (especially the first one), we group together answers 1 and 2. Table II shows average statistics of our risk indicators, separately for groups of households divided by their response to the self-assessed risk aversion question. A priori one should expect our risk indicators to decrease with self-assessed risk aversion. From the table it emerges that our hypothesis is indeed confirmed, which suggests that households hold portfolios consistent with their personal taste of risk.

TABLE II ABOUT HERE

Table III reports the average levels of risk we derive from the household portfolios in each SCF wave. All the measures, apart from the constrained one, agree in indicating higher risk in the years 1998 and 2001 rather than in the following years, in correspondence to high stock shares, high volatility of bonds and high correlation between bonds and stocks. All the indicators but the financial one also show an increase in risk between 2007 and 2010, reflecting higher risk in real estate and business wealth. The latest period in the sample also testifies higher risk in stocks, which is however mitigated in the financial measure by the reduction in the frequency of holders and the size of the stock share.

TABLE III ABOUT HERE

All in all, the trend we observe is coherent with the distinction in three phases we introduced in Subsection 3.1: the *stock market boom* between 1998 and 2001, with high values of all the indicators; the *housing market boom* between 2004 and 2007, with high values of the constrained indicator; and finally the *downturn* in 2010, with a rise in all the indicators involving non-financial assets.

However, the time variations we observe might be due to not only different asset risks over time, but also different portfolio shares. The shares we observe might originate from investors' decisions to trade assets (active portfolio management) or initial asset allocations modified by changes in the asset market value (passive portfolio management). There is discussion in the literature on the fact that investors do not frequently adjust their portfolios (Agnew et al., 2003; Brunnermeier and Nagel, 2008; Calvet et al., 2009). The portfolio shares we observe might therefore reflect slow portfolio rebalancing, and their variations might depend on different market values of the assets. To gain insight about the role played by portfolio rebalancing we perform a counterfactual exercise using the aggregate portfolio shares observed in 1998 (see panel c) of Table I). We let them vary over the years, according to the market realizations but without reallocation. Panel a) of Table IV suggests that passive portfolio management does not predict accurately the same shares as observed in aggregate: in particular, compared to the reality, the counterfactual shares do not fall in real estate in 2010, fall in stocks in 2001 rather than in 2004, and in general are less stable on business wealth. As a consequence, the time trend of the risk indicators built from these counterfactual portfolios is also rather different from the one based on the observed aggregate portfolio. Overall, it seems that market realizations are less determinant than active portfolio management in shaping the risk of household portfolios.

TABLE IV ABOUT HERE

We then turn our attention to the empirical distribution of the risk indicators. 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 bear portfolio risk. This is particularly evident for the financial standard deviation, that is equal to zero for a fraction of households between 20 and 40 percent in a given year. The constrained standard deviation is also set to zero for about 20 percent of the sample. In the other cases, the risk measure is usually larger than zero because households hold at least risk free deposits and another risky asset. Notice that the cdfs referring to the waves 1998 and 2001 are typically drawn below the cdfs for the other waves, which means that over those years the distributions are shifted toward higher levels of risk. This difference over the years is consistent with the findings discussed above regarding Table III, namely, that households progressively shifted their portfolios toward safer assets. The only exception to this pattern regards the constrained standard deviation, whose cdf is instead rather stable over the years.

FIGURE 4 ABOUT HERE

The indicators then show a similar time trend and wide heterogeneity of portfolio risk. However, they may provide different results at the single household level. Figure 5 reports the scatter plots for each pair of indicators. In addition we report the financial portfolio share held in stocks, a measure of portfolio risk commonly used in the literature. The correlation is very high (0.94 taken as the average correlation over the five waves) between the two indicators based on the financial portfolio (stock share and standard deviation), and smaller (0.37) between the indicators based on the financial and complete portfolio definitions. The complete portfolio standard deviation has a 0.84 correlation with the conditional standard deviation and smaller, though still high correlation (0.78) with the constrained standard deviation. Overall, the correlations suggest 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.

FIGURE 5 ABOUT HERE

5. Portfolio Risk and Observable Household Characteristics

In this section we investigate the correlations between our measures of risk and observable household characteristics. A well known problem with this type of data is the identification of the age, period and cohort effects, which we discuss in Subsection 5.1. Subsection 5.2 comments on our estimates.

5.1. THE ECONOMETRIC PROBLEM

Consider a time series of independent cross-sectional surveys. This data structure allows us to observe the variable $Y_{i,p}$ for household $i=1,\ldots,N_p$ in period $p = 1, \ldots, P$, together with the age of its reference person ($age_{i,p}$), its cohort of birth ($cohort_{i,p}$) and other characteristics ($X_{i,p}$)[5].

More precisely, we consider the specification

$$Y_{i,p} = \mu + \sum_{a=1}^{A} \alpha_a A_{i,p}^a + \sum_{p=1}^{P} \pi_p D_{i,p}^p + \sum_{c=1}^{C} \gamma_c C_{i,p}^c + X_{i,p}' \delta + \varepsilon_{i,p} \qquad (8)$$

where $A_{i,p}^a = \mathbf{1}\left(age_{i,p} = a\right)$ and $C_{i,p}^c = \mathbf{1}\left(cohort_{i,p} = c\right)$ are dummy variables which take the value one respectively if the age of household i interviewed in period p is equal to a, and its cohort is c; $D_{i,p}^p$ is a dummy variable equal to 1 for those households surveyed in period p. Unique identification of the parameters of Equation (8) is not possible because there is a perfect linear relationship between age, period and cohort: $p = cohort_{i,p} + age_{i,p}$. To make estimation feasible, researchers usually impose arbitrary parameter restrictions based on economic arguments. For instance, Deaton and Paxson (1994) impose that the coefficients of the period effects are orthogonal to a linear trend, assuming that the time effect is made of a linear component and a transitory shock. However constraints like this may be dangerous, especially when few periods are available (Deaton, 1997 p.126), because they may

[5] Not necessarily there must be one year gap between two consecutive ages or periods. In particular in the SCF, three years elapse between one period and the other.

force the data to follow a specific pattern. In fact, estimates may vary largely depending on the specific restriction considered (see, e.g., Ameriks and Zeldes, 2004).

Although in general a unique solution does not exist, second-order age, period and cohort differences can be exactly identified without imposing further constraints to the parameters (McKenzie, 2006). The model in Equation (8) can be linearly aggregated by age and period, giving

$$Y_{a,p} = \mu + \sum_{a=1}^{A} \alpha_a A_a + \sum_{p=1}^{P} \pi_p D_p + \sum_{c=1}^{C} \gamma_c C_{a,p}^{c} + X'_{a,p}\delta + \varepsilon_{a,p} \tag{9}$$

where $Y_{a,p}$ is the mean of $Y_{i,p}$ for those households aged a interviewed in period p, $X_{a,p}$ and $\varepsilon_{a,p}$ are similar means, D_p and A_a are period and age dummies, while the cohort dummies are defined as $C_{a,p}^{c} = \mathbf{1}(c = p - a)$. At time p the difference between households aged a and those aged $a-1$ is given by:

$$\Delta_a Y_{a,p} = Y_{a,p} - Y_{a-1,p} = (\alpha_a - \alpha_{a-1}) + (\gamma_c - \gamma_{c+1}) + (X_{a,p} - X_{a-1,p})' \beta + (\varepsilon_{a,p} - \varepsilon_{a-1,p}). \tag{10}$$

The first-order difference depends on age (α) and cohort (γ) effect parameters, but not on period effect parameters (π). For the same cohorts, we can compute the same difference in the previous period, when they were one year younger:

$$\begin{aligned} \Delta_a Y_{a-1,p-1} = Y_{a-1,p-1} - Y_{a-2,p-1} &= (\alpha_{a-1} - \alpha_{a-2}) + (\gamma_c - \gamma_{c+1}) \\ &+ (X_{a-1,p-1} - X_{a-2,p-1})' \beta + (\varepsilon_{a-1,p-1} - \varepsilon_{a-2,p-1}). \end{aligned} \tag{11}$$

