Depression Babies:
Do Macroeconomic Experiences Affect Risk-Taking? *

Ulrike Malmendier
UC Berkeley and NBER

Stefan Nagel
Stanford University and NBER

February 2009

Abstract

We investigate whether individuals' experiences of macro-economic outcomes have long-term effects on their risk attitudes, as often suggested for the generation that experienced the Great Depression. Using data from the Survey of Consumer Finances from 1964-2004, we find that individuals who have experienced low stock-market returns throughout their lives report lower willingness to take financial risk, are less likely to participate in the stock market, and, conditional on participating, invest a lower fraction of their liquid assets in stocks. Individuals who have experienced low bond returns are less likely to own bonds. All results are estimated controlling for age, year effects, and a broad set of household characteristics. Our estimates indicate that more recent return experiences have stronger effects, but experiences early in life still have significant influence, even several decades later. Our results can explain, for example, the relatively low stock-market participation of young households in the early 1980s, following the disappointing stock-market returns in the 1970s, and the relatively high participation of young investors in the late 1990s, following the boom years in the 1990s. In the aggregate, investors' lifetime stock-market return experiences predict aggregate stock-price dynamics as captured by the price-earnings ratio.

* We thank John Ameriks, Brad Barber, Randy Cohen, Wayne Ferson, Tim Johnson, John Sabelhaus, Karthryn Shaw, Stephen Zeldes, and seminar participants at Berkeley, Bowling Green State, Erasmus University Rotterdam, Federal Reserve Bank of Chicago, Harvard, Hong-Kong University of Science and Technology, London School of Economics, Nanyang Technological University, National University of Singapore, New York University, NHH Bergen, Singapore Management University, Stanford, Tilburg, University of British Columbia, University of Illinois Urbana/Champaign, University of Michigan, University of Southern California, the World Bank, the American Finance Association Meeting, the Annual Meeting of German Economists Abroad, the European Symposium on Economics and Psychology, the NBER MIDM, AP, and Cohort Studies meetings, as well as the Wharton Conference on Household Portfolio Choice and Financial Decision-Making for comments, and Sith Chaisurote and Nelli Oster for excellent research assistance.

I. Introduction

Does the personal experience of economic fluctuations shape individuals' risk attitudes? For the generation of "Depression Babies" it has often been suggested that their experience of a large macro-economic shock, the Great Depression, had a long-lasting effect on their attitudes towards risk. In this paper, we ask more generally whether people who live through different macroeconomic histories make different risky choices.

Standard models in economics assume that individuals are endowed with stable risk preferences, unaltered by economic experiences. Standard models also assume that individuals incorporate all available historical data when forming beliefs about risky outcomes. In contrast, the psychology literature argues that personal experiences, especially recent ones, exert a greater influence on personal decisions than statistical summary information in books or via education (Nisbett and Ross 1980; Weber et al. 1993; Hertwig et al. 2004). Recent literature in economics suggests that the cultural and political environment in which individuals grow up affects their preference and belief formation, such as the level of trust in financial institutions, stock market participation, and preferences over social policies (Guiso, Sapienza, and Zingales 2004 and 2008; Osili and Paulson 2008; Alesina and Fuchs-Schündeln 2007).

We examine empirically whether individuals' risk attitudes differ depending on the macroeconomic history they experienced over the course of their lives. In particular, we test whether individuals who experienced periods of low stock-market returns express a lower willingness to take financial risk, are less likely to participate in the stock market and invest less in stocks, and whether individuals who lived through periods of low bond returns are more wary of participating in the long-term bond market. We also ask how long such experience effects last and how specific they are: do households who experienced bad stock-market outcomes shy away from stock investment and those with bad bond-market experiences from bond investment, but without cross effects?. Our analysis does not attempt to disentangle whether macroeconomic experiences affect preferences or beliefs, though we discuss evidence suggestive of the beliefs channel.

A key implication of the experience hypothesis is that differences between old and young people in their risk attitudes should be correlated with differences in their life-time experiences. After years of low stock-market returns, e.g., after the recessions of the 1970s and early 1980s, the stock-market participation of young people should be lower relative to that of old people (who have also experienced better times in their lifetime) than after years of high returns, e.g., in the 1960s when older individuals at the time still had the memory of the Great Depression and hence a worse average experience than young investors in their lives so far. A simple scatter-plot of differences in stock-market participation against differences in experienced stock market returns (Figure 1) confirms this pattern in the raw data.

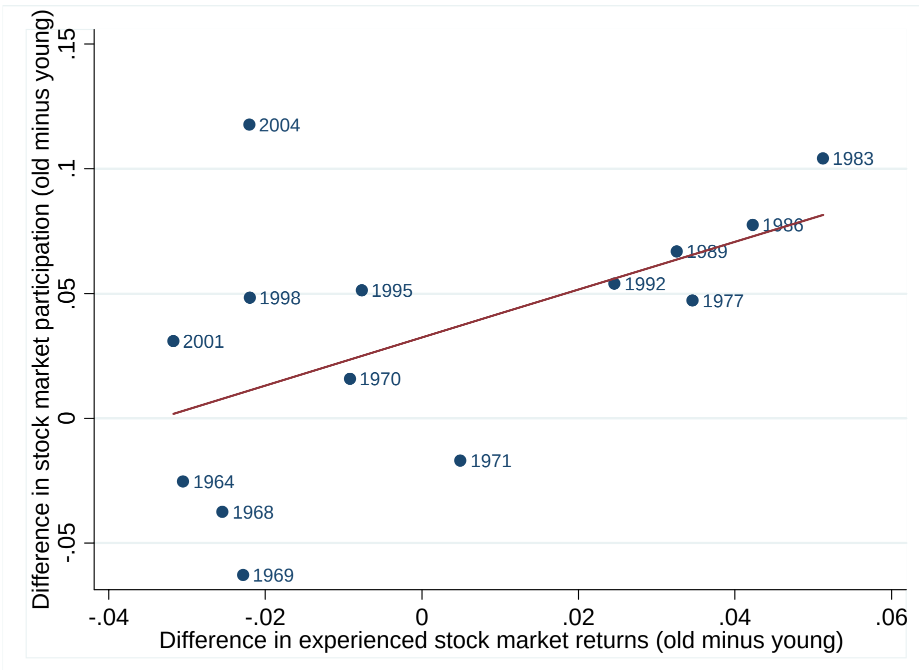

Figure 1: Differences in stock-market participation rates of old and young individuals plotted against differences in lifetime average stock-market returns. Stock market participation rates are the fraction of households who invest in stocks (including stock mutual funds). The y-axis shows the participation rate of old (household head age > 60 years) minus the rate of young (household head age ≤ 40 years) households. The x-axis shows the average real stock market return (S&P500 index) over the prior 50 years (as proxy for the return experienced by old households) minus the return over the prior 20 years (as proxy for the return experienced by young households). The years refer to the respective SCF survey waves.

In this paper, we test whether these differences persist when we use a broad range of risk-attitude proxies, allow for different weighting of recent and distant experiences, and include a wide range of controls for demographics, wealth, income, and other variables. We use repeated cross-section data on household asset allocation from the Survey of Consumer Finances (SCF) from 1964-2004, and construct four measures of risk-taking: (i) the responses to a survey question about individuals' willingness to take financial risk; (ii) stock-market participation; (iii) bond-market participation, (iv) the proportion of their liquid assets invested in stocks. All four measures are likely to reflect a mixture between risk aversion and beliefs about future payoffs on risky investments.

We relate these measures of risk-taking to households' experienced histories of stock and bond returns. For each household at each SCF survey date, we calculate the annual real returns of the U.S. stock-market and of long-term government bonds since the birth year of the household head. While individuals' true "experiences" of past returns presumably differs depending on previous investments, interest in economic matters, and other unobservables, these experiences likely have substantial positive correlation with the market-wide risky asset return series. In our estimation, we allow recent observations and those early in life to carry different weights in influencing current risk-taking. In other words, we let the data simultaneously determine how households weight past observations and how strongly their risk-taking is correlated with the resulting weighted averages of stock and bond returns.

We find that households' risk taking is strongly related to their life-time return experiences. Households with higher experienced stock-market returns express a higher willingness to take financial risk, participate more in the stock market, and, conditional on participating, invest more of their liquid assets in stocks. The latter result also holds if we evaluate individuals' experiences with stocks relative to their experiences with bonds and, hence, measure experienced stock returns in excess of long-term bond returns. In addition, households with higher experienced bond returns are more likely to participate in the bond market. The estimated weights are similar for all four risk-taking measures. More recent experiences receive higher weights, and thus have a stronger influence on risk-taking than those early in life, but even returns experienced decades earlier still have some impact for older households. We also find that only stock returns, but not bond returns have a positive influence on stock-based risk taking measures, while bond market participation is positively influenced by experienced bond returns, but not by stock returns.

All of our estimations control for year effects, age effects, wealth and income. Year effects remove time trends or any aggregate effects, in particular a mechanical positive relation between recent stock returns and households' stock allocation due to market clearing.[1] As illustrated in Figure 1, our identification of the experience effect comes from cross-sectional differences in risk-taking and in macroeconomic histories, and from changes of those cross-sectional differences over time, not from *common* variation over time. Age effects allow us to distinguish our results from life-cycle effects, e.g., possible increases in risk aversion with age or the effects of the absence of labor income in retirement. The inclusion of wealth and income controls addresses the possibility that a positive correlation between past returns and current wealth explains the relation between experienced returns and current risk taking if risk aversion is wealth-dependent. Moreover, to the extent that unobserved differences in wealth remain, they are unlikely to explain all four of our risk-taking measures. Prior literature finds significant wealth effects only for stock-market participation, (see, e.g., Vissing-Jorgensen 2003), but not for the risky asset share of stock-market participants (Brunnermeier and Nagel 2008) and elicited risk aversion (Sahm 2007). Finally, the lack of cross-effects from stock market experiences on bond investment and bond experiences on stock investment is at odds with a wealth-effects explanation, as both stock and bond returns should be positively correlated with wealth, and hence risk-taking, under this alternative story.

A major advantage of our methodology is that we are able to simultaneously control for age and time effects. Previous work, which has looked at cross-cohort differences in risk-taking with cohort dummy variable regressions (see, e.g., Ameriks and Zeldes 2004) faced the problem that cohort effects cannot be separated from age and time effects due to the collinearity of age, time, and cohort (see, e.g., Heckman and Robb 1985, and the discussion in Campbell 2001). Since our identification strategy does not rely on estimating cohort effects, we can control for age and year effects simultaneously. Moreover, since experienced returns vary not only across, but also within cohorts over time, we can include an almost full set of cohort dummies and therefore control for any omitted variable that has cohort-level

[1] Holding the supply of stocks fixed, the average portfolio share invested in stocks increases when aggregate stock market prices increase and, hence, past returns are high.

variation. Finally, our hypothesis is distinct from unrestricted cohort effects since it predicts a *specific*, signed relationship between macroeconomic experiences and risk-taking.

In summary, our findings suggest that individual investors' willingness to bear financial risk depends on personal experiences of macroeconomic history. This behavior could be explained either with endogenous preferences, where risk aversion depends on the risky asset payoffs experienced in the past, or with learning, where current beliefs depend on the realizations experienced in the past. In the latter case, learning from personal experience would lead to beliefs that do not converge across overlapping generations, even in the long-run. Such belief heterogeneity is a departure from standard learning models in macroeconomics and finance, in which all agents at a given point in time have access to and make use of the same history of past data.

Our paper connects to several strands of literature. Several papers in macroeconomics and public finance analyze the impact of age and demographic composition on economic decisions. Most closely related is the work by Poterba (2001), who studies the effect of age on individual investment decisions, controlling for cohort effects but not for time effects (to avoid collinearity). Other work links demographic changes to the aggregate demand for stocks and bonds (Goyal 2004; Ang and Maddaloni 2005; Geneakoplos, Magill, and Quinzii 2004), and evaluates the effect of cohort size on family choices (Easterlin 1987), social security (Auerbach and Lee 2001; Gruber and Wise 1999), college graduation (Card and Lemieux 2000; Bound and Turner,2003), research and development (Acemoglu and Lin 2004), industry returns (DellaVigna and Pollet 2007), and a range of macro variables (Fair and Dominguez 1991). None of the above papers consider cohort experiences beyond those induced by size.

