Depression Babies:

Do Macroeconomic Experiences Affect Risk-Taking? *

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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 1960-2007, 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, the average investors' lifetime stock-market return experiences predict aggregate stock-price dynamics as captured by the price-earnings ratio.

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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 whether they are asset-specific: do households who experienced bad stock-market outcomes shy away only from stock investment, and do those with bad bond-market experiences shy away only from bond investment, or are there 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 in the risk attitudes of old and young people 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 between old and young against differences in experienced stock market returns (Figure 1) confirms this pattern in the raw data.

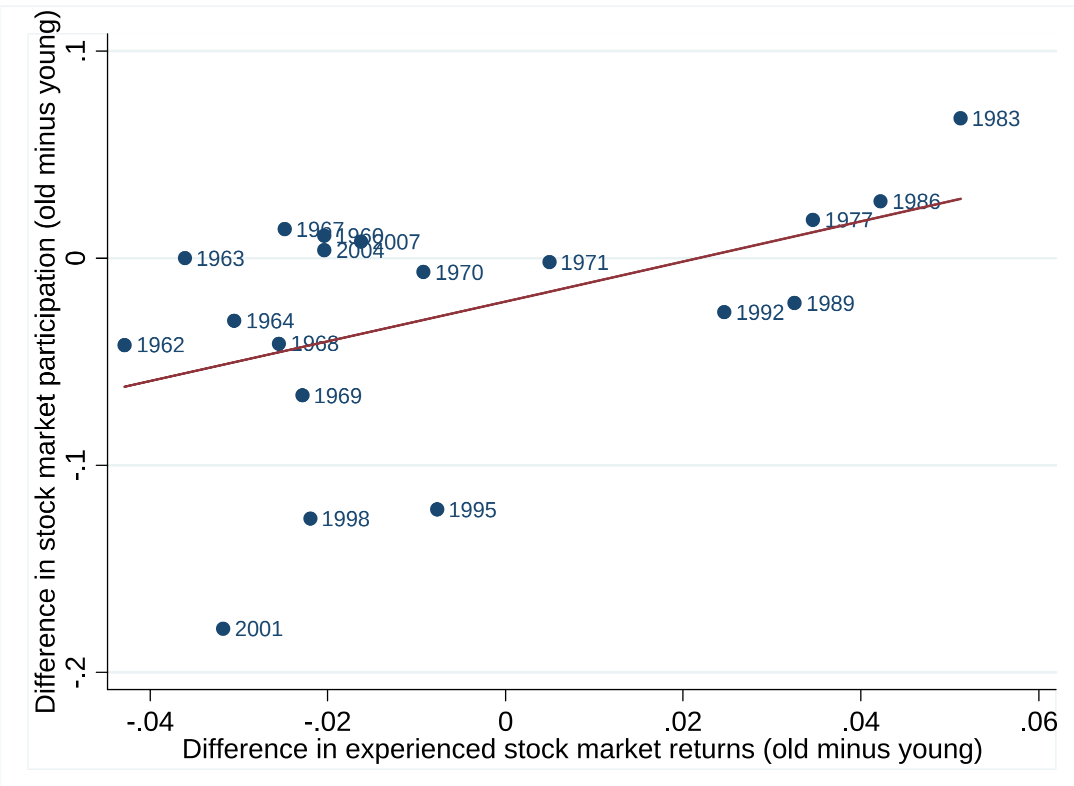

Figure 1: Differences in stock-market participation rates of old and young individuals plotted against differences in lifetime average stock-market returns. Stock market participation rates are the fraction of households who invest in stocks (including stock mutual funds and stocks held in retirement accounts). 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. Observations are weighted with SCF sample weights.

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 1960-2007, 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 preferences 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 differ depending on previous investments, interest in economic matters, and other unobservables, stock-market and bond-market returns likely have substantial positive correlation with their experiences of financial asset payoffs. 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 estimates of the weights that individuals apply to their past experiences are similar for all four risk-taking measures. More recent experiences always 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.

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 tolerance (Sahm 2007). Our results also hold when retirement account holdings are excluded from the asset holding measures.

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

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[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.

almost full set of cohort dummies and therefore control for any omitted variable that has cohort-level variation. Finally, our hypothesis is distinct from unrestricted cohort effects since it predicts a *specific*, signed relationship between macroeconomic experiences and risk-taking.