Similarly to above, the π coefficients are irrelevant. Furthermore, the cohort effect parameters (γ) enter the equation in the same way in the two differences. Therefore, the second-order difference will depend solely on the age effect parameters α:

$$\begin{aligned}\Delta_a^2 Y = \Delta_a Y_{a,p} - \Delta_{a-1} Y_{a-1,p-1} &= \left(\alpha_a - \alpha_{a-1}\right) - \left(\alpha_{a-1} - \alpha_{a-2}\right) \\ &+ \left[\left(X_{a,p} - X_{a-1,p}\right) - \left(X_{a-1,p-1} - X_{a-2,p-1}\right)\right]' \beta \\ &+ \left(\varepsilon_{a,p} - \varepsilon_{a-1,p}\right) - \left(\varepsilon_{a-1,p-1} - \varepsilon_{a-2,p-1}\right).\end{aligned} \tag{12}$$

This result states that, even though the α parameters cannot be identified, the second differences with respect to age are identified. That is, even though neither the age effect α_a nor the age marginal effect $\alpha_a - \alpha_{a-1}$ is identifiable, we can estimate how the effect of age on Y changes over age. In a similar fashion we can compute second-order differences and identify second differences with respect to periods and cohorts. This is useful because second differences inform on structural breaks and the concavity of the age, period and cohort effects. In our analysis we look at their characteristics to gain confidence on our results. We estimate the second differences of the age, period and cohort effects controlling for the set of covariates X that will be discussed in Subsection 5.2. Including the covariates allows us to account for composition effects of the dataset.

Figure 6 shows the estimated second differences of the age, period and cohort effects resulting from our data for each risk indicator; estimates are reported together with a 95% bootstrap confidence interval.[6] Neither the second differences of age effects, $\left(\alpha_a - \alpha_{a-1}\right) - \left(\alpha_{a-1} - \alpha_{a-2}\right)$, nor the second differences of cohort effects, $\left(\gamma_c - \gamma_{c-1}\right) - \left(\gamma_{c-1} - \gamma_{c-2}\right)$, are significantly different from zero at any age and date of birth for any of the indicators. The same conclusion does not hold for the second differences of the period effects, $\left(\pi_p - \pi_{p-1}\right) - \left(\pi_{p-1} - \pi_{p-2}\right)$: these are estimated to be negative in 2004 and positive in 2007 and 2010 for the standard deviation of the financial portfolio, σ_{it}^f, the stan-

[6] We bootstrap 100 times the second differences of the age, period and cohort effects.

dard deviation of the complete portfolio, σ_{it}^{c}, and the conditional standard deviation $\sigma_{it}^{f|n}$. For the constrained component $\bar{\sigma}_{it}^{n|f}$ the second difference is estimated to be positive in 2004, insignificantly different from zero in 2007, and positive again in 2010.

FIGURE 6 ABOUT HERE

The results for all the risk indicators are consistent with the presence of approximately linear profiles in age and cohort, and a non-linear profile in time. This suggests us an approach in which we estimate Equation (8) imposing no restriction on the age and cohort profiles, but restricting the period effects to be coherent with the estimated second period differences.

Assume the second differences with respect to time are known:

$$\Delta^2\pi_p = \pi_p - 2\pi_{p-1} + \pi_{p-2}. \tag{13}$$

The period effects can therefore be written as $\pi_p = \Delta^2\pi_p + 2\pi_{p-1} - \pi_{p-2}$ and, by repeated substitutions,

$$\pi_p = \sum\nolimits_{j=1}^{p-2} j\Delta^2\pi_{p+1-j} + (p-1)\pi_2 - (p-2)\pi_1. \tag{14}$$

If we impose the standard restrictions $\alpha_1 = \pi_1 = \gamma_1 = 0$ (that is, we drop one dummy variable for each type) and substitute Equation (14) in the regression Equation (8) we have

$$Y_{i,p} - \tilde{\Delta}^2\pi_{i,p} = \mu + \sum\nolimits_{a=2}^{A}\alpha_a A_{i,p}^{a} + \sum\nolimits_{c=2}^{C}\gamma_c C_{i,p}^{c} + \pi_2 p + X_{i,p}'\delta + \varepsilon_{i,p} \tag{15}$$

with

$$\tilde{\Delta}^2\pi_{i,p} = \sum\nolimits_{j=3}^{P}\left(\sum\nolimits_{k=3}^{j}(j+1-k)\Delta^2\pi_k\right)D_{ip}^{j}. \tag{16}$$

As the linear trend *p* is a linear combination of age and cohort dummies, we need to impose at least one further restriction in order to be able to identify all the parameters in Equation (15), because:

$$\begin{aligned} Y_{i,p}-\tilde{\Delta}^2\pi_{i,p} &= \mu+\sum\nolimits_{a=2}^{A}\alpha_a A_{i,p}^a+\sum\nolimits_{c=2}^{C}\gamma_c C_{i,p}^c \\ &\quad +\pi_2\left(\sum\nolimits_{a=1}^{A} aA_{i,p}^a+\sum\nolimits_{c=1}^{C} cC_{i,p}^c\right)+X_{i,p}'\delta+\varepsilon_{i,p} \\ &=\left(\mu+2\pi_2\right)+\sum\nolimits_{a=2}^{A}\left(\alpha_a+\pi_2\left(a-1\right)\right)A_{i,p}^a \\ &\quad +\sum\nolimits_{c=2}^{C}\left(\gamma_c+\pi_2\left(c-1\right)\right)C_{i,p}^c+X_{i,p}'\delta+\varepsilon_{i,p} \end{aligned} \tag{17}$$

A natural restriction to impose is that two adjacent cohorts are characterized by the same effect. If $\gamma_1=\gamma_2=0$, then the time effect π_2 is univocally associated with the cohort dummy $C_{i,p}^2$, and the values of the remaining time effects, π_p, can be retrieved using the rule in Equation (14). In practice $\tilde{\Delta}^2\pi_{i,p}$ is not directly observable; in our empirical exercise we replace it with the estimated values depicted in Figure 6 and estimate Equation (15) by OLS after imposing $\gamma_2=0$.

5.2. ESTIMATES

In the following we estimate four constrained regression equations, one for each risk indicator, using a "data-driven" approach where the second difference of the period effect is constrained to be equal to the value we observe in the data.[7] The specification includes, in addition to dummy variables for the age, period and cohort effects (in groups of three years), explanatory variables on wealth, socio-demographics, and financial sophistication. As wealth variable we consider the logarithm of complete wealth from financial, business and real assets. In the set of demographic variables we treat variables for race, gender, edu-

[7] We have three such constraints, for the second difference at years 2004, 2007 and 2010.

cation, marital status, number of household members, children (yes or no), and occupational status of the household head. Following Rosen and Wu (2004), we also include one dummy variable for the self-perceived good or excellent health status of the head. In the same vein as Bucciol and Miniaci (2011), 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 household head works in the finance sector.

Table V shows the estimated coefficients on the control variables, separately for each of the indicators rescaled by their average in the sample (to have comparable estimates). We first focus on the measure based on the financial portfolio definition (Column 1). This measure correlates positively with wealth, college education, self-assessed good health status, and the variables on financial sophistication; it correlates negatively with the dummy variables for non-white, female, married and self-employed individuals. All the above-mentioned coefficients are significant at least at a 5 percent level. Our results support previous literature on portfolio risk, finding similar correlations with wealth (e.g., Siegel and Hoban, 1982; Morin and Fernandez Suarez, 1983), education and gender (Halek and Eisenhauer, 2001), and financial sophistication (Bucciol and Miniaci, 2011).

Fewer variables remain significant at 5% in the regression taking the complete standard deviation as dependent variable (Column 2): wealth, self-employment, good health (with positive correlation) and non-white race (with negative correlation). The direction of the correlation is the same as in Column (1), with the exception of self-employment status. According to Column (2), self-employed workers hold riskier complete portfolios. We believe this case is paradigmatic. Self-employed individuals hold most of their wealth in a business. Ignoring this, and focusing on just their financial portfolio – as in Column (1) of the table – would suggest that they face less risk than employees. Actually, they choose their financial portfolio conditional on the business risk they already bear. 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 with, for instance, Heaton and Lucas (2000).