The literature on endogenous preference formation includes work on the influence of market institutions, e.g., by determining social norms (Bowles 1998), and on the influence of market risk (Palacios-Huerta and Santos 2004). For example, the Great Depression may have affected stock-market participation by changing the attitudes of society towards investing in the stock market. Several papers analyze how experiences early in life affect preferences. In addition to the literature cited above, Fernandez, Fogli, and Olivetti (2004) study male support for female labor market participation. Becker and Mulligan (1997) suggest that individuals can actively form their (time) preferences.

Experimental evidence suggests that information is weighted more heavily if it arises from direct experience rather than from observation. The literature on reinforcement learning posits that subjects' choice of actions strongly depends on the payoffs they obtained from the same actions in the past, even if circumstances (beliefs about other players' behavior and hence predicted payoffs) have changed. Experimental tests of the "experience-weighted attraction" model in Camerer and Ho (1999), which links reinforcement and belief learning, show that the actual payoffs obtained from past behavior have a large impact on subsequent choices. Relatedly, Schlag's (1999a and 1999b) models and experimental tests of social learning suggest that individuals tend to imitate behavior that has worked well in the past. Simonsohn, Karlsson, Loewenstein, and Ariely (2008) show, in a series of repeated weak-link and prisoner's-dilemma games, that subjects' decision-making responds more strongly to the behavior of players they directly interact with than to the behavior by those they only observe. Similar behavior is found with respect to the role of advice: Schotter (2003) reports that subjects respond to the advice of previous generations of players more than to historical data about the behavior and outcomes in the games of those previous generations.

In the context of financial decision making, Kaustia and Knüpfer (2008) find that the returns investors experience on their own investments in initial public offerings (IPO) are positively related to their future IPO subscriptions. Greenwood and Nagel (2007) show that young mutual fund managers chose higher exposure to technology stocks in the late 1990s than older managers, consistent with our finding that young individuals' allocation to stocks is most sensitive to recent stock-market returns. In a similar vein, Vissing-Jorgensen (2003) shows that young retail investors with little investment experience had the highest stock-market return expectations during the stock-market boom in the late 1990s. While these papers focus on effects of relatively recent returns on investment behavior, our paper uses a long-term sample and a broad range of risk-taking measures to estimate the long-run effect of stock-market returns on risk-taking and controls for age effects.

Other papers include circumstantial evidence consistent with the view that personal experience matters. Piazzesi and Schneider (2006) report that in the late 1970s old households expected lower inflation than young households. Young households apparently had a stronger tendency to extrapolate from their recent personal experiences of high inflation. Malmendier and Tate (2005) find that corporate managers who are born in the 1930s ("depression babies") shy away from external sources of financing, and Graham and Narasimhan (2004) find that those who experienced the Great Depression as managers choose a more conservative capital structure with less leverage.

Finally, Cogley and Sargent (2005) build a model that explains the equity premium based on the assumption that the Great Depression had a long-lasting effect on investors' model uncertainty about the 'true stochastic model' determining consumption growth and hence investment behavior, along the lines suggested by Friedman and Schwartz (1963). If individuals learn from personal experiences of economic events and asset payoffs, as our evidence suggests, a big disaster like the Great Depression could indeed have these kinds of effects.

II. Data and Methodology

The key variables for our analysis are several measures of risk-taking from household microdata and, as explanatory variables, historical stock and bond market returns. Since our household data, described below, extends back to the 1960s, and we include individuals up to age 74 in our sample, we need stock and bond return data stretching back to the late 19th century. We obtain data on the annual real returns of the S&P500 stock market index going back to 1871 from Shiller (2005)[2], and we calculate annual real bond returns from a total return index of 10-year U.S. Treasury bonds provided by Global Financial Data, and the CPI inflation rate from Shiller (2005). Unless otherwise noted, returns are always measured in real terms.

[2] The S&P index series consists of the S&P Composite index in the early part of the series and the S&P500 index in the later part. We thank Bob Shiller for providing the data on his website.

A. Survey of Consumer Finances

Our source of household-level microdata is the Survey of Consumer Finances (SCF), which provides repeated cross-section observations on asset holdings and various household background characteristics. Our sample has two parts. The first one is the standard SCF from 1983 to 2004, obtained from the Board of Governors of the Federal Reserve System and available every three years. The second source is the precursor of the "modern" SCF, obtained from the Inter-university Consortium for Political and Social Research at the University of Michigan. The precursor surveys start in 1947, partly annually, but with some gaps. In the data prior to 1964, however, information on stock holdings is either missing or very crude, and the sampling unit is the "spending unit" rather than the "family unit" used in later surveys. To ensure comparability across years we start in 1964 and use all survey waves that offer stock-market participation information, i.e., the 1964, 1968, 1969, 1970, 1971, and 1977 surveys. We briefly describe the key variables here. More details are available in Appendix A.

Our first risk-attitude measure is individuals' elicited willingness to take financial risk. In the 1983 and 1989-2004 survey waves, interviewees are asked whether they are willing to take (1) substantial financial risks expecting to earn substantial returns; (2) above average financial risks expecting to earn above average returns; (3) average financial risks expecting to earn average returns; or (4) not willing to take any financial risk. We code the answer as an ordinal variable with integer values from 1 to 4. For ease of reference, we refer to the measure as "elicited risk aversion," but note that the survey answer does not disentangle risk aversion (in the Arrow-Pratt sense) from beliefs.[3] We also note that we cannot interpret the measure in a cardinal sense since individuals may differ in how they interpret the available options quantitatively, e.g., "substantial" or "above average" risks and returns. The survey answers may also differ from interviewees' actual risky choices. Prior literature documents, however, that the measure predicts individual willingness to take risks, e.g., households' allocation to risky assets (Faig and Shum 2006) and differences in their willingness to make risky human capital investments and in wage growth

[3] For example, an individual with optimistic beliefs about future risky asset returns might answer that she is willing to take substantial financial risk *because* she expects to earn very high returns.

(Shaw 1996). In our analysis, using both the elicited risk aversion measure and direct measures of asset allocation ameliorates concerns about alternative interpretations.

The second measure is a binary variable for stock-market participation, available from 1964-2004. It indicates whether a household holds more than zero stocks. We define stock holdings as the sum of directly held stocks (including stock held through investment clubs) and the equity portion of mutual fund holdings.

Our third measure of risk taking is a binary variable for bond-market participation, available from 1968-2004, which indicates whether a household holds more than zero bonds. We define bond holdings as the sum of direct holdings of government bonds and corporate bonds, tax-free mutual fund holdings, and, in 1989 and later, the bond share of non-money market mutual funds. Investments in bonds, even those in default-free government bonds, are risky in real terms because of unexpected inflation.

Our fourth measure of risk taking is the fraction of liquid assets invested in stocks (directly held stocks plus the equity share of mutual funds), which can be calculated in all surveys from 1968-2004, with the exception of 1971. Liquid assets are defined as stock holdings plus bonds plus cash and cash equivalents (checking accounts, savings accounts, money market mutual funds, certificates of deposit) plus other liquid assets.

All of our asset holdings variables exclude assets in retirement accounts since the survey waves prior to 1989 do not provide information on the composition of assets in retirement accounts (e.g., IRA, Keogh, and 401(k) plans). Even from 1989 on (but prior to 2004), the SCF offers only very coarse information on the allocation of retirement assets (mostly stocks, mostly interest bearing, or split), precluding any meaningful calculation of stock holdings. We do, however, conduct robustness checks with data that includes retirement account holdings.

As a control variable for income we use total family income. All income, wealth, and asset holdings variables are deflated into September 2004 dollars using the consumer price index. When we use the liquid assets variables from the 1964 survey in our regressions, we always interact them with a 1964 dummy, because the definition of the wealth variables in that year differs from the other survey years. (In 1964, the liquid assets variable includes, for example, some real-estate assets that we cannot remove.)

Following previous SCF literature, we eliminate observations that are likely to be miscoded and households for which a meaningful asset allocation measure does not exist because they do not have any significant liquid asset holdings.[4] Specifically, we require that households have at least $100 of liquid assets and annual family income greater than $1,000. We also require that the household head is more than 24 years and less than 75 years old. Our results are robust to using the full sample.

The 1983-2004 waves of the SCF oversample high-income households. The oversampling provides a substantial number of observations on households with significant wealth holdings, which is helpful for our analysis of asset allocation, but could also induce selection bias. We deal with this issue in two ways. For our summary statistics and graphical descriptive analyses, we weight the data using SCF sample weights[5]. The weighted statistics are representative of the U.S. population. In our subsequent econometric estimation we start with unweighted estimates, since weighting is, in principle, inefficient use of the data (see, e.g., Deaton (1997), p. 70). Instead, we employ control variables for wealth and income. For robustness, we also present results from weighted estimation.

We also adjust standard errors for multiple imputation. From 1989 onwards, the SCF employs a multiple imputation technique to impute missing values from other information in the survey, and to disguise observations that could potentially reveal the identity of the respondent (see Kennickell 2000). The data set contains five complete copies ("implicates"), and only imputed values vary across implicates to represent the sampling uncertainty inherent in the imputation. To obtain point estimates and to adjust the standard errors for this uncertainty, we follow the method of Rubin (1987): We first estimate our models separately on each implicate and average the values of the parameter estimates from the separate estimations to produce a single point estimate. We also average the coefficient variances across implicates

[4] For example, Dynan, Skinner, and Zeldes (2002) exclude households with income below $1,000. Caroll, Dynan, and Krane (2003) exclude households in the top and bottom 0.1 percent of wealth and income.

[5] The SCF sampling weights are equal to the inverse of the probability that a given household was included in the survey sample, based on the U.S. population, adjusted for survey non-response. Following Poterba and Samwick (2001), we normalize the sample weights each year so that the sum of the weights in each year is the same.

and then add a term that accounts for the variance of point estimates across implicates (see Appendix B for more details).

B. Methodology

Our objective is to investigate the relationship between risk-taking and long-term return experiences. We want to allow for the possibility that experiences in the distant past have a different influence than more recent experiences. For example, the memory of past returns might fade away as time progresses. Alternatively, experiences at young age (perhaps conveyed by parents) might be particularly formative and have a relatively strong influence on individuals' decisions today. We aim to allow for both possibilities. Such a flexible estimation, however, faces some hurdles. In a regression that simply includes separate explanatory variables for each past year of return experience (back to the year of birth, for example) it would be impossible to estimate the large number of coefficients on those past returns with any meaningful precision. Moreover, the number of explanatory variables would differ across households depending on their age.

To solve both problems, we summarize a household head's experienced returns as a weighted average. We use a parsimonious specification of weights that introduces only one additional parameter but is flexible enough to allow the weights to decline, be constant, or increase with distance in time since the return was realized. In this way, we can let the data speak which weighting scheme works best in explaining households' risk-taking. Specifically, for each household *i* in year *t*, we calculate the following weighted average of past asset returns,

$$A_{it}\left(\lambda\right) = \frac{\sum_{k=1}^{age_{it}-1} w_{it}\left(k,\lambda\right) R_{t-k}}{\sum_{k=1}^{age_{it}-1} w_{it}\left(k,\lambda\right)}, \text{ where } w_{it}\left(k,\lambda\right) = \left(\frac{age_{it}-k}{age_{it}}\right)^{\lambda}, \tag{1}$$

where R_{t-k} is the return in year t-k. In our main specification, we include returns as far back as the household head's birth year. The weights w_{it} depend on the age of the household head and a parameter λ, which controls the shape of the weighting function. We estimate λ from the data. If $\lambda < 0$, then the weighting function is increasing and convex as the time lag k approaches age_{it}. In this case returns close to birth receive a higher weight than more recent returns. If $\lambda = 0$, we have constant weights and $A_{it}(\lambda)$ is a simple average of past returns since birth. With $\lambda > 0$ weights are decreasing in the lag k (concave for $\lambda < 1$, linear for $\lambda = 1$, and convex for $\lambda > 1$).