The fall in the stock market in 2008 can be used to illustrate the economic magnitudes of the experience effects we estimate. The real return of the S&P 500 index in 2008 was about -36%. These large negative returns strongly altered investors' (weighted) life-time average returns, and the effect was strongest for young investors. For example, compared with the counterfactual benchmark of a return equal to 8.2%, the 2008 downturn lowered the experienced return of a 30-year old by about 4.0 percentage points (pp), while the experienced return of a 60-year old was lowered by roughly 2.0 pp. According to our estimates, this should lower 30-year olds participation rate, everything else equal, by about 10 pp (compared with an overall participation rate for this age in 2007 of about 54.6%), whereas the effect on the participation rate of 60-year olds should be half as big, approximately 5 pp.[2] Our results also imply how long-lasting the effects of the crash will be. According to our estimates, the 2008 return receives a weight of about 8.9% in the experienced return of someone who is 30 years old in 2009. In 2019, when this individual is 40 years old, the weight on the 2008 return will be reduced to 4.0%, and a further 20 years later to 2.0%. Hence, after 30 years most of the effect has faded away.

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

[2] As a note of caution, hypothetical counterfactual of "no 2008 market crash" holds everything else equal and does not consider the effect on asset prices in general equilibrium that would arise if the level stock market participation changed. In particular, such changes could feed back into changes in participation rates.

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. Choi et al. (2009) report that high personally experienced returns in 401(k) accounts induce higher 401(k) savings rates in the future. 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)[3], 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.

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 2007, 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,

[3] 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.

but with some gaps. The data before 1960 contains information in stock holdings in some years, but age is measured in 5 or 10-year brackets, which would make our measurement of experienced returns imprecise, particularly for younger individuals. For this reason, we start in 1960 and use all survey waves that offer stock-market participation information, i.e., the 1960, 1962, 1963, 1964, 1967, 1968, 1969, 1970, 1971, and 1977 surveys. We briefly describe the key variables here. More details are available in the Supplementary Appendix A.

Our first risk-attitude measure is individuals' elicited willingness to take financial risk. In the 1983 and 1989-2007 survey waves, interviewees are asked which of the following statements comes closest to describing the amount of financial risk that they are willing to take when they save or make investments: (1) not willing to take any financial risk; (2) take average financial risks expecting to earn average returns; (3) take above average financial risks expecting to earn above average returns; (4) take substantial financial risks expecting to earn substantial returns. We code the answer as an ordinal variable with integer values from 1 to 4, where a value of four indicates the highest risk tolerance. For ease of reference, we refer to the measure as "elicited risk tolerance," but note that the survey answer does not disentangle risk aversion (in the Arrow-Pratt sense) from beliefs.[4] 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 (Shaw 1996). Dohmen et al. (2009) find that a similar financial risk tolerance measure in the German Socio-Economic Panel is strongly related to financial risk-taking, and a simple risk-taking measure of this kind also is a strong predictor of risky behavior in a real-stakes lottery field experiment. In our analysis,

[4] 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.

using both the elicited risk tolerance measure and direct measures of asset allocation ameliorates concerns about the connection between self-reported risk tolerance and actual behavior.

The second measure is a binary variable for stock-market participation, available from 1960-2007 in each survey wave of our sample. 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. In our main tests, we also include stock holdings in retirement accounts (e.g., IRA, Keogh, and 401(k) plans). For this purpose, we need to impute the stock component of retirement account holdings from the total amount in these accounts in years 1983 and 1986. From 1989 to 2004, the SCF offers only very coarse information on the allocation of retirement assets (mostly stocks, mostly interest bearing, or split), and we follow the conventions of the SCF in assigning portfolio shares. Supplementary Appendix A provides more details, and it also reports robustness checks that exclude retirement account holdings from the analysis.

Our third measure of risk taking is a binary variable for bond-market participation, available from 1960-2007, with the exception of 1971, which indicates whether a household holds more than zero bonds. Investments in bonds, even those in default-free government bonds, are risky in real terms because of unexpected inflation. 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. Our definition of bond holdings does not include retirement account holdings, because the SCF does not separate bonds from short-term debt holdings (e.g., money market funds) in retirement accounts.

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 1960-2007, 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).

As a control variable for