We then focus on the complete portfolio risk components. Looking at conditional standard deviation (Column 3), all the significant effects found for the measures based on the complete portfolios are confirmed. In addition, there is a significantly positive effect of college education, having children and working in the financial sector, and a significantly negative effect of being female, married and retired. Most of these variables were significant, and with the same sign of the coefficient, also in Column (1) for the financial standard deviation. In addition, the sign of the self-employment variable again becomes negative as in Column (1). With the constrained standard deviation (Column 4) some of the effects change sign or become non-significant, while new significant effects are found. Overall fewer coefficients are significant: wealth, marital status and family composition, self-employment status (positive) and college education (negative). In particular notice the negative coefficient on college education that, combined with the positive coefficient in Column (3), determines an overall insignificant coefficient when taking the complete measure in Column (2). The inconsistency of the findings when focusing separately on the two components of complete standard deviation is not surprising: recall indeed from Figure 5 the relatively low correlation between the different indicators. As regards the coefficients changing sign, it can be shown that an increase in the financial share negatively affects the constrained standard deviations, and is likely to positively affect the conditional standard deviation. In Appendix A 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 positively affect the conditional standard deviation, but may negatively affect the constrained standard deviation. Our finding on education simply states that college graduates hold more of their wealth in financial assets.

TABLE V ABOUT HERE

The four regression models include age, period and cohort dummy variables. In Figure 7 we depict the estimated age, period and cohort profiles, relative to the baseline category. As explained in Subsection 5.1, different profiles may result from different choices of the specification of the age, period and cohort effects. For this reason, for each profile of each measure we report four alternative lines (together with a 95% confidence interval), each derived from an alternative specification of the regression model. All the models share the same control variables, but treat different functions of the age, period and cohort effects. Our benchmark is the model including age, period and cohort dummies discussed above, with constraints on the second-order differences of the period coefficients; we call it *data-driven* and label it DD in the figure. We compare it with three alternative models popular in the literature:

- *Deaton-Paxson (DP)*: the specification includes age and cohort dummies, plus three variables derived from imposing orthogonality between time dummies and a linear time trend. This constraint was first used in Deaton and Paxson (2004).
- *Market History (MH)*: the specification includes age and cohort dummies, plus two variables on the historical returns and standard deviation of the stock market in the three

years before data collection. This model mimics one used in Ameriks and Zeldes (2004).

- *Cohort History (CH)*: the specification includes age and period dummies, plus two variables on the historical return and standard deviation of the stock market when the individual was aged between 20 and 24. This model replicates one used in Malmendier and Nagel (2011).

Estimates of the coefficients of the explanatory variables in these three models are reported in Appendix B, and they show no relevant differences with respect to Table V. Figure 7 allows us to assess to what extent the estimation of the cohort and age effects depends on the identification assumptions. The profiles of the DP and MH approaches are almost identical for the risk indicator of the financial portfolio and statistically indistinguishable for the conditional and constrained standard deviations. Imposing the DD constraints on the same indicators delivers age and cohort profiles with opposite slopes. According to the CH approach both the effects are barely significant. The only case in which the four sets of constraints give comparable profiles is for the standard deviation of the complete portfolio. All the estimated age and cohort profiles are well approximated by linear functions, consistently with the evidence provided on the second differences in Figure 6.

We then turn to the estimate of the period effect. Regardless of the approach, financial, complete and conditional standard deviations fall abruptly in 2004. The methods also agree on the recovering of this fall in 2010 for the complete risk, but not for the financial and conditional indicators (with concordance between DP and MH as well as between CH and DD). Lower levels of risk in 2004 and 2007 are predicted by the DP and MH also for the risk of the constrained component of the complete portfolio, while the profile is steadily increasing for CH and DD. The DD estimates are obtained imposing only constraints drawn from the data on the concavity of the time profile; we therefore consider the time profiles estimated with this approach the most reliable.

FIGURE 7 ABOUT HERE

6. Robustness Checks

Our findings lie on assumptions on the construction of the portfolio shares and the variances and covariances of asset returns. To assess the importance of these assumptions, in this section we describe the robustness checks we performed along various dimensions. Specifically, we enrich the definition of the complete portfolio by including human capital (Subsection 6.1), we change the asset variances and covariances moments (Subsection 6.2), and the sample composition (Subsection 6.3). 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.

6.1. HUMAN CAPITAL

We first expand the definition of complete portfolio by incorporating human capital as further illiquid asset. We take for human capital a discounted projection of the current and future realizations of gross income, for the head and the spouse (if any). The stock of human capital is estimated conditional on age, gender, race and education of the household head using an approach similar to Jorgenson and Fraumeni (1989). Annual returns on human capital are derived from Equation (7) as for business wealth, in such a way to incorporate returns from both capital and earnings.

Our approach associates a positive stock of human capital to each household; this larger portfolio is highly concentrated in the human capital share, which on average accounts for about 80% of the complete portfolio, roughly in line with estimates in Jorgenson and Fraumeni (1989) and simulation studies in Cocco (2005). Human capital shows a clear life-cycle pattern, with its share equal to around 100% in young individuals (who have relatively little wealth and expect to receive income flows over many years) and then progressively declining with age. This might affect our estimated age profile. The risk we associate to human capital is relatively low, which makes the asset close to a risk free asset (as in the prevailing literature: for instance see Heaton and Lucas, 2000; Viceira, 2001).

Our benchmark findings are largely confirmed; in addition we find all the measures of portfolio risk to positively correlate with working in the financial sector, and with good health status. Not surprisingly, the estimated age and cohort profiles of the conditional and constrained standard deviation differ from the benchmark case (the profiles follow a linearly increasing pattern for the conditional standard deviation, and an almost linearly decreasing pattern for the constrained standard deviation). Nevertheless, our finding on the period effects obtained with the DD approach are confirmed for all the risk indicators.

6.2. ASSET VARIANCES AND COVARIANCES

6.2.1. No Hedging

There is no consensus in the literature on the size and direction 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 for real estate see Flavin and Yamashita, 2002), 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). The covariance between bond and stock returns remains unchanged and coincides with the one in the benchmark analysis.

In this case our benchmark results are virtually unchanged, indicating that the covariances between financial and non-financial assets are not fundamental drivers of our results.

6.2.2. Fixed Moments

The variations we observe in the risk indicators 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.

The analysis based on the risk indicators estimated this way basically provides the same results as in the benchmark case. In fact, also in this case we cannot reject the hypothesis that the fall of the standard deviation of the complete portfolio in 2004 is completely recovered by 2010. Nevertheless, the change of the cohort profile estimated with the DD approach is significant, with younger cohorts bearing relatively more risk than in the benchmark case. This suggests that changing over time the risk properties of the assets is not a key driver of our results for what concerns the period effects, but it may affect our conclusions on cohort effects.

6.2.3. Alternative Moment Estimates

In our benchmark 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 therefore give rise to different results. As a robustness check we derive new estimates in which the moments of the asset returns are obtained from a time series of 15 years instead of 20 years; similar conclusions arise using a 10-year window.

Although this exercise replaces the whole set of asset risk properties with a new one, our main conclusions are largely confirmed for what concerns the period effects. In contrast to the benchmark case, in this setting with the DP and MH approaches we estimate an increasing cohort profile of the complete standard deviation indicator, while the CH and DD profiles are flat. Furthermore, for the constrained standard deviation the DD age and cohort profiles are now consistent with the DP and MH ones.

6.2.4. Idiosyncratic Risk

Households face both market and idiosyncratic risk. One may assume that idiosyncratic risk can be 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 should be augmented to include a component reflecting the idiosyncratic risk of these assets, which is uncorrelated with the other sources of risk.

Properly measuring idiosyncratic risk would require time series of the asset returns on firm sectors and regional real estate. 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. We proxy for idiosyncratic risk by inflating the variance of the non-financial assets of a fixed proportion factor $\theta = 9$. In our intention, this choice should represent an upper bound for idiosyncratic variance following the existing literature (e.g., Meghir and Pistaferri, 2004; Cocco et al., 2005). However, choosing a different constant value of θ, or a value differentiated by asset category, would not alter our conclusions.