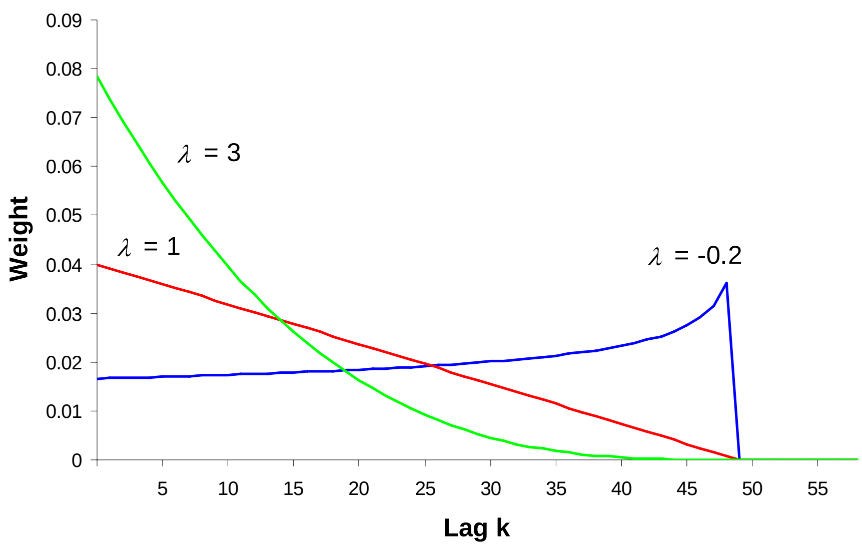

Figure 2: Three examples for the life-time returns weighting function for a household with a 50-year old household head.

Figure 2 provides an example of the weighting functions for three values of λ for a household head of age 50. As the figure shows, the weighting function is quite flexible in accommodating different weighing schemes. The weights can be monotonically increasing, decreasing, or flat. We also experimented with quadratic weighting functions that allow "humps" or U-shaped weights, but found the best fit with the monotonically decreasing pattern resulting from our original weighting function. While the true weighting function may feature more complex weighting patterns, our specification restriction biases the estimation against finding any significant effect of the resulting weighted-average returns on risk-taking.

As an example for how we estimate the weights and individuals' sensitivity to average returns calculated with those weights, consider the following generic regression model, with y_{it} as the dependent variable and weighted-average returns $A_{it}(\lambda)$ and a vector of control variables x_{it} as the explanatory variables:

$$y_{it} = \alpha + \beta A_{it}\left(\lambda\right) + \gamma' x_{it} + \varepsilon_{it} \tag{2}$$

We simultaneously estimate β and λ. Note that $A_{it}(\lambda)$ is a non-linear function of the weighting parameter λ, and hence non-linear estimation methods are required. For regression models, we choose β and λ to minimize the sum of squared residuals; for Probit models, we choose them to maximize the likelihood. To ensure we are finding the global optimum, we first estimate the model on a tightly spaced grid of values for λ.[6] We then choose the estimates that resulted in the lowest sum of square (or highest likelihood) as an initial guess for further numerical optimization. We compute robust standard errors.[7] We also check the robustness of our findings to clustering. As reported below, there is little effect on our results.

The parameter β measures the partial effect of $A_{it}(\lambda)$ on y_{it}, i.e., conditional on the weighting parameter λ, it tells us how much y_{it} changes when $A_{it}(\lambda)$ changes, holding everything else equal. Given λ and the age of a household, one can calculate the weights $w_{it}(k, \lambda)$ as in Eq. (1). Multiplying weight $w_{it}(k, \lambda)$ with β (and normalizing by the sum of weights, $\sum_{k=1}^{age_{it}-1} w_{it}(k,\lambda)$) yields, for a household of that age, the partial effect of a return experienced k years ago on the dependent variable. As an example, if $\lambda = 0$, then all returns in the household head's history since birth are weighted equally, and so their partial effects are all equal to their normalized weight (one divided by age) times β.

Note that where we set the starting point for the experienced return calculation is of little importance for our results. If this setting the starting point at birth is "too early" in the sense that individuals are not much influenced by experiences early in their lives, our weighting function can accommodate this with weights that decline relatively fast. If the starting point is "too late" in the sense that individuals are also influenced by observations realized prior to their birth (e.g., through their parents and social network), then setting the starting point earlier than birth could only improve the explanatory

[6] Given a value for the weighting parameter λ, the regression model is linear. (The probit model is still non-linear due to the non-linear transformation into probabilities.)
[7] Details are in Appendix B.

power of weighted average returns compared with our specification. Below, we report some tests in which we vary the starting point to 10 years before or 10 years after birth, and find that this has little effect on our results. Finally, if households are influenced by all historical data, and, contrary to our hypothesis, do not place higher weights on observations realized during their life-time, then the cross-sectional differences in risk attitudes are not correlated with differences in life-time experiences, and hence we will estimate an insignificant coefficient β.

C. Summary Statistics

Table I provides some summary statistics on our sample. Panel A includes all households that satisfy our sample requirements. Panel B restricts the sample to stock-market participants, i.e., households that have at least $1 in stocks or mutual funds. Panel C restricts the sample to bond-market participants, i.e., households that have at least $1 directly invested in bonds. Since we have bond holding information only from 1968 onwards, the sample in Panel C is restricted to 1968-2004. Comparing Panels B and C, we see that stock-market participants tend to be wealthier. For example, the median holding of liquid assets is $9,820 in the full sample, but $47,676 in the sample of stock-market participants. Panel C shows that bond-market participants are also wealthier, though less than stock-market participants, with median liquid assets of $22,191. The pattern is similar for median income.

As Panel A shows, 28.5% of households participate on average in the stock market in the 1964-2004 period. These rates represent the U.S. population (not the SCF sample) since we apply the SCF sample weights.[8] Stock-market participation rates also show interesting time-variation during our long sample. It is sometimes argued that stock-market participation has been trending upward since the 1980s because of improved communications technology and reduced transaction costs (Choi, Laibson, Metrick 2002). However, the early SCF data shows that participation was quite high in the late 1960s (above 30%, comparable to the levels reached in the late 1990s), before falling in the 1970s and early 1980s. The

[8] The actual proportion of stock holders in the SCF is higher because high-income households are oversampled. This explains why the number of observations in Panel B is higher than 28.5% of the number of observations in Panel A.

technological improvements story therefore may not be the sole explanation for the recent surge. Our hypothesis that past returns experienced by investors over their lifetime play a role in generating variation in stock-market participation over time and across individuals may help explain this pattern.

The three other risk-attitude measures also show considerable dispersion across households. The bond-market participation rate is similar to the stock-market participation rate. The proportion of liquid assets invested in stocks in Panel B has 10^{th} and 90^{th} percentiles of 5.9% and 90.3%. The 10^{th} and 90^{th} percentiles for elicited risk aversion in Panel A are 2.0 and 4.0, respectively. It is noteworthy that mean elicited risk aversion is *lower* for the stock-market participants in Panel B (2.787) than for the full sample in Panel B (3.120) and lies in the middle for bond market participants in Panel C (2.977). That is, the elicited risk-aversion measure is indeed correlated with households' actual attitudes towards financial risk-taking as revealed by their participation choices.

Our main question of interest is whether the variation in risk-taking measures across households is related to experienced stock and bond returns. To get a sense of the variation in these experienced returns for the households in our sample, we calculate the weighted average returns, $A_{it}(\lambda)$, from Eq. (1), for both stock and bond returns. For stock-market returns, we set $\lambda = 1.25$, and for bond returns we set $\lambda = 0.75$, which are both in the ballpark of the estimates of λ that we find later. As Panel A shows, the 10^{th} and 90^{th} percentile for the experienced (real) stock return are 5.9% and 11.0% in the 1964-2004 sample. The 10^{th} and 90^{th} percentile for experienced (real) bond returns are -0.2% and 4.6%. Thus, over our sample period, experienced bond returns are almost as volatile in real terms as experienced stock returns. Overall, there are considerable differences in the returns experienced by different cohorts. The amount of variation in experienced returns is similar for a range of values around the chosen values for λ. For example, with $\lambda = 1.00$ and $\lambda = 1.50$, values that are roughly the boundaries of the interval that contains the point estimates we obtain subsequently in our estimation, we get differences between the 10^{th} and 90^{th} percentile of 4.7% and 5.6% for real stock-market returns, respectively.

III. Results

A. Elicited Risk Aversion

We start by relating experienced stock-market returns to elicited risk aversion. We use y_{it} to denote the categorical SCF risk-aversion measure. It has four distinct categories, $y_{it} \in \{1, 2, 3, 4\}$. We model the cumulative probability of these ordinal outcomes with an ordered probit model

$$P\left(y_{it} \leq j \mid x_{it}, A_{it}(\lambda)\right) = \Phi\left(\alpha_j - \beta A_{it}(\lambda) - \gamma' x_{it}\right) \qquad j \in \{1, 2, .., 4\}, \tag{3}$$

where $\Phi(.)$ denotes the cumulative standard normal distribution function, the α_j denote the cutoff points that must be estimated ($\alpha_1 = 0 < \alpha_2 < \alpha_3 < \alpha_4 = \infty$), and x_{it} is a vector of control variables and includes income controls (log income, log income squared), demographics controls (a second-order polynomial in the number of children, dummies for retirement, completed high school education, completed college education, marital status, race, and for having a defined benefit pension plan), age dummies, and year dummies. We also control for the level of liquid assets held by the household (log liquid assets, log liquid assets squared). $A_{it}(\lambda)$ is the weighted-average stock-market return. Unlike the standard ordered probit model, $\Phi(.)$ does not map a linear function of explanatory variables into the response probability P. Instead, $A_{it}(\lambda)$ is a non-linear function of the weighting parameter λ.

We estimate the model with maximum likelihood to obtain estimates of β, λ, and γ. The coefficient vector β does not have a direct economic interpretation. To interpret the results, we focus on the partial effects of the experienced return $A_{it}(\lambda)$ on the probabilities for being in one of the four risk-aversion categories, i.e., $\partial P\left(y_{it} = j \mid x_{it}, A_{it}(\lambda)\right) / \partial A_{it}(\lambda)$. We evaluate the partial effects at each sample observation, given the estimated parameters and observations of x_{it} and $A_{it}(\lambda)$ and calculate the average partial effect across sample observations. To aid in the interpretation of the partial effects, we will compare their magnitude to the unconditional frequencies with which individuals fall into the four elicited risk aversion categories. As shown in Table II, only few of them fall into the lowest risk aversion category 1, and the highest share of more than 40% is accounted for by category 3.

Before showing the results, it is useful to reiterate two identification issues. First, our method does not rely on estimating cohort effects. If we wanted to estimate unrestricted cohort effects, we would face the problem of non-separability of cohort, age, and year (Heckman and Robb 1985). Instead, the experience hypothesis predicts that a specific variable (experienced stock returns) is positively related to risk taking, allowing us to control for age and time effects at the same time. Moreover, this explanatory variable is predicted to generate variation in risk-taking not only across but also within cohorts as they experience new return realizations over time.

A second important identification issue is reverse causality. For example, if investors' risk aversion is time-varying for reasons other than experience, past stock market returns and current risk aversion could be mechanically correlated: stock prices rise when investors become less risk averse, and drop when investors risk aversion rises. This reverse-causality concern is addressed by our identification strategy. The effect of experienced stock returns is estimated from cross-sectional differences in risk taking and variation of those cross-sectional differences over time, but not from aggregate time-variation. The year dummies absorb all aggregate time effects including variation in average risk aversion. For our other measures of risk-taking, which we consider below, year dummies also absorb all other unobserved aggregate factors that might affect stock and bond prices and, hence, simultaneously change past returns and investors' current aggregate allocation to stocks and bonds (through market clearing).