Not surprisingly given the way it is derived, the idiosyncratic risk indicator behaves similarly to the constrained risk indicator. Overall the total standard deviation, which is made of the conditional, constrained and idiosyncratic components, depends more largely on the non-financial asset components. In fact, in this case regression results and age, period and cohort profiles replicate more closely those of the constrained and idiosyncratic measures.

6.3. SAMPLE COMPOSITION

6.3.1. Only Investors in Risky Assets

A large fraction of households (28.10% of the sample) hold neither bonds nor stocks. These households are more frequently headed by a female, non-white and non-college graduate individual than in the rest of the sample; they are also generally poorer and less likely to make use of financial advisors. In this exercise we exclude them from the analysis, as they might be intrinsically different from those who choose to make an even small investment in risky assets.

Our benchmark results are largely confirmed. In particular the period effects do not vary, and the linearity of the age and cohort effects is preserved. In this case we only find that age and cohort profiles of the DD estimator for the complete risk indicator change their slopes and that in the constrained standard deviation the DD profiles become very similar to the CH ones.

6.3.2. 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 side costs. 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 benchmark analysis on a restricted subsample made of the top 33% wealthiest households. Compared to the full sample, on average the subsample of the wealthiest households is more highly educated and financially sophisticated, earns higher income, has more financial wealth, and invests more heavily in risky assets.

Despite having reduced the sample to a large extent, the analysis on these fewer data confirms our previous results. The level of wealth also keeps showing a significantly positive correlation with all the risk indicators. The implication of this analysis is that entry barriers and transaction costs do not severely affect our results.

7. Concluding Remarks

In this paper we use data from the waves 1998-2010 of the US Survey of Consumer Finances (SCF) to shed light on the evolution of US households' portfolio risk, its distribution over the population, and its correlation with observable household characteristics. In our analysis we consider different indicators of ex-ante portfolio risk, based on the ex-ante standard deviation of two alternative definitions of portfolio: financial and complete, with the former including deposits, bonds and stocks, and the latter also including business wealth, real estate, and related debt.

The indicators inform that the distribution of household risk is skewed to the left, with many households bearing little risk. Moreover, in all the cases we find our measures of risk to positively correlate with wealth. However, the indicators are imperfectly correlated with each other and with popular risk measures such as the financial portfolio share invested in stocks. The correlation is particularly low when comparing the measures based on the financial portfolio with those based on the complete portfolio. This suggests that financial asset shares are not enough informative on the heterogeneity in portfolio risk, which largely depends on real estate holdings. Depending on the assumptions we make on the specification, estimates of the age-period-cohort effects vary. We use alternative approaches to disentangle the effects, and all of them show that three out of four of our risk indicators fell at the beginning of the sample period and rose at the end, in line with different phases of the business cycle. Only for the illiquid component of the portfolio the conclusions differ across approaches. In this case, according to our preferred strategy (driven by observations on the second-order period differences), portfolio risk increased over time.

There are several avenues for future research. On an exploratory side, it seems interesting to compare portfolio risk among households of different countries having similar characteristics, and over an extended time period to include several business cycles. On a theoretical side, it may be useful to infer household risk attitude from observations on portfolio risk. In this regard, we plan to extend previous work from Bucciol and Miniaci (2011) to a multi-period framework from which to estimate risk attitude from observed portfolio holdings, separately from time discounting.

Appendix A. 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

$$\sigma_{it}^{f|n}=\omega_{it}^{f|n}\sigma_{t}^{f}=\left(\omega_{it}^{f}+\frac{\sigma_{t}^{fn}}{\left(\sigma_{t}^{f}\right)^{2}}\omega_{it}^{n}\right)\sigma_{t}^{f} \tag{A.1}$$

while the formula for the constrained standard deviation reduces to

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

The derivatives of Equations (A.1)-(A.2) with respect to ω_{it}^{f} are:

$$\begin{aligned}
\frac{\partial\sigma_{it}^{f|n}}{\partial\omega_{it}^{f}}&=-\frac{\partial\sigma_{it}^{f|n}}{\partial\omega_{it}^{n}}=\sigma_{t}^{f}\left(1-\rho_{t}^{fn}\frac{\sigma_{t}^{n}}{\sigma_{t}^{f}}\right);\\
\frac{\partial\sigma_{it}^{n|f}}{\partial\omega_{it}^{f}}&=-\frac{\partial\sigma_{it}^{n|f}}{\partial\omega_{it}^{n}}=-\sigma_{t}^{n}\left(1-\left(\rho_{t}^{fn}\right)^{2}\right)^{\frac{1}{2}}
\end{aligned} \tag{A.3}$$

with ρ_t^{fn} correlation at time t between financial and non-financial assets. The second derivative is always negative, while the first derivative is positive if the correlation between financial and non-financial assets, ρ_t^{fn}, 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 the conditional standard deviation, and negatively the constrained standard deviation.

Appendix B. Regression Results for Alternative Estimators

TABLE B.I ABOUT HERE

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Table I. Statistics on portfolio shares

	1998	2001	2004	2007	2010
a) Wealth (thousands USD)					
Financial wealth, average	205.342	276.481	259.479	269.152	275.705
Financial wealth, median	35.959	45.151	39.528	42.263	33.600
Complete wealth, average	432.384	574.359	602.139	672.392	607.540
Complete wealth, median	122.762	152.575	159.645	190.319	143.000
b) Asset share participation (%)					
Deposits	97.797	97.615	98.662	99.252	99.228
Bonds and/or mortgages	72.513	71.945	70.396	70.304	65.045
Stocks	61.282	64.552	58.196	57.137	52.796
Real estate	73.634	76.247	75.565	76.311	73.180
Business wealth	13.790	15.106	13.826	14.330	14.698
c) Aggregate portfolio shares (in bold) and their composition (%)					
Checking accounts	2.176	2.085	1.869	1.522	1.816
Savings and money market accounts	1.172	1.642	2.842	2.638	3.535
Certificates of deposit	1.800	1.277	1.279	1.354	1.785
Call accounts at brokerages	0.539	0.583	0.433	0.334	0.684
IRA-KEOGH accounts	*0.750*	*0.697*	*0.789*	*0.786*	*1.114*
Retirement accounts	*0.807*	*0.895*	*5.022*	*5.268*	*6.583*
Annuities	*0*	*0.101*	*0.794*	*0.433*	*0.576*
Trust-managed accounts	*0*	*0.391*	*1.914*	*0.559*	*0.802*
Deposits	**9.685**	**10.497**	**14.942**	**12.895**	**16.894**
Directly held govt. bonds	1.629	1.851	1.712	1.302	1.583
Directly held corp. bonds	0.486	0.358	0.448	0.231	0.391
Savings bonds	0.335	0.323	0.231	0.160	0.157
Tax free mutual funds	0.813	0.863	0.566	0.912	0.920
Govt. bond mutual funds	0.238	0.158	0.168	0.275	0.224
Other bond mutual funds	0.582	0.190	0.396	0.280	0.661
½ Balanced mutual funds	0.227	0.305	0.231	0.242	0.328
½ Other mutual funds	0.005	0.000	0.235	0.292	0.413
Life insurance (cash value)	3.469	2.688	1.290	1.303	1.187
Loans on primary residence (-)	-10.931	-9.366	-11.140	-10.743	-10.736
Loans on other real estate (-)	-2.859	-1.898	-3.059	-2.945	-3.301
Loans on business (-)	-0.247	-0.312	-0.282	-0.370	-0.394
IRA-KEOGH accounts	*0.705*	*0.985*	*2.108*	*2.112*	*3.050*
Retirement accounts	*0*	*0.001*	*0.008*	*0.001*	*0.011*
Annuities	*0.139*	*0.075*	*0.003*	*0.010*	*0.001*
Trust-managed accounts	*0.323*	*0.015*	*0.028*	*0.032*	*0.087*
Bonds	**-3.693**	**-3.069**	**-7.058**	**-6.906**	**-5.418**
Directly held stocks	11.041	10.101	7.386	7.094	6.474
Stock mutual funds	4.138	4.187	4.252	4.113	3.736
½ Balanced mutual funds	0.227	0.305	0.231	0.242	0.328
½ Other mutual funds	0.005	0.000	0.235	0.292	0.413
IRA-KEOGH accounts	*4.577*	*4.810*	*4.171*	*4.088*	*4.501*
Retirement accounts	*3.301*	*4.013*	*2.876*	*2.874*	*2.672*
Annuities	*0.282*	*0.425*	*0.458*	*0.514*	*0.453*
Trust-managed accounts	*1.190*	*2.007*	*1.117*	*0.764*	*0.896*
Stocks	**27.462**	**29.134**	**20.727**	**19.981**	**19.474**
Owner-occupied primary residence	37.127	31.951	37.707	37.896	34.521
Other real estate	12.277	11.173	14.071	13.658	14.155
IRA-KEOGH accounts	*0.144*	*0*	*0*	*0*	*0*
Retirement accounts	*0.081*	*0.023*	*0*	*0*	*0*
Annuities	*0*	*0*	*0*	*0*	*0*
Trust-managed accounts	*0.333*	*0.192*	*0*	*0*	*0*
Real estate	**45.962**	**43.339**	**51.778**	**51.554**	**48.677**
Business wealth	20.584	20.099	19.611	22.476	20.373
Business wealth	**20.584**	**20.099**	**19.611**	**22.476**	**20.373**
Genuine observations	3,249	3,384	3,611	3,472	4,656

Note: composite assets (in italics) are allocated in the asset categories according to their composition declared in the survey.

Table II. Average risk indicators (× 100) by self-assessed risk aversion

		Self assessed risk aversion		
Risk scale	**Total**	**Low**	**Moderate**	**High**
Financial	5.191	7.476	5.881	2.972
Complete	6.427	8.224	6.941	4.714
Conditional	4.507	6.135	4.982	2.945
Constrained	3.528	4.098	3.747	2.921
Frequency (%)	100	22.680	41.160	36.160

Note. The "low", "moderate" and "high" categories are based on the answer to a question on self-assessed risk aversion. "Low" = risk options 1-2; "Moderate" = risk option 3; "High" = risk option 4.

Table III. Average values of the risk indicators (× 100)

	1998	**2001**	**2004**	**2007**	**2010**
Financial	6.684	7.148	4.425	4.015	3.992
Complete	7.285	7.145	5.812	5.444	6.646
Conditional	5.977	5.796	4.022	3.259	3.757
Constrained	3.094	3.006	3.333	3.628	4.532

Table IV. Counterfactual: evolution of aggregate 1998 portfolio shares without rebalancing

	1998	**2001**	**2004**	**2007**	**2010**
			a) Portfolio share (%)		
Observed					
Deposits	9.685	10.497	14.942	12.895	16.894
Bonds	-3.693	-3.069	-7.058	-6.906	-5.418
Stocks	27.462	29.134	20.727	19.981	19.474
Real estate	45.962	43.339	51.778	51.554	48.677
Business wealth	20.584	20.099	19.611	22.476	20.373
Counterfactual					
Deposits	9.685	9.432	9.077	9.134	10.298
Bonds	-3.693	-3.736	-4.171	-4.248	-5.554
Stocks	27.462	21.187	20.533	22.400	21.514
Real estate	45.962	48.811	56.048	57.532	56.770
Business wealth	20.584	24.306	18.513	15.183	16.973
			b) Risk indicators (× 100)		
Observed					
Financial	6.185	6.930	4.926	4.624	5.062
Complete	13.917	13.531	13.482	11.989	17.921
Conditional	8.642	9.097	5.483	4.187	4.963
Constrained	10.909	10.016	12.317	11.234	17.220
Counterfactual					
Financial	6.185	5.472	5.019	4.970	5.448
Complete	13.917	14.043	14.507	13.458	20.929
Conditional	8.642	8.350	5.730	4.810	5.639
Constrained	10.909	11.340	13.328	12.569	20.155

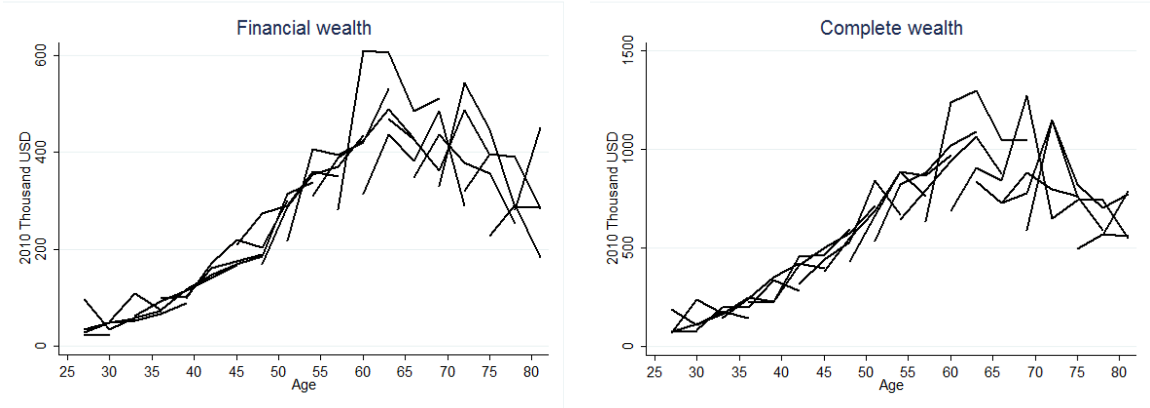
Note. We take the 1998 aggregate shares of the complete portfolio (as in Table 1) and let them vary over the years according to the market realizations, with no adjustment or rebalancing. The risk indicators are based on the composition of the aggregate financial and complete portfolios generated in this way.

Table V. Portfolio risk and observable characteristics

Measure	**Financial**	**Complete**	**Conditional**	**Constrained**
Ln(wealth)	0.096***	0.090***	0.055***	0.162***
	(0.004)	(0.005)	(0.004)	(0.008)
Non-white	-0.071***	-0.055***	-0.077***	-0.033
	(0.016)	(0.019)	(0.018)	(0.034)
Female	-0.052**	-0.041*	-0.069***	0.022
	(0.022)	(0.021)	(0.022)	(0.037)
College graduate	0.129***	-0.024*	0.067***	-0.225***
	(0.014)	(0.014)	(0.016)	(0.021)
Married	-0.051***	-0.040*	-0.064***	0.083**
	(0.018)	(0.020)	(0.021)	(0.033)
N. household members	-0.017**	0.004	-0.012	0.034*
	(0.007)	(0.011)	(0.010)	(0.018)
With children	-0.001	0.035*	0.047**	0.076**
	(0.019)	(0.021)	(0.023)	(0.034)
Self-employed	-0.148***	0.410***	-0.137***	1.456***
	(0.021)	(0.027)	(0.019)	(0.066)
Retired	-0.037*	-0.027	-0.065***	0.022
	(0.020)	(0.020)	(0.021)	(0.033)
Good self-assessed health	0.037***	0.024***	0.040***	0.004
	(0.003)	(0.003)	(0.004)	(0.005)
N. financial institutions	0.028**	-0.002	0.011	-0.034
where doing business	(0.013)	(0.014)	(0.015)	(0.024)
With financial advisor	0.057***	0.027	0.034	0.005
	(0.020)	(0.027)	(0.024)	(0.047)
Works in financial sector	0.048***	0.022	0.033**	0.002
	(0.015)	(0.014)	(0.015)	(0.023)
Constant	-0.230**	-0.435***	-0.022	-1.370***
	(0.114)	(0.094)	(0.128)	(0.125)
Age dummies	YES	YES	YES	YES
Period dummies	YES	YES	YES	YES
Cohort dummies	YES	YES	YES	YES
Genuine observations	18,372	18,372	18,372	18,372

*Note. The dependent variable is rescaled by its average in the sample. The regression is constrained to the second-order differences of the period dummy variables. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