Table III presents the results of the ordered probit model. We show the estimates of the parameters of interest (β and λ) at the top of the table, and the average partial effects for the experienced returns variable at the bottom.[9] Each average partial effect shows how a partial change in $A_{it}(\lambda)$ affects the probability of being in the respective risk-aversion category, $P(y_{it} = j \mid x_{it}, A_{it}(\lambda))$. Standard errors are shown in parentheses. Column (i), estimated on the 1983-2004 sample, shows that higher experienced stock-market returns increase the probability that risk aversion is in the low categories (1 and 2), have little effect on the probability of being in category 3, and decrease the probability that the reported risk

[9] The unreported coefficients of the control variables have the sign and magnitude that one would expect given the prior literature. We report the control variable coefficients in the Appendix.

aversion is in the highest category (category 4). Thus, stock-market returns experienced in the past have a significant and positive effect on risk tolerance. Recall from Table I that the difference between the 10th and 90th percentile of life-time average stock returns is about 5.1%. Applied to the average partial effects in Table III, Column (i), a change from the 10th to the 90th percentile implies a change in the probability of being in the highest risk-aversion category of about -1.210 × 5.1% ≈ -6.2%. Compared with the unconditional frequency 28.77% of this category (see Table II), this is an economically significant effect.

The estimate of 1.466 (s.e. 0.303) for the weighting parameter λ implies that more recent returns are weighted more heavily, but also that even returns experienced many years in the past still affect households' level of risk aversion. Of course, there is a substantial standard error around the point estimate, but weights that are increasing with the time lag ($\lambda < 0$) are ruled out and the estimates imply non-negligible weights of returns early in life. Apparently, the memory of these early experiences fades away only very slowly.

As Table III shows, adding the liquid asset controls in Column (ii), or applying SCF sample weights to undo to the oversampling of high-income households in Columns (iii) and (iv) does not lead to any substantial change in the results.

B. Stock-market Participation

For our second estimation, the effect of life-time average returns on stock-market participation, we estimate the following probit model,

$$\mathrm{P}\left(y_{it}=1\,|\,x_{it},A_{it}(\lambda)\right)=\Phi\left(\alpha+\beta A_{it}(\lambda)+\gamma' x_{it}\right), \tag{4}$$

where the binary indicator y_{it} equals 1 if the stock holdings of household i at time t are greater than zero. We estimate the model with maximum likelihood. We are interested in the effect of experienced returns, $A_{it}(\lambda)$, on the probability of stock-market participation and focus on the partial effect $\partial \mathrm{P}\left(y_{it}=1\,|\,x_{it},A_{it}(\lambda)\right)/\partial A_{it}(\lambda)$. Given the estimated parameters, we evaluate this partial effect at every sample observation and average across all observations to obtain the average partial effect.

The vector x_{it} includes the same income and demographics controls as in the ordered probit model above. Controlling for liquid assets is particularly important in this context since a standard fixed participation-cost model predicts that stock-market participation is positively related to the level of liquid assets and past stock returns are likely to be positively correlated with current liquid assets.

Table IV reports the estimates from our probit model. As shown in Column (i), the life-time average returns have a positive and highly significant effect on stock-market participation. The average partial effect of 2.086 (s.e. 0.334) means that a change from the 10th to the 90th percentile of experienced stock returns (5.1%, taken from Table I) leads to an increase of about 2.086 × 5.1% ≈ 10.6% in the probability that a household participates in the stock market. Thus, the stock-market return experience of different cohorts appears to have a large effect on stock-market participation.

As with the previous measure, elicited risk aversion, the estimate of 1.300 (s.e. 0.188) for the weighting parameter λ implies that households' stock-market participation decisions are affected by returns many years in the past, but rules out weights that are increasing with the time lag ($\lambda < 0$). The weighting parameter is remarkably similar to the estimate from the elicited risk-aversion model in Table III, even though the first measure is based on risk aversion reported by the interviewee and, thus, very different from risk-taking measures based on asset holdings. Yet, a significant part of the variation in both risk-taking measures can be traced to variation in experienced stock-market returns, with roughly similar weights on the history of past returns.

In Column (ii), we add the liquid assets controls. The estimated average partial effect of life-time average returns (1.514; s.e. 0.306) is slightly lower than in Column (i). The point estimate for λ is 1.162 (s.e. 0.266), which suggests somewhat higher weights on returns in the distant past than in Column (i). Columns (v) and (vi) redo the estimation with observations weighted with SCF sample weights. As the table shows, this has little effect on the results.

C. Bond-market Participation

As our third measure of risk taking, we turn to investment in long-term bonds and test how participation in bond markets is related to experienced (real) returns on long-term government bonds. We estimate the same probit model as for our stock-market participation measure. As column (i) of Table V shows, experienced bond returns have a positive effect on bond-market participation, very similar to the effect of experienced stock returns on stock-market participation. The average partial effect of 2.289 (s.e. 0.484) implies that that a change from the 10^{th} to the 90^{th} percentile of experienced bond returns (4.8%, see Table I) leads to an increase of about $2.289 \times 5.1\% \approx 11.0\%$ in the probability that a household participates in the bond market. The point estimate for λ is lower than in case of stock-market participation, although the standard error (0.328) is quite high. Including liquid asset controls or weighting with SCF sample weights does not influence the results in a substantial way. Thus, bond-market participation and stock-market participation both show positive correlation with the returns that individuals' experienced over their lifetimes in those markets.

D. Proportion of Liquid Assets Invested in Stocks

Panel A of Table VI shows the estimated effect of experienced stock returns on the proportion of liquid assets that households invest in stocks. This measure allows us to control for fixed costs of stock-market participation, which are likely to affect stock-market participation but not the share of stocks conditional on participating. We use a non-linear regression model to estimate the effect of experienced returns,

$$y_{it} = \alpha + \beta A_{it}\left(\lambda\right) + \gamma' x_{it} + \varepsilon_{it} \tag{3}$$

where y_{it} refers to the proportion of liquid assets invested in stocks. The model is nonlinear, because the experienced stock-market return, $A_{it}(\lambda)$, is a nonlinear function of λ. We estimate the model with nonlinear least-squares. Unlike in the probit model, the partial effect of $A_{it}(\lambda)$ is now equal to the parameter β. The control variables are the same as in Tables III-V.

As column (i) shows, the life-time average return has a positive and large effect on the proportion of liquid assets invested in stocks. The point estimate of 1.121 (s.e. 0.462) implies that a change from the 10th to the 90th percentile of life-time average returns (5.1%) leads to an increase of about 1.121 × 5.1% ≈ 5.7% in the percentage allocated to stocks. Adding the liquid asset controls in column (ii) has little effect on the estimates. Weighting observations with SCF sample weights in columns (iii) and (iv), however, yields somewhat higher point estimates for both β and lower estimates for λ.

This finding is remarkable since it is a common result in the empirical literature on household portfolio choice that, once one restricts the sample to stock-market participants, it is hard to find *any* household characteristics that have economically significant correlations with the portfolio risky asset share (see Curcuru, Heaton, Lucas, and Moore (2004), and Brunnermeier and Nagel (2008) for recent evidence, and the control variable coefficients reported in Appendix C and Table A.1). In light of this evidence, experienced stock-market returns emerge as one of the major factors that influence a households' willingness to bear stock-market risk.

The point estimate for λ in column (i) is 1.553 (s.e. 0.616), which suggests weights that are declining a little faster than linearly. This estimate for λ is in the ballpark of the λ-estimates in the elicited risk-aversion model in Table III and the stock-market participation model in Table IV. The similarity of the estimates is noteworthy since elicited risk aversion is a measure based on a very different approach (survey question versus investment choice) and stock-market participation and choice of the risky asset share conditional on participation are possibly quite distinct decisions. The similarity is reassuring for our interpretation that the all of these variables capture a common attitude to financial risks and are subject to a common influence of macroeconomic experience.

We also test how the proportion of liquid assets allocated to stocks responds to the differential returns of stocks and bonds. Assuming the perspective of an investor choosing between investment in stocks and in bonds, the experience hypothesis predicts that only if stocks performed better than bonds over the lifetime of the investor, she will increase her investment in stocks relative to bonds. Panel B of

Table VI repeats the regressions of Panel A with experienced excess returns, measured as stock-market returns in excess of long-term bond returns. We find that experienced excess returns explain household's allocation to stocks even better than mere stock returns. The point estimates for β are higher than in Panel A, and the estimates for λ are moderately higher, too. The results are also similar if we restrict the sample to households that participate both in stock and bond markets and, hence, can presumably change their allocation to both stocks and bonds relatively flexibly, without facing some fixed participation cost. Repeating the regressions of column (ii) with the sample restricted to only households that participate in both stock and bond markets (not tabulated) yields estimates for β of 2.736 (s.e. 0.73) and 1.782 (s.e. 0.384) for λ.

E. Using Stock and Bond Returns Jointly to Explain Risk-taking

As an additional test of the experience hypothesis, we compare the predictive power of experienced stock returns and experienced bond returns for all of our risk measures. The experience hypothesis predicts that stock-market experiences are most relevant for the stock-based measures and bond-market experiences are most relevant for bond-based measures, but not cross effects.

To test these more subtle implications of the experience hypothesis, we relate all four of our risk measures simultaneously to experienced stock returns and to experienced bond returns. That is, we re-run the specifications of column (ii) in Tables III, IV, V, and VI (Panel A) with both experienced real stock returns and experienced real bond returns as explanatory variables. Since estimating separate weighting parameters for both stock and bond returns within the same model would be too demanding on the data and would not produce statistically reliable results, we fix the weighting parameters at the values obtained in Tables III, IV, VI, and VI (Panel A) for stock returns and Table V for bond returns. Table VII reports the results. In the first three columns, labeled "Full sample," we use all the available data, as in Tables III-V. In the last two columns, the regressions with the percentage share invested in stocks as the dependent variable are run both for the sample of stock market participants (as in Table VI) and for the sample of those that participate both in stock and bond markets.

We find that stock-based risk-taking measures are strongly positively related to experienced stock returns but unrelated or slightly negatively related to bond return experiences. Bond-market participation, in contrast, is strongly positively correlated with bond return experiences but unrelated or slightly negatively related to stock return experiences. Elicited risk aversion is negatively related to both stock (weakly) and bond return (strongly) experiences. Hence, all estimates corroborate the experience story.

The results also help to further address concerns about unobserved wealth effects, i.e., the alternative interpretation that the correlation of return experiences with unobserved wealth components, coupled with wealth-dependent risk aversion, explains our results. Since both past stock and bond returns should be positively related to wealth, one would expect both stock and bond returns to predict each of the risk-taking measures with the same sign. This is not the case.

Disentangling the joint roles of stock and bond returns also provides some hints on the question whether the life-time experiences we measure affect preferences or beliefs. The results are most easily reconciled with a belief-based story: If individuals' beliefs about future returns are positively related to their return experience with this *particular* asset class, stock returns should matter most for the stock-investment-based risk-taking measures, while bond returns should matter most for bond-market participation. A simple preference-based story, instead, in which individuals' level of relative risk aversion depends on past experiences of stock and bond returns, would not predict such differential effects of stock and bond returns on the different risk-taking measures. Only more elaborate preference-based theories, where individuals' "tastes" for different asset classes depend on their return experiences with this particular asset class, could match the last set of results.

F. Methodological Variations and Robustness Checks

We check the robustness of our results to several further variations in methodology, all of which are reported in detail in Appendix D and Appendix-Table A.2.

Including retirement assets. First, we add retirement assets to our measure of liquid assets and include stocks held in retirement accounts in our stock market participation and percentage allocation to stocks measures. The SCF offers information on the allocation of retirement assets (IRA, Keogh, 401(k), etc.) from 1989 on (when these assets become quantitatively more important as a fraction of households' total asset holdings). Before 2004, the allocation information is based on the very coarse categories of "most," "some," or "no" assets being in stocks, requiring additional assumptions for the estimations with liquid assets invested in stocks as the dependent variable. Because the survey provides no information on the split between bonds and short-term deposits and money market funds in those years, we cannot re-estimate the model bond-market participation measure with retirement assets included. (See Appendix D for more details.) For the other risk measures, the results are generally similar to those reported above. As shown in the first block of Appendix-Table A.2, we obtain the coefficient estimates β = -3.214 (s.e. 1.096) for the measure of elicited risk aversion, β = 9.652 (s.e. 1.218) for stock-market participation, and β = 1.086 (s.e. 0.365) for the percentage of liquid assets invested in stocks related to experienced real stock returns, which are close to the prior estimates of -3.384, 6.275, and 1.408 estimated in Tables III, IV, and VI (Panel A). The estimates for λ are also quite similar, albeit a bit higher in case of the percentage of liquid assets invested stocks.

Variation in starting point. In our analyses above, the starting point for life-time experiences is set at birth. This should not be a crucial assumption because our weighting function can place low or high weight on returns experienced early in life. For example, if returns realized during the first 10 or 20 years of their life do not matter much, our weighting function should be able to approximately adapt to this with a relatively high value of λ. In this example, if the starting point was set later than birth, then the weighting function should adapt to this with a lower value of λ. In Table A.2 we test this intuition, setting the starting point either at 10 years after or at 10 years before birth. For all risk-taking measures, we still find a statistically highly significant effect of experienced returns on risk taking, but the magnitudes of β and λ vary depending on the starting point. With a starting point 10 years after birth, for example, λ is lower, as observations early in life are now excluded from the weighted-average return, and there is less need to downweight early observations. The point estimates for β are generally lower, too, which partly reflects the fact that the experienced return, now averaged over are shorter sample, is more volatile, which is partly compensated for by the lower value of β.

Including cohort dummies. A major advantage of our empirical approach over prior attempts to estimate personal-history dependent risk-taking (via cohort dummies) is that we can simultaneously control for age and time effects. We are also able to distinguish our findings from unrestricted cohort effects since the experience hypothesis predicts a *specific*, signed relationship between macroeconomic experiences and risk-taking. Sufficient statistical precision permitting, we can go even further and include cohort dummies in addition to time and age dummies. Our main explanatory variable, the life-time weighted average return, varies not only across, but also within cohorts. Since neither age nor time effects fully capture the within-cohort variation, we can, in principle, identify the experience effect just from within-cohort variation. In the estimation shown in the fourth block of estimates in Table A.2, we include as many cohort dummies as possible up to the point that age, time, and cohort dummies are not perfectly collinear. In this way, the control variables span as much as possible of the variation that can be spanned by age, time, and cohort effects. This approach allows us to rule out the possibility that the experienced returns effects pick up the effects of some unobserved cohort effect that happens to be correlated with experienced returns. The statistical limit to including cohort dummies is that it restricts the identifying variation to just within-cohort variation orthogonal to age and time effects and excludes variation across cohorts, making it difficult, statistically, to detect the experienced return effects on risk-taking.

In the regressions with stock market participation and with percentage invested in stocks as the dependent variable, the point estimates remain similar after including cohort dummies, albeit with considerably higher standard errors. For the ordered probit with elicited risk aversion and the probit with bond-market participation, instead, the standard errors blow up to such high numbers that the estimates are rendered completely meaningless. Evidently, the within-cohort variation does not suffice to separate out cohort effects and, at the same time, also estimate the weighting function parameter λ. For that reason, we investigate specifications in which we fix λ at the point estimates from the main analysis in the paper: λ = 1.422, from column (ii), Table III, and λ = 0.347 from column (ii), Table V. We then estimate the remaining parameters. For elicited risk aversion, we obtain a point estimate of β that is smaller but of the same sign as in Table III and insignificantly different from zero. This implies that it is difficult to rule out that elicited risk aversion results could be driven by some unobserved cohort effects. For the bond-market participation results, we obtain a point estimate that is very close to that in Table V, but here, too, the standard error is too high to have much confidence in the estimate.

Including Experienced Volatility. We also test whether the experience hypothesis extends to an effect of experienced volatility on households' investment decisions. In the bottom block of Table A.2, we include an experienced volatility variable in addition to the weighted-average experienced returns. To calculate experienced volatility, we apply the same weighting function used for the experienced returns, but now estimating the weighted standard deviation instead of the weighted average of returns. To limit the demands on the estimation, we fix the weighting parameter at the point estimate for λ obtained in column (ii) of Tables III-VI and apply it both to the weighted average and the weighted standard deviation. We find that experienced volatility tends to be negatively associated with risk taking (with the exception of elicited risk aversion), but the effect is not consistently statistically significant. Most importantly, the inclusion of experienced volatility has little effect on the coefficient on weighted-average returns. While we do not conduct in an in-depth investigation of experienced volatility effects, it is useful to note that absence of a consistently strong relationship between the risk-taking measures and experienced volatility does not mean that households ignore the volatility of stock returns when making investment decisions. Rather, *differences* in experienced volatility do not seem to strongly relate to *differences* in risk-taking between individuals. It is also possible that experience of extreme events, in particular extreme downside events, affect risk-taking more strongly than volatility measures would suggest. But the rare nature of extreme events, combined with the unavoidable arbitrariness in deciding what constitutes an extreme event, means that their effects are difficult to investigate empirically within our framework, and we leave an investigation of extreme events to future work.

Clustered standard errors. To check whether our regression residuals might have some positive correlation that leads to an understatement of standard errors, we cluster standard errors by year or by cohort. We find that clustering has little effect. For example, for the stock market participation probit model in Table IV, column (ii), clustering by year leads to slightly higher standard error estimates than the ones we reported in Table IV (1.408 for β; 0.296 for λ), while clustering by cohort leads to slightly lower standard error estimates (1.216 for β; 0.296 for λ). We obtain similar results for the other risk-taking measures.

IV. An Aggregate Perspective

Our microdata estimates suggest that investors' personally experienced history of risky asset returns affects their willingness to take financial risks. Since experienced returns are correlated with risky asset demand at the micro-level, they should also be correlated with risky asset demand at the aggregate level. These experience-driven variations in aggregate demand could then help to explain variation in stock-market valuation levels over time. To provide some perspective on this issue, we perform a simple aggregation exercise: Based on our microdata estimates of how individuals weight their past return experiences, we aggregate the experienced stock-market returns across all U.S. households in each year and check whether this aggregate experienced stock-market return is correlated with stock-market valuation levels.

Since experienced returns are identical for individuals of the same age, we calculate experienced stock-market returns for each age group, in each year, based on a weighting parameter of $\lambda = 1.25$ (i.e., roughly the average parameter estimate across all specifications with experienced stock returns as explanatory variable). Then we compute the weighted average of these experienced returns across age group, where each age group is weighted by its liquid asset holdings (as higher liquid assets means higher impact on aggregate demand for stocks) multiplied with the SCF survey weight. The data on the liquid asset distribution across age groups, which is necessary to calculate the weights, is available only in those in years in which the SCF was administered. However, it turns out this liquid assets distribution is very stable over time. As plotted in Figure 3, the only exception is the year 1964, when the wealth definition in the SCF was substantially different.

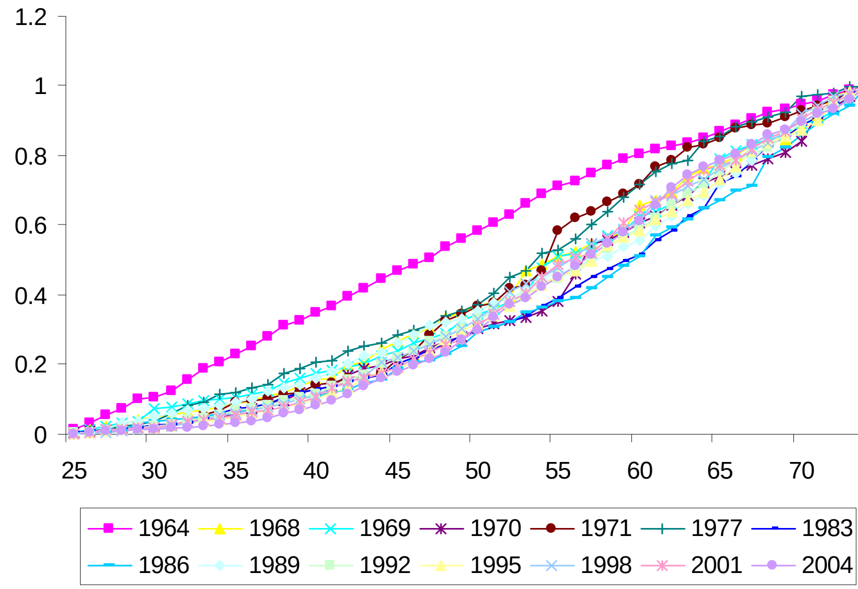

Figure 3: Distribution of liquid assets across age groups in each survey year. For each survey year, we calculate the proportion of total aggregate liquid assets held by each age group, weighted by SCF sample weights. The graph shows the cumulated proportions from age 25 to 74.

The relative stability of the liquid asset distribution suggests that we can extend our calculation of the aggregate experienced returns beyond the SCF survey years by making the assumption that the liquid asset distribution in other years was similar to the one in the observed years. We therefore use the average of the liquid asset distribution from the SCF waves from 1968 - 2004 to weight experienced returns across age groups in all years from 1946 – 2004, the longest possible sample given that our stock return data starts in 1871 and we include investors up to age 74.

Figure 4 presents the results from this exercise. Each bar represents the aggregated experienced stock-market return of U.S. investors in the corresponding year. Figure 4 also plots the annual price-to-earnings (P/E) ratio from Shiller (2005), which uses a ten-year moving average of earnings in the denominator and which is known to be negatively related to future stock-market returns. The two series are highly positively correlated. Periods of high equity market valuations (the 1960s and 1990s) coincide with periods when investors have high experienced stock-market returns, and periods of low valuation (late 1970s and early 1980s) coincide with investors having low experienced stock-market returns.

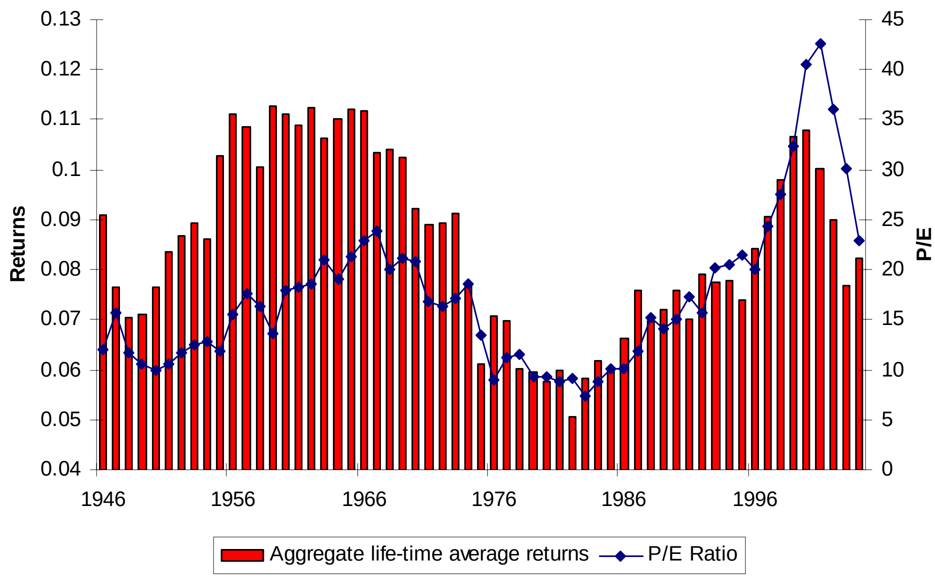

Figure 4: Aggregated experienced real stock returns (λ = 1.25) and equity market valuation 1946-2004.