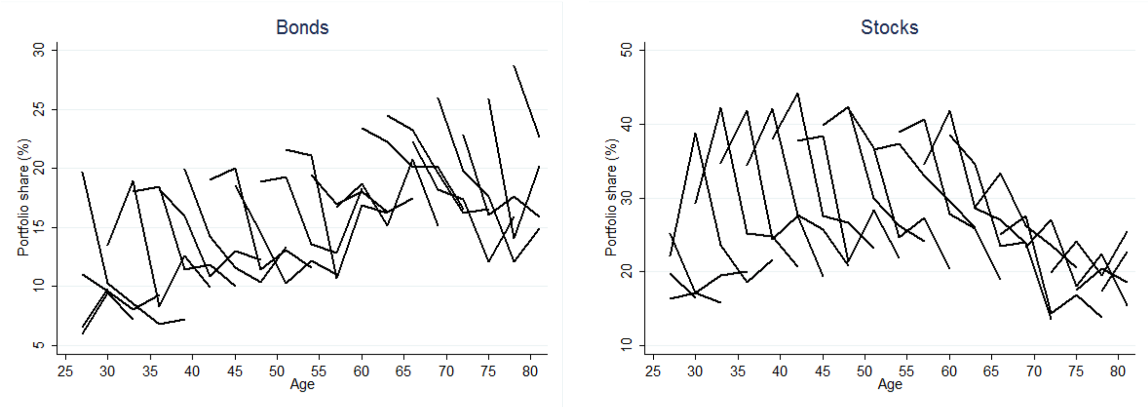
Figure 1. Average cohort wealth size by age



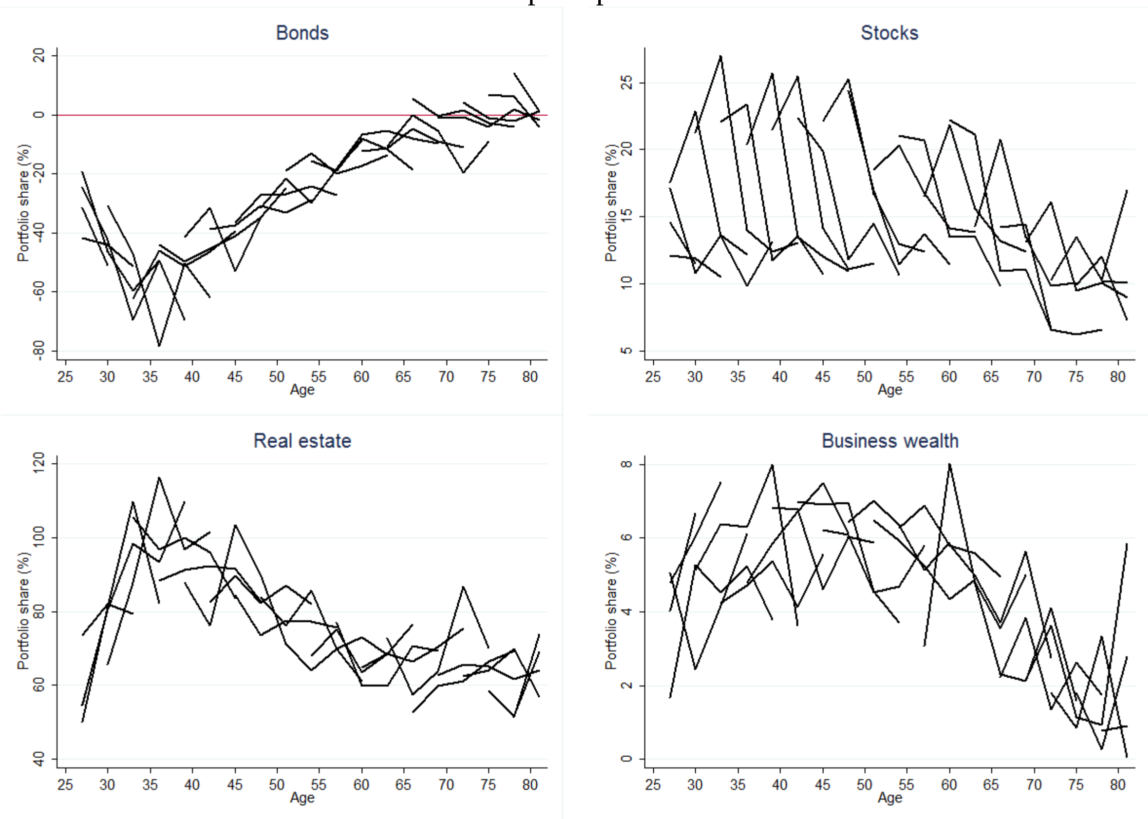
Note. The definition of cohort includes all those born in a 3-year range.

Figure 2. Average cohort portfolio holdings by age

a. Financial portfolio



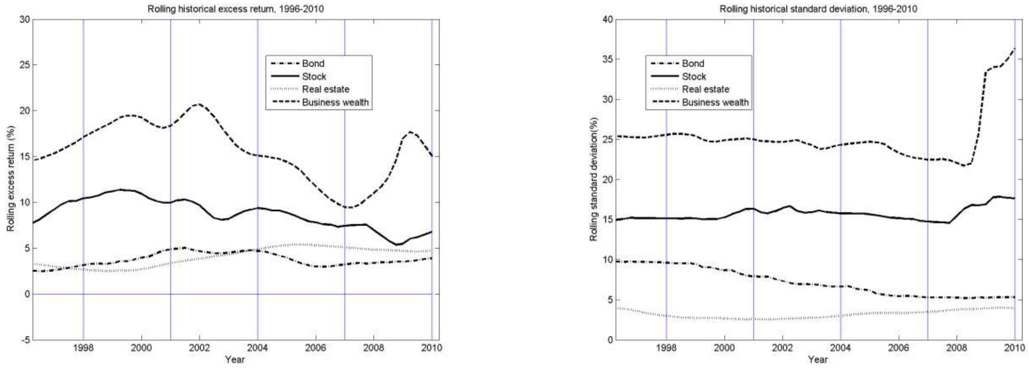
b. Complete portfolio



Note. The definition of cohort includes all those born in a 3-year range.