Note that this correlation does not mechanically reflect the well-known positive correlation between P/E ratios and past returns. We estimate the weighting parameter λ from *microdata* on cross-sectional differences between investors' risk-taking measures. We do not use aggregate data in the estimation, and λ is not chosen to match movements in the P/E ratio over time. For example, the weighting parameter estimated from the microdata could have turned out to be strongly negative, which would mean that investors place a lot of weight on returns experienced early in life, but less on more recent returns. In that case, the aggregate life-time average return would have been uncorrelated with recent stock-market returns and the time pattern of the bars in Figures 4 would look very different.

This point is underscored in Figure 5. The figure shows the correlation between aggregated experienced stock returns and the P/E ratio for different choices of the weighting parameter λ. The figure demonstrates that the correlation between life-time average returns and the P/E ratios could easily have been smaller if the microdata-estimates of λ had turned out differently. The value of λ = 1.25 is actually close to the maximum in Figure 5. And the range of point estimates between 1.0 and 2.0 that we obtained in most of our estimated models all yield a high correlation of around 0.6.

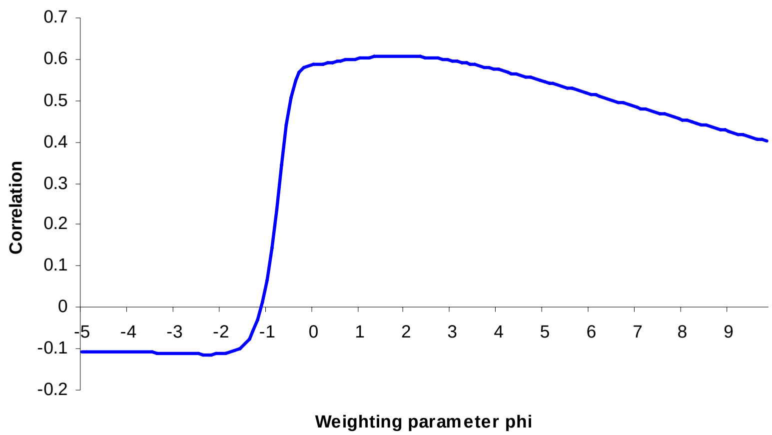

Figure 5: Correlation between experienced real stock returns and P/E ratio for different choices of the weighting parameter λ.

The high correlation between aggregate experienced stock returns and stock-market valuation levels adds credibility to our microdata estimates, as the estimates imply plausible time-variation in aggregate demand for risky assets. Our results thus suggest the possibility that personally experienced risky asset returns affect asset prices via changes in investors' willingness to take risk. We leave a further exploration of such asset-pricing effects to future work, as the scope of the current paper is focused on estimating relationships in microdata.

V. Conclusion

Our results show that risky asset returns experienced over the course of an individual's life have a significant effect on the willingness to take financial risks. Individuals who have experienced high stock-market returns report lower aversion to financial risks, are more likely to participate in the stock market, and allocate a higher proportion of their liquid asset portfolio to risky assets. Individuals who have experienced high real bond returns are more likely to participate in the bond market. While individuals put more weight on recent returns than on more distant realizations, the impact fades only slowly with time. According to our estimates, even experiences several decades ago still have some impact on current risk-taking of older households.

Our results are consistent with the view that economic events experienced over the course of one's life have a more significant impact on individuals' risk taking than historical facts learned from summary information in books and other sources. If all investors at a given point in time were influenced by the same set of historical data, and all placed the same weight on past return observations, then the effect of those experiences would be absorbed by the time dummies in our regressions. It is the differential weighting of returns in the past by investors of different age that the experienced-return variables pick up in our regressions.

We remain agnostic at this point whether the experience effects on risk taking arise from experience-dependent beliefs or from endogenous risk preferences. In both cases, the dependence on "experienced data"—as opposed to "available data" in standard rational and boundedly rational learning models, for example—could have important implications for both explaining heterogeneity between economic agents at the micro-level and the dynamics of asset prices at the macro level. We offer some evidence that the beliefs channel seems to be important in follow-up work, Malmendier and Nagel (2009), where we show that inflation expectations are influenced by individuals' inflation experiences in similar ways as risk-taking is influenced by experiences of risky asset returns.

References

Acemoglu, Daron and Joshua Linn, 2004. Market Size in Innovation: Theory and Evidence From the Pharmaceutical Industry, *Quarterly Journal of Economics*, 199, 1049-1090.

Alesina, Alberto, and Nicola Fuchs-Schündeln, 2007. Good-bye Lenin (or Not?): The Effect of Communism on People's Preferences, *American Economic Review*, 97, 1507-1528.

Ameriks, John, and Stephen Zeldes, 2004. How Do Household Portfolio Shares Vary With Age? *Columbia University Working Paper*.

Ang, Andrew and Angela Maddaloni, 2005. Do Demographic Changes Affect Risk Premiums? Evidence from International Data, *Journal of Business*, 78, 341-380.

Auerbach, Alan and Ronald Lee (eds), 2001. *Demographic Change and Fiscal Policy*. Cambridge University Press, Cambridge.

Avery, Robert B., and Gregory E. Elliehausen, 1990. 1983 Survey of Consumer Finances: Technical Manual and Codebook, *Board of Governers of the Federal Reserve System Working Paper*.

Becker, Gary and Casey Mulligan, 1997. The Endogenous Determination of Time Preference, *Quarterly Journal of Economics*, 112, 729-758.

Bound, John and Sarah Turner, 2007. Cohort Crowding: How Resources Affect Collegiate Attainment *Journal of Public Economics* 91, 877-899.

Bowles, Samuel, 1998. Endogenous Preferences: The Cultural Consequences of Markets and other Economic Institutions, *Journal of Economic Literature* 36, 75-111.

Brunnermeier, Markus, and Stefan Nagel, 2008. Do Wealth Fluctuations Generate Time-Varying Risk Aversion? Micro-Evidence on Individuals' Asset Allocation, *American Economic Review* 98, 713-736.

Camerer, Colin and Teck Ho, 1999. Experience-Weighted Attraction Learning in Normal Form Games, *Econometrica* 67, 827-874.

Campbell, John Y., 2001. A Comment on James Poterba's "Demographic Structure and Asset Returns", *Review of Economics and Statistics* 83, 585-588.

Card, David, and Lemieux, Thomas, 2000. Dropout and Enrollment Trends in the Post-War Period: What Went Wrong in the 1970s? In: J. Gruber (ed.), *An Economic Analysis of Risky Behavior Among Youth*. University of Chicago Press, Chicago, 439-482.

Caroll, Christopher D., Karen Dynan, and Spencer D. Krane, 2003. Unemployment Risk and Precautionary Wealth: Evidence from Households' Balance Sheets, *Review of Economics and Statistics* 85, 586-604.

Cogley, Timothy, and Thomas J. Sargent, 2005. The Market Price of Risk and the Equity Premium: A Legacy of the Great Depression?, *New York University Working Paper*.

Choi, James; Laibson, David, and Andrew Metrick, 2002. Does the Internet Increase Trading? Evidence from Investor Behavior in 401k Plans, *Journal of Financial Economics* 64, 397-421.

Curcuru, Stephanie, John Heaton, Deborah Lucas, and Damien Moore, 2004. Heterogeneity and Portfolio Choice: Theory and Evidence, *Handbook of Financial Econometrics*, forthcoming.

Deaton, Angus, 1997. *The Analysis of Household Surveys: A Microeconometric Approach to Development Policy*, Johns Hopkins University Press, Baltimore MD.

DellaVigna, Stefano and Joshua Pollet, 2007. Demographics and Industry Returns, *American Economic Review*, 97, 1667-1702.

Dynan, Karen, Jonathan Skinner, and Stephen P. Zeldes, 2002. The Importance of Bequests and Life-Cycle Saving in Capital Accumulation: A New Answer, *American Economic Review* 92, 274-278.

Easterlin, Richard A., 1987. *Birth and Fortune: The Impact of Numbers on Personal Welfare*. University of Chicago Press, Chicago.

Faig, Miquel, and Pauline Shum, 2006. What Explains Household Stock Holdings?, *Journal of Banking and Finance* 30, 2579-2597.

Fair, Ray C. and Kathryn M. Dominguez, 1991. Effects of the Changing U.S. Age Distribution on Macroeconomic Equations, *American Economic Review* 81, 1276-1294.

Fernandez, Raquel, Alessandra Fogli, and Claudia Olivetti, 2004. Mothers and Sons: Preference Formation and Female Labor Force Dynamics, *Quarterly Journal of Economics*, 119, 1249-1299, 2004.

Friedman, Milton, and Anna J. Schwartz, 1963. *A Monetary History of the United States, 1867-1960*, Princeton University Press, Princeton, NJ.

Geneakoplos, John, Michael J.P. Magill and Martine Quinzii, 2004. Demography and the Long-Run Predictability of the Stock Market, *Brookings Papers on Economic Activity*, 1, 241-307.

Goyal, Amit, 2004. Demographics, Stock Market Flows, and Stock Returns, *Journal of Financial and Quantitative Analysis* 39, 115-142.

Graham, John R., and Krishnamoorthy Narasimhan, 2004. Corporate Survival and Managerial Experiences During the Great Depression, *Duke University Working Paper*.

Greenwood, Robin, and Stefan Nagel, 2007. Inexperienced Investors and Bubbles, *Journal of Financial Economics, forthcoming.*

Gruber, Jonathan and David Wise, 1999. Social Security Programs and Retirement Around the World, *Research on Labor Economics*, 18, 1-40.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales, 2004. The Role of Social Capital in Financial Development, *American Economic Review*, 94, 526-556.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales, 2008. Trusting the Stock Market, *Journal of Finance*, 63, 2557-2600.

Hertwig, Ralph, Greg Barron, Elke U. Weber, and Ido Erev, 2004. Decisions from Experience and the Effect of Rare Events in Risky Choice, *Psychological Science* 15, 534-539.

Kennickell, Arthur B., 1998. Multiple Imputation in the Survey of Consumer Finances, *Board of Governors of the Federal Reserve System Working Paper*.

Kaustia, Markku, and Samuli Knüpfer, 2008. Do Investors Overweight Personal Experience? Evidence from IPO Subscriptions, *Journal of Finance* 63, 2679-2702.

Malmendier, Ulrike, and Stefan Nagel, 2009. Learning from Inflation Experiences, *Stanford University and UC Berkeley Working Paper.*

Malmendier, Ulrike, and Geoffrey Tate, 2005. CEO Overconfidence and Corporate Investment, *Journal of Finance*, 60, 2661-2700.

Nisbett, Richard E., and Lee D. Ross, 1980. *Human Inference: Strategies and Shortcomings of Social Judgment*, Englewood Cliffs, N.J.: Prentice Hall.

Osili, Una Okonkwo, and Anna L. Paulson, 2008. "Institutions and Financial Development: Evidence from International Migrants in the United States," *Review of Economics and Statistics*, 90 (3), 498-517.

Palacios-Huerta, Ignacio and Tano J. Santos, 2004. A Theory of Markets, Institutions, and Endogenous Preferences, *Journal of Public Economics* 88, 601– 627.

Piazzesi, Monika, and Martin Schneider, 2006. Inflation and the Price of Real Assets, *University of Chicago Working Paper*.

Poterba, James M., 2001. Demographic Structure and Asset Returns, *Review of Economics and Statistics* 83, 565-584.

Poterba, James M., and Andrew Samwick, 2001. Household Portfolio Allocations Over the Life-Cycle, in S. Ogura, T. Tachibanaki, and D. Wise, ed., *Aging Issues in the U.S. and Japan* (University of Chicago Press, Chicago), 65-103.

Rubin, Donald B.,1987. *Multiple Imputation for Nonresponse in Surveys* (J. Wiley & Sons, New York).

Sahm, Claudia R., 2007. Stability of Risk Preference, *Federal Reserve Board of Governors Working Paper*.

Samuelson, Paul A., 1969. Lifetime Portfolio Selection by Dynamic Stochastic Programming, *Review of Economics and Statistics* 51, 239-243.

Schlag, Karl, 1999a. Which One Should I Imitate?, *Journal of Mathematical Economics* 31, 493-522.

Schlag, Karl, 1999b. Why Imitate, and If So, How?, *Journal of Economic Theory* 78, 130-156.

Schotter, Andrew, 2003. Decision Making with Naïve Advice, *American Economic Review, Papers & Proceedings* 93, 196-201.

Shaw, Kathryn L., 1996. An Empirical Analysis of Risk Aversion and Income Growth, *Journal of Labor Economics* 14, 626-653.

Shiller, Robert J., 2005. *Irrational Exuberance* (second edition), Princeton University Press, Princeton NJ.

Simonsohn, Uri; Karlsson, Niklas; Loewenstein, George; and Dan Ariely, 2008. The Tree of Experience in the Forest of Information: Overweighing Experienced Relative to Observed Information, *Games and Economic Behavior* 263-286.

Weber, Elke U., Ulf Böckenholt, Denis J. Hilton, and Brian Wallace, 1993. Determinants of Diagnostic Hypothesis Generation: Effects of Information, Base Rates, and Experience, *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 19, 1151-1164.

Vissing-Jorgensen, Annette 2003. Perspectives on Behavioral Finance: Does "Irrationality" Disappear with Wealth? Evidence from Expectations and Actions, *NBER Macroeconomics Annual*.

Table I: Summary Statistics

	10th pctile	Median	90th pctile	Mean	Stddev	#Obs.
Panel A: All households 1964 – 2004						
Liquid assets	696	9,820	205,590	119.858	721,755	33,600
Income	16,819	48,849	109,957	65,679	178,229	33,600
Experienced real stock return ($\lambda = 1.25$)	0.059	0.086	0.110	0.085	0.021	33,600
Experienced real bond return ($\lambda = 0.75$)	-0.002	0.012	0.046	0.018	0.019	33,600
Stock market participation	0	0	1	0.285	0.451	33,591
Bond market participation	0	0	1	0.322	0.467	32,269
Elicited risk aversion (1983-2004)	2	3	4	3.120	0.834	22,316
Panel B: Stock market participants 1964-2004						
Liquid assets	5,375	47,676	431,419	224,766	1,258,931	12,977
Income	29,382	69,828	171,645	104,040	313,501	12,977
Bond market participation	0	0	1	0.496	0.498	12,736
% Liquid assets in stocks	0.059	0.427	0.903	0.473	0.439	12,117
Elicited risk aversion (1983-2004)	2	3	4	2.787	0.776	9,531
Panel C: Bond market participants 1968-2004						
Liquid assets	1,950	22,191	302,054	166,977	1,139,639	12,226
Income	26,939	62,690	140,487	89,377	263,974	12,226
Stock market participation	0	0	1	0.454	0.497	11,225
% Liquid assets in stocks	0.000	0.000	0.649	0.179	0.272	11,542
Elicited risk aversion (1983-2004)	2	3	4	2.977	0.796	8,749

Notes: Stock returns and bond returns are real returns, calculated with CPI inflation. Wealth and income variables are deflated by the CPI into September 2004 dollars. Observations are weighted by SCF sample weights.

Table II: Frequency Distribution of Elicited Risk Aversion

Category	Unweighted	Weighted
1 (Low risk aversion)	5.85%	4.45%
2	21.15%	16.11%
3	44.23%	42.40%
4 (High risk aversion)	28.77%	37.04%

Notes: Sample period runs from 1983 to 2004, excluding the 1986 survey (elicited risk aversion not available). Weighted estimates are based on observations weighted with SCF sample weights.

Table III: Elicited Risk Aversion

	(i) 1983-2004	(ii) 1983-2004	(iii) 1983-2004 weighted	(iv) 1983-2004 weighted
Ordered Probit coefficient estimates:				
Experienced stock return coefficient β	-4.055	-3.384	-4.735	-3.930
	(1.091)	(1.091)	(1.213)	(1.221)
Weighting parameter λ	1.466	1.422	1.743	1.774
	(0.303)	(0.511)	(0.536)	(0.652)
Income controls	Yes	Yes	Yes	Yes
Liquid assets controls	-	Yes	-	Yes
Demographics controls	Yes	Yes	Yes	Yes
Age dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Average partial effect of experienced stock return on category probability				
Risk aversion = 1 (low)	0.444	0.369	0.628	0.522
	(0.119)	(0.119)	(0.161)	(0.162)
Risk aversion = 2	0.742	0.606	0.707	0.594
	(0.200)	(0.195)	(0.181)	(0.185)
Risk aversion = 3	0.024	0.017	0.085	0.043
	(0.006)	(0.005)	(0.022)	(0.013)
Risk aversion = 4 (high)	-1.210	-0.992	-1.419	-1.159
	(0.325)	(0.320)	(0.364)	(0.360)
#Obs.	22,260	22,260	22,260	22,260
Pseudo R^2	0.08	0.10	0.07	0.08

Notes: Ordered probit model estimated with maximum likelihood. Sample period excludes the 1986 survey (elicited risk aversion not available). The experienced stock return is calculated from the real return on the S&P500 index. Average partial effects are the sample averages of partial effects on each category probability (given the estimated β and λ) evaluated at each sample observation. Demographic controls (coefficients not reported) include the number of children and number of children squared, as well as dummies for marital status, retirement, race, education, and for having a defined benefit pension plan. In column (iii) and (iv) observations are weighted with SCF sample weights. Standard errors shown in parentheses are robust to misspecification of the likelihood function and adjusted for multiple imputation.

Table IV: Stock-market Participation

	(i) 1964-2004	(ii) 1964-2004	(iii) 1964-2004 weighted	(iv) 1964-2004 weighted
Probit coefficient estimates:				
Experienced stock return coefficient β	7.230	6.275	7.724	5.834
	(1.157)	(1.270)	(1.287)	(1.447)
Weighting parameter λ	1.300	1.162	1.382	1.117
	(0.188)	(0.266)	(0.237)	(0.313)
Income controls	Yes	Yes	Yes	Yes
Liquid assets controls	-	Yes	-	Yes
Demographics controls	Yes	Yes	Yes	Yes
Age dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Average partial effect of experienced stock return on participation probability	2.086	1.514	2.075	1.440
	(0.334)	(0.306)	(0.346)	(0.357)
#Obs.	33,535	33,535	33,535	33,535
Pseudo R^2	0.24	0.36	0.16	0.26

Notes: Probit model estimated with maximum likelihood. The experienced stock return is calculated from the real return on the S&P500 index. Average partial effects are the sample averages of partial effects evaluated at each sample observation (given the estimated β and λ). Demographic controls (coefficients not reported) include the number of children and number of children squared, as well as dummies for marital status, retirement, race, education, and for having a defined benefit pension plan. In column (iii) and (iv) observations are weighted with SCF sample weights. Standard errors shown in parentheses are robust to misspecification of the likelihood function and adjusted for multiple imputation.

Table V: Bond-market Participation

	(i) 1968-2004	(ii) 1968-2004	(iii) 1968-2004 weighted	(iv) 1968-2004 weighted
Probit coefficient estimates:				
Experienced bond return coefficient β	6.819	5.653	7.744	5.151
	(1.443)	(1.342)	(1.830)	(1.709))
Weighting parameter λ	0.597	0.347	0.997	0.825
	(0.328)	(0.288)	(0.452)	(0.540)
Income controls	Yes	Yes	Yes	Yes
Liquid assets controls	-	Yes	-	Yes
Demographics controls	Yes	Yes	Yes	Yes
Age dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Average partial effect of experienced bond return on participation probability	2.289	1.782	2.593	1.660
	(0.484)	(0.423)	(0.613)	(0.551)
#Obs.	32,213	32,213	32,213	32,213
Pseudo R^2	0.11	0.16	0.08	0.12

Notes: Probit model estimated with maximum likelihood. The experienced bond return is calculated from the real return on long-term U.S. Treasury bonds. Average partial effects are the sample averages of partial effects evaluated at each sample observation (given the estimated β and λ). Demographic controls (coefficients not reported) include the number of children and number of children squared, as well as dummies for marital status, retirement, race, education, and for having a defined benefit pension plan. In column (iii) and (iv) observations are weighted with SCF sample weights. Standard errors shown in parentheses are robust to misspecification of the likelihood function and adjusted for multiple imputation.

Table VI: Percentage of Liquid Assets Invested in Stocks

Panel A. Experienced Stock Returns

	(i) 1968-2004	(ii) 1968-2004	(iii) 1968-2004 weighted	(iv) 1968-2004 weighted
Experienced stock return coefficient β	1.121	1.120	1.408	1.436
	(0.462)	(0.463)	(0.563)	(0.564)
Weighting parameter λ	1.553	1.549	1.134	1.129
	(0.616)	(0.609)	(0.513)	(0.492)
Income controls	Yes	Yes	Yes	Yes
Liquid assets controls	-	Yes	-	Yes
Demographics controls	Yes	Yes	Yes	Yes
Age dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
#Obs.	11,859	11,859	11,859	11,859
R^2	0.06	0.06	0.08	0.08

Panel B. Experienced Excess Returns of Stocks Over Bonds

	(i) 1968-2004	(ii) 1968-2004	(iii) 1968-2004 weighted	(iv) 1968-2004 weighted
Experienced excess return coefficient β	1.892	1.899	2.020	2.059
	(0.556)	(0.556)	(0.662)	(0.662)
Weighting parameter λ	1.925	1.923	1.812	1.783
	(0.471)	(0.468)	(0.489)	(0.471)
Income controls	Yes	Yes	Yes	Yes
Liquid assets controls	-	Yes	-	Yes
Demographics controls	Yes	Yes	Yes	Yes
Age dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
#Obs.	11,859	11,859	11,859	11,859
R^2	0.06	0.06	0.08	0.09

Notes: Model estimated with nonlinear least squares on the sample of stock market participants. Sample period excludes the 1971 survey (percentage allocation not available). Experienced returns in Panel A are calculated from the real return on the S&P500 index and experienced excess return in Panel B from the return on the S&P500 index minus the return on long-term U.S. Treasury bonds. Demographic controls (coefficients not reported) include the number of children and number of children squared, as well as dummies for marital status, retirement, race, education, and for having a defined benefit pension plan. In column (iii) and (iv) of both panels observations are weighted with SCF sample weights. Standard errors shown in parentheses are robust to heteroskedasticity and adjusted for multiple imputation.

Table VII: Using stock and bond returns jointly

Dependent variable	Elicited risk aversion	Stock mkt. participation	Bond market participation	% liquid assets in stocks	% liquid assets in stocks
Sample	Full	Full	Full	Stock market participation required	Stock and bond market participation required
Experienced stock return coeff. β_{stock}	-0.941	6.539	-1.727	1.899	2.555
	(1.696)	(1.413)	(1.286)	(0.569)	(0.757)
Weighting parameter for stocks λ_{stock}	1.422	1.162	1.162	1.549	1.549
	[fixed]	[fixed]	[fixed]	[fixed]	[fixed]
Experienced bond return coeff. β_{bond}	-5.162	-0.619	6.564	-1.180	-1.170
	(2.772)	(1.489)	(1.399)	(0.650)	(0.848)
Weighting parameter for bonds λ_{bond}	0.347	0.347	0.347	0.347	0.347
	[fixed]	[fixed]	[fixed]	[fixed]	[fixed]

Notes: Models and controls as in columns (ii) in Tables III, IV, V, and VI (Panel A), but with both experienced real stock returns and experienced real bond returns jointly included as explanatory variables and λ parameters fixed at the values obtained in Tables III, IV, VI, and VI (Panel A) for stock returns and Table V for bond returns. The experienced stock return is calculated from the real return on the S&P500 index. The experienced bond return is calculated from the real return on long-term U.S. Treasury bonds. Estimations in the columns labeled "Full sample" use all available data; estimations in the last two columns use both the sample of stock market participants and the sample of those investing both in stocks and in bonds, respectively.