Figure 3. Rolling moments of excess returns

a. Excess returns and standard deviation



b. Correlations

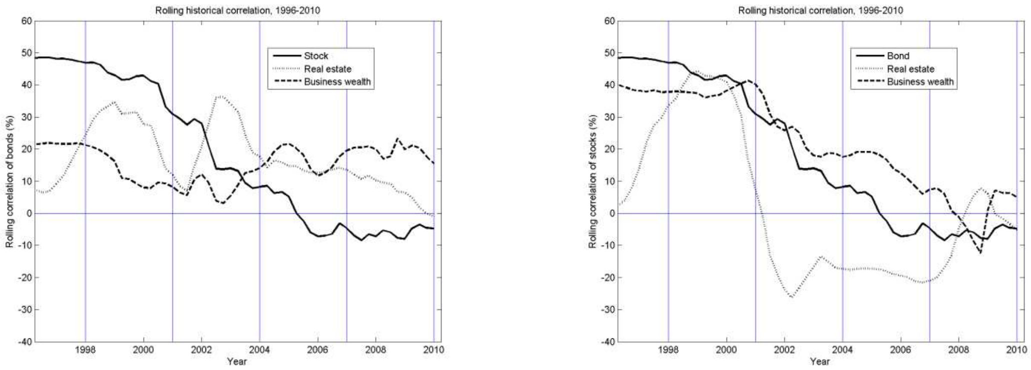


Figure 4. Empirical cdf of portfolio risk

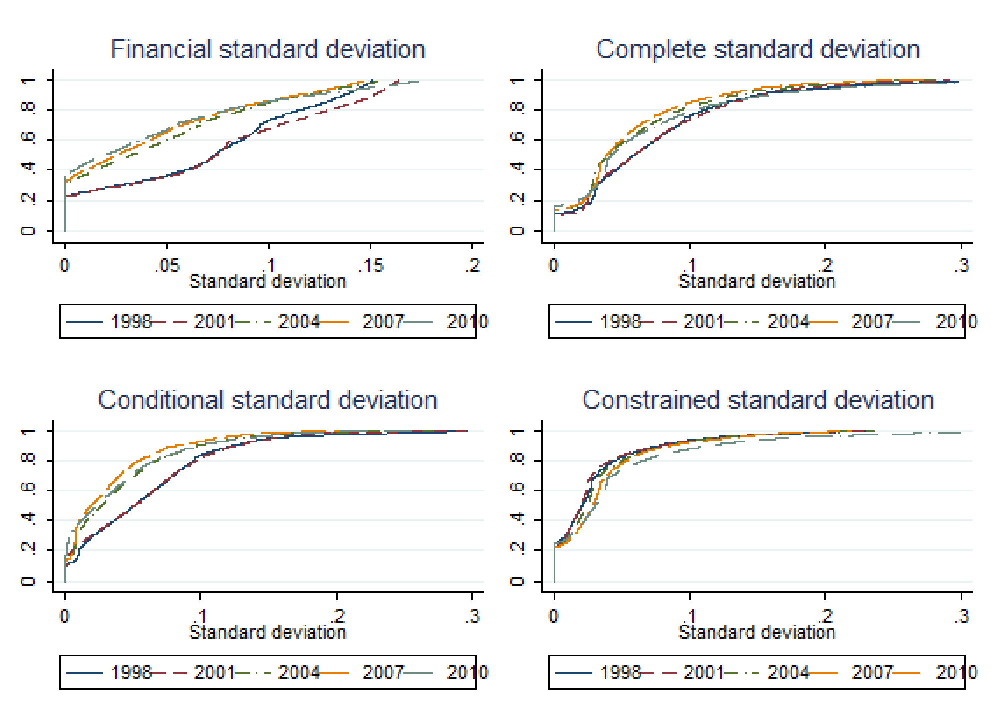


Figure 5. Correlations among risk indicators

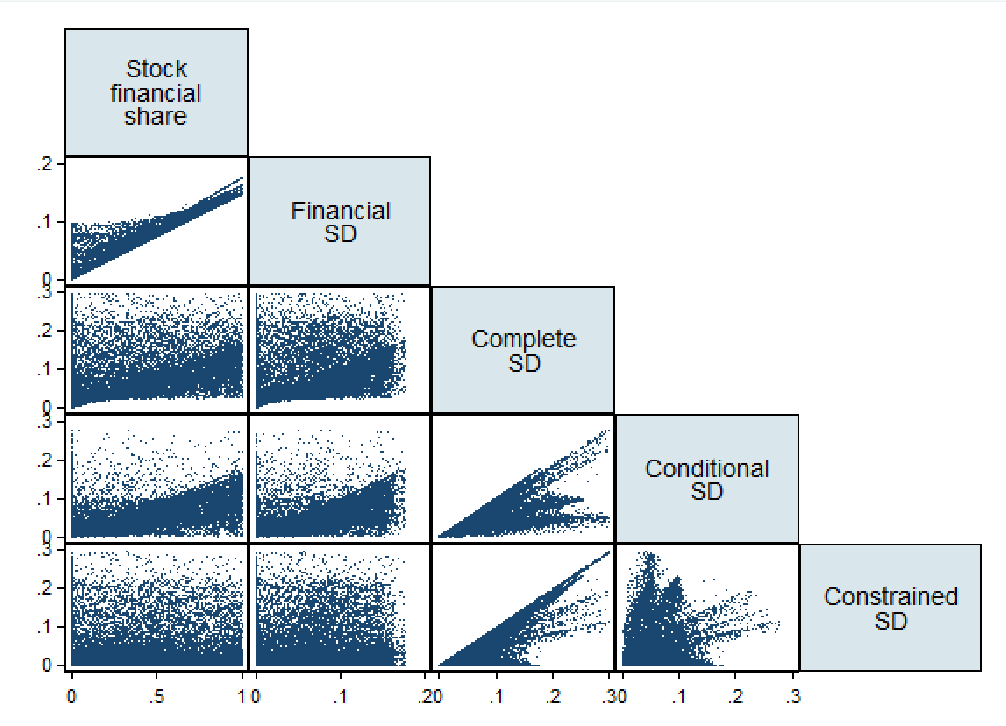


Figure 6. Second difference of age, period and cohort effects

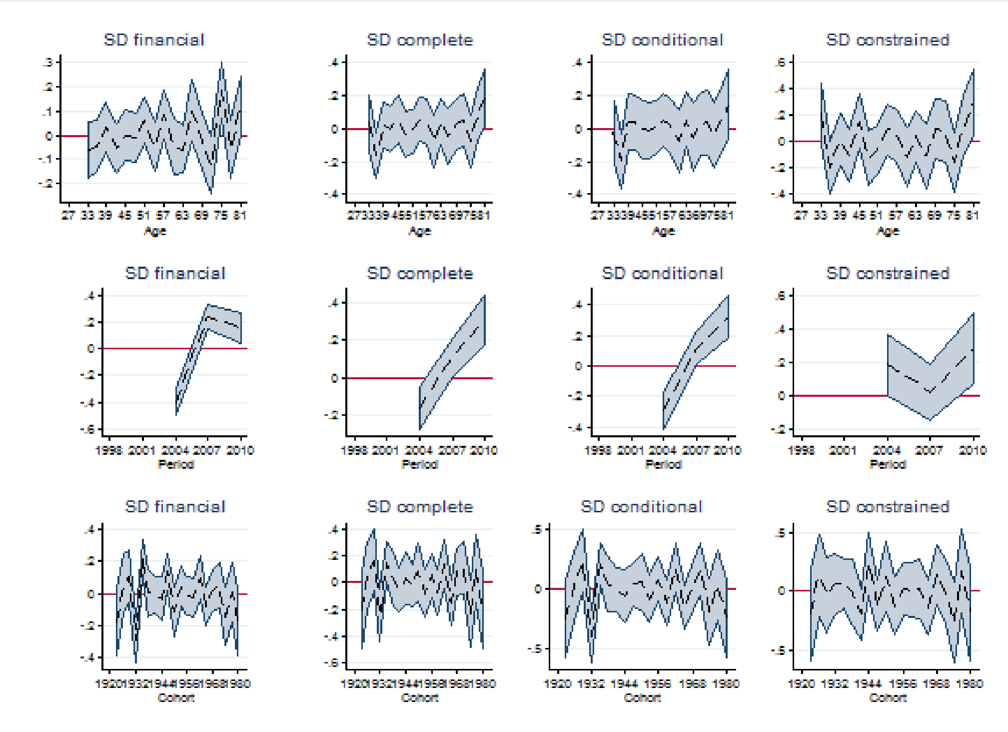


Figure 7. Level of age, period and cohort effects

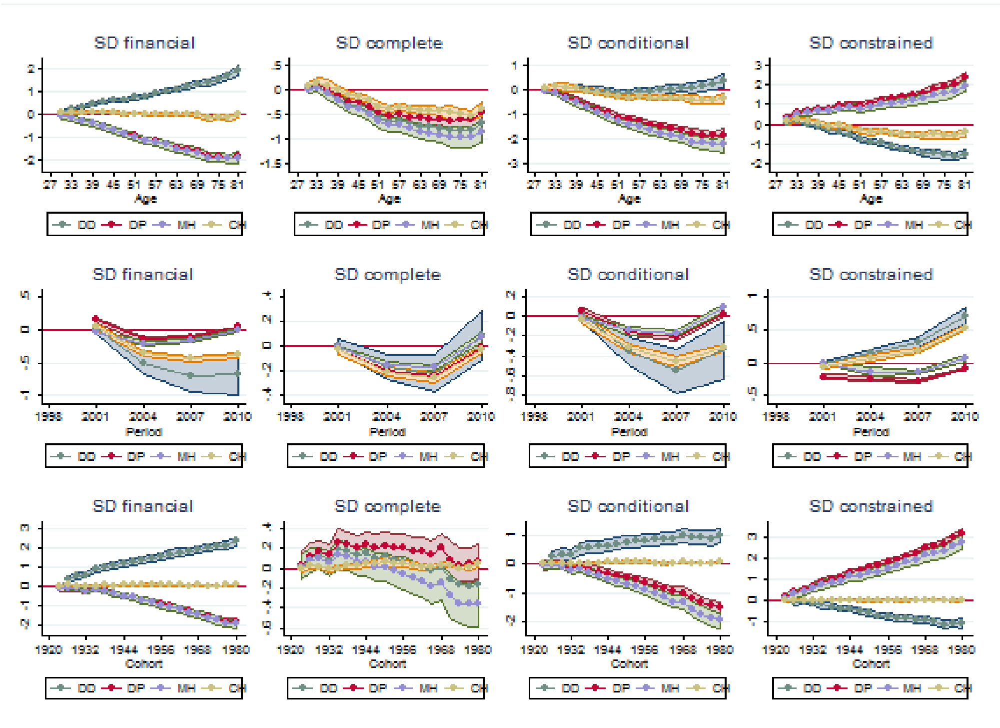


Table B.I. Portfolio risk and observable characteristics: Deaton-Paxson

Measure	Financial	Complete	Conditional	Constrained
Ln(wealth)	0.096***	0.089***	0.054***	0.162***
	(0.004)	(0.005)	(0.004)	(0.008)
Non-white	-0.070***	-0.055***	-0.076***	-0.033
	(0.016)	(0.019)	(0.018)	(0.034)
Female	-0.052**	-0.042*	-0.070***	0.022
	(0.022)	(0.021)	(0.022)	(0.037)
College graduate	0.129***	-0.023	0.069***	-0.225***
	(0.014)	(0.014)	(0.016)	(0.021)
Married	-0.050***	-0.040*	-0.063***	0.083**
	(0.018)	(0.020)	(0.021)	(0.033)
N. household members	-0.017**	0.004	-0.012	0.035*
	(0.007)	(0.011)	(0.010)	(0.018)
With children	-0.002	0.035	0.046**	0.075**
	(0.019)	(0.021)	(0.023)	(0.034)
Self-employed	-0.147***	0.412***	-0.135***	1.456***
	(0.021)	(0.027)	(0.019)	(0.066)
Retired	-0.038*	-0.027	-0.066***	0.022
	(0.020)	(0.020)	(0.021)	(0.033)
Good self-assessed health	0.037***	0.023***	0.039***	0.004
	(0.003)	(0.003)	(0.004)	(0.005)
N. financial institutions	0.029**	-0.001	0.012	-0.034
where doing business	(0.013)	(0.014)	(0.015)	(0.024)
With financial advisor	0.059***	0.027	0.036	0.005
	(0.020)	(0.028)	(0.025)	(0.047)
Works in financial sector	0.048***	0.023*	0.034**	0.002
	(0.015)	(0.014)	(0.015)	(0.023)
Constant	-0.467***	-0.536***	-0.201*	-1.337***
	(0.095)	(0.089)	(0.103)	(0.126)
Age dummies	YES	YES	YES	YES
Deaton-Paxson conditions	YES	YES	YES	YES
Cohort dummies	YES	YES	YES	YES
Genuine observations	18,372	18,372	18,372	18,372

*Note. The dependent variable is rescaled by its average in the sample. The "Deaton-Paxson conditions" are measured with three variables derived from the condition of orthogonality between time dummies and a linear trend. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table B.II. Portfolio risk and observable characteristics: Market history

Measure	**Financial**	**Complete**	**Conditional**	**Constrained**
Ln(wealth)	0.097***	0.089***	0.055***	0.160***
	(0.004)	(0.005)	(0.004)	(0.008)
Non-white	-0.069***	-0.055***	-0.076***	-0.035
	(0.016)	(0.019)	(0.018)	(0.034)
Female	-0.052**	-0.042*	-0.070***	0.021
	(0.022)	(0.021)	(0.022)	(0.037)
College graduate	0.129***	-0.023	0.068***	-0.225***
	(0.014)	(0.014)	(0.016)	(0.021)
Married	-0.048***	-0.040*	-0.062***	0.081**
	(0.018)	(0.020)	(0.021)	(0.033)
N. household members	-0.017**	0.004	-0.012	0.035*
	(0.007)	(0.011)	(0.010)	(0.018)
With children	-0.004	0.035	0.045*	0.077**
	(0.020)	(0.021)	(0.023)	(0.034)
Self-employed	-0.148***	0.412***	-0.136***	1.458***
	(0.021)	(0.027)	(0.019)	(0.066)
Retired	-0.042**	-0.027	-0.067***	0.026