Appendix

A. Details on SCF Data

For our empirical analysis, we employ both the SCF and its precursor surveys. One challenge in the construction of such a pooled data set over a relatively long periods of time is that the definitions of some data items change over time. Such changes reflect changes in the survey methodology and its level of detail, but also changes in the investment environment that occurred over the last 40 years. In this section, we detail how we dealt with these issues.

One problem concerns the construction of the stock-market participation indicator variable and the share of liquid assets invested in stocks. Information on the equity portion of mutual fund holdings is not available in the SCF prior to 1989. However, money-market mutual funds and tax-free mutual funds are reported separately in 1983 and 1986. In those years, we count the portion of mutual fund holdings not accounted for by money market funds and tax-free mutual funds as stock holdings. Prior to 1983, we include the total holding of mutual funds. Note that in those earlier years, mutual fund holdings are rather trivial relative to direct stock holdings, and money-market mutual funds were just emerging. For example, according to the Flow of Fund accounts of the Federal Reserve, in 1977 the household and non-profit sector held about \$631 billion of corporate equities directly, but only \$40 billion of mutual fund shares. Even in 1983, mutual fund holdings are less than one tenth of direct corporate equity holdings of the household and non-profit sector. In 2004, this number is almost 50%. Hence, the coding imprecision due to this missing information is unlikely to affect our results much.

The same issue appears for bond market participation. From 1989 onwards, bond holdings include the bond share of mutual fund holdings, while prior to 1989, it comprises only direct holdings of bonds (government bonds, corporate bonds, and foreign bonds) and tax-free bond fund holdings.

A second set of issues concerns the construction of liquid assets. One item that one could potentially include is the cash value life insurance. We have chosen to exclude this item for two reasons. First, the cash value information is not available prior to 1983. Second, even in subsequent surveys, cash value life insurance is notoriously badly measured (see Avery and Elliehausen 1990).

Another problem is that, in 1964 and 1977, asset holding values are not given in a direct dollar number, but instead as a categorical variable, where each category corresponds to a range of values. We assign the midpoint of these ranges as the dollar value. Moreover, in 1964, we can measure liquid assets only with a variable that include real estate, which is different from all the other years. We therefore do not calculate the stock share of liquid assets in 1964. In 1971, we do not have a separate dollar amount of stock holdings, only a combined number for stocks and bonds, and an indicator variable for greater than zero stock holdings. Hence, we only construct the stock-market participation variable but not the stock share of liquid assets for 1971.

B. Details on Estimation

As described in Section II.A, our estimations follow the method of Rubin (1987) to account for multiple imputation. The details are as follows: Let b_m be the estimated coefficient vector obtained from implicate m, m = 1, …, M, and denote the corresponding covariance matrix estimate by V_m. The overall point estimates are given by the average of the individual implicate point estimates:

$$\bar{b} = \frac{1}{M}\sum_{m=1}^{M} b_m \,. \tag{A.1}$$

From the b_m we also calculate the between-implicate variance of the estimates,

$$Q = \frac{1}{M-1}\sum_{m=1}^{M}\left(b_m - \bar{b}\right)\left(b_m - \bar{b}\right), \tag{A.2}$$

which is then combined with the average covariance matrix of the individual implicate estimates,

$$\bar{V} = \frac{1}{M}\sum_{m=1}^{M} V_m \tag{A.3}$$

to get Ω, the overall covariance matrix of the coefficient estimates,

$$\Omega = \bar{V} + \left(1 + \frac{1}{M}\right)Q \tag{A.4}$$

For further details see Rubin (1987).

We compute standard errors using a robust "sandwich" asymptotic covariance matrix estimator. In the case of the probit and ordered probit, the estimator for the asymptotic covariance of $\sqrt{N}\left(b-\theta\right)$ is

$$V = \left\{-H(b)\right\}^{-1}\left\{\frac{1}{N}\sum_{i=1}^{N} g_i(b)g_i(b)'\right\}\left\{-H(b)\right\}^{-1} \tag{A.5}$$

where b is the estimated coefficient vector, θ is the true coefficient vector, N is the number of observations in the total pooled sample, $H(b)$ is the Hessian matrix of the likelihood function, evaluated at b, and $g(b)$ is the gradient vector of the likelihood function.

In the case of non-linear least squares,

$$V = \left\{\sum_{i=1}^{N} g_i(b)g_i(b)'\right\}^{-1}\left\{\sum_{i=1}^{N} \varepsilon_i^2 g_i(b)g_i(b)'\right\}\left\{\sum_{i=1}^{N} g_i(b)g_i(b)'\right\}^{-1} \tag{A.6}$$

where $g(b)$ now denotes the gradient vector of the regression function with respect to the parameter vector.

C. Coefficients on control variables

The tables in the main text omit the coefficients on the control variables, as those are not directly relevant for our analysis. However, the coefficients on the control variables may be of general interest, and are also useful to see that the regressions are picking up systematic differences between individuals in their risk attitudes. Table A.1 reports the coefficient estimates for the control variables from the estimations in column (ii) of Tables III-VII, i.e., the specification that includes liquid asset controls and is unweighted. The age and year dummy coefficient estimates are not reported. As the table shows, non-white race and higher education as well as higher income and liquid assets are most strongly associated with lower elicited risk aversion and with higher stock and bond market participation. For the percentage allocation to stocks, however, none of the control variables except the dummy for college degree has any statistically significant relationship with the dependent variable.

D. Robustness checks

Table A.2 checks the robustness of our results with respect to several additional changes in methodology. We report the estimates for beta and lambda in each case. The specification corresponds to column (ii) in Tables III-VII, i.e., it includes the liquid asset controls and is unweighted.

The first block of results shows estimates obtained when including retirement assets in the asset holdings variables from 1989 on. As described in the main text, the allocation information in stock and other assets is very coarse (categories of "most," "some," or "no" assets being in stocks), and it does not split of other assets into long-term bonds and short-term instruments such as money market accounts and certificates of deposit. Hence, we cannot rerun the estimations for bond market participation. We also cannot re-estimate the effect on the liquid asset share of stocks without making additional approximative assumptions. We follow the SCF and assume 100% stocks for the category "mostly invested in stock", 50% for "split between stocks/bonds or stocks/money market" in the case of IRAs/Keoghs and for "split between stocks and interest earning assets" in the case of thrift-type retirement accounts including 401k plans, and 33% for "split between stocks/bonds/money market." The resulting λ estimates are higher than before though still within two standard errors from the estimates in Table VI, given that the standard error is also substantially higher.

In the second and third blocks, we vary the starting point for the weighting function to 10 years before the birth of the household head and to 10 years after. In the fourth block, we introduce cohort dummies, described in the main text. The bottom block of results in Table A.2 shows tests in which we also include experienced volatility measures along with the experienced returns variable. All estimations and results are described in the main text.

Table A.1: Control variable coefficient estimates

Dependent variable	Elicited risk aversion	Stock mkt. participation	Bond market participation	% liquid assets in stocks	%liquid assets in stocks
Experienced return variable	Real stock returns	Real stock returns	Real bond returns	Real stock returns	Excess returns of stocks over bonds
African American	0.073	-0.176	-0.159	-0.002	-0.002
	(0.034)	(0.046)	(0.038)	(0.019)	(0.018)
Hispanic	0.142	-0.369	-0.527	-0.014	-0.014
	(0.048)	(0.065)	(0.056)	(0.027)	(0.027)
Other non-White	0.164	-0.229	-0.359	-0.005	-0.005
	(0.045)	(0.057)	(0.053)	(0.018)	(0.019)
Non-White (pre-1983)	-	-0.432	0.021	0.043	0.041
	-	(0.077)	(0.060)	(0.048)	(0.048)
High School completed	-0.267	0.394	0.154	0.005	0.003
	(0.035)	(0.031)	(0.026)	(0.015)	(0.015)
College degree	-0.214	0.254	0.059	0.021	0.021
	(0.018)	(0.019)	(0.018)	(0.007)	(0.007)
Married	0.023	0.022	0.083	0.005	0.005
	(0.021)	(0.023)	(0.021)	(0.008)	(0.008)
Retired	0.142	-0.006	-0.010\	-0.015	-0.015
	(0.027)	(0.033)	(0.029)	(0.010)	(0.010)
#Children	0.065	0.006	0.227	0.003	0.003
	(0.017)	(0.017)	(0.016)	(0.006)	(0.006)
$\#Children^2$	-0.009	0.000	-0.034	-0.001	-0.001
	(0.004)	(0.004)	(0.004)	(0.001)	(0.001)
Log Income	-0.522	0.988	0.788	0.007	0.005
	(0.075)	(0.096)	(0.078)	(0.027)	(0.027)
$(\text{Log Income})^2$	0.016	-0.039	-0.033	-0.001	-0.001
	(0.003)	(0.004)	(0.003)	(0.001)	(0.001)
Has defined benefit plan	0.035	0.106	0.235	0.005	0.005
	(0.016)	(0.021)	(0.019)	(0.006)	(0.006)
Log liquid assets	-0.222	0.634	0.154	0.003	0.003
	(0.020)	(0.036)	(0.023)	(0.011)	(0.011)
$(\text{Log liquid assets})^2$	0.006	-0.012	0.003	0.000	0.000
	(0.001)	(0.002)	(0.001)	(0.000)	(0.000)
Log liquid assets in 1964	-	1.943	-	-	-
		(0.276)			
$(\text{Log liquid assets})^2$ in 1964	-	-0.106	-	-	-
		(0.012)			

Table A.2: Methodological variations

Dependent variable	Elicited risk aversion	Stock mkt. participation	Bond market participation	% liquid assets in stocks	%liquid assets in stocks
Experienced return variable	Real stock returns	Real stock returns	Real bond returns	Real stock returns	Excess returns of stocks over bonds
Retirement assets included:					
β	-3.214	9.652	-	1.086	1.488
	(1.096)	(1.218)		(0.365)	(0.453)
λ	1.309	1.572	-	2.394	3.259
	(0.439)	(0.196)		(0.721)	(1.018)
Starting 10 yrs after birth:					
β	-2.294	3.661	4.518	0.857	1.233
	(0.733)	(0.718)	(1.229)	(0.284)	(0.379)
λ	0.737	0.376	0.886	0.728	1.028
	(0.352)	(0.176)	(0.340)	(0.359)	(0.370)
Starting 10 yrs before birth:					
β	-4.983	9.508	8.058	1.759	2.508
	(1.876)	(2.132)	(1.885)	(0.781)	(0.748)
λ	1.823	1.645	1.257	1.904	2.785
	(0.911)	(0.326)	(0.562)	(0.850)	(0.613)
Cohort dummies included:					
β	-0.155	8.270	5.886	1.778	2.022
	(1.009)	(2.478)	(4.100)	(0.858)	(0.777)
λ	1.422	0.726	0.347	0.853	1.414
	[fixed]	(0.436)	[fixed]	(0.754)	(0.851)
Experienced volatility included:					
β	-3.193	6.360	7.008	1.359	1.963
	(1.092)	(1.258)	(1.510)	(0.455)	(0.553)
Experienced volatility	-6.555	-1.211	-2.277	-1.457	-0.762
	(2.631)	(1.552)	(1.507)	(0.637)	(0.515)
λ	1.422	1.162	0.347	1.549	1.923
	[fixed]	[fixed]	[fixed]	[fixed]	[fixed]