	(0.020)	(0.020)	(0.021)	(0.033)
Good self-assessed health	0.036***	0.023***	0.039***	0.005
	(0.003)	(0.003)	(0.004)	(0.005)
N. financial institutions	0.028**	-0.001	0.012	-0.033
where doing business	(0.013)	(0.014)	(0.015)	(0.024)
With financial advisor	0.064***	0.027	0.038	-0.001
	(0.020)	(0.028)	(0.025)	(0.047)
Works in financial sector	0.049***	0.023*	0.034**	0.001
	(0.015)	(0.014)	(0.015)	(0.023)
Constant	-0.896***	-1.003***	-0.671***	-1.710***
	(0.076)	(0.100)	(0.097)	(0.155)
Period market characteristics:				
Return	1.260***	1.227***	1.188***	1.034***
	(0.098)	(0.075)	(0.094)	(0.124)
Standard deviation	2.910***	3.470***	3.456***	2.913***
	(0.201)	(0.197)	(0.241)	(0.277)
Age dummies	YES	YES	YES	YES
Cohort dummies	YES	YES	YES	YES
Genuine observations	18,372	18,372	18,372	18,372

*Note. The dependent variable is rescaled by its average in the sample. The "period market characteristics" are measured with two variables, informing on the historical return and standard deviation of the stock market in the three years before data collection. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table B.III. Portfolio risk and observable characteristics: Cohort history

Measure	**Financial**	**Complete**	**Conditional**	**Constrained**
Ln(wealth)	0.096***	0.089***	0.054***	0.161***
	(0.004)	(0.005)	(0.004)	(0.008)
Non-white	-0.069***	-0.055***	-0.075***	-0.034
	(0.016)	(0.019)	(0.018)	(0.034)
Female	-0.052**	-0.041*	-0.069***	0.020
	(0.022)	(0.021)	(0.022)	(0.037)
College graduate	0.129***	-0.023	0.068***	-0.224***
	(0.014)	(0.014)	(0.016)	(0.021)
Married	-0.051***	-0.040**	-0.064***	0.083**
	(0.018)	(0.020)	(0.021)	(0.033)
N. household members	-0.017**	0.004	-0.012	0.034*
	(0.007)	(0.011)	(0.010)	(0.018)
With children	-0.002	0.035*	0.048**	0.074**
	(0.019)	(0.021)	(0.023)	(0.034)
Self-employed	-0.147***	0.412***	-0.135***	1.457***
	(0.021)	(0.027)	(0.019)	(0.066)
Retired	-0.041**	-0.027	-0.067***	0.024
	(0.021)	(0.019)	(0.021)	(0.033)
Good self-assessed health	0.037***	0.023***	0.039***	0.004
	(0.003)	(0.003)	(0.004)	(0.005)
N. financial institutions	0.028**	-0.002	0.011	-0.033
where doing business	(0.013)	(0.014)	(0.015)	(0.024)
With financial advisor	0.062***	0.030	0.040	0.004
	(0.020)	(0.028)	(0.025)	(0.047)
Works in financial sector	0.049***	0.023*	0.034**	0.002
	(0.015)	(0.013)	(0.015)	(0.023)
Constant	-0.226**	-0.256***	0.151	-1.231***
	(0.090)	(0.088)	(0.107)	(0.136)
Cohort market characteristics:				
Return	-0.229*	-0.293**	-0.378***	-0.076
	(0.132)	(0.117)	(0.136)	(0.179)
Standard deviation	0.076	-0.143	-0.183	-0.161
	(0.198)	(0.176)	(0.232)	(0.207)
Age dummies	YES	YES	YES	YES
Period dummies	YES	YES	YES	YES
Genuine observations	18,372	18,372	18,372	18,372

*Note. The dependent variable is rescaled by its average in the sample. The "cohort market characteristics" are measured with two variables, informing on the historical return and standard deviation of the stock market when the individual was aged between 20 and 24. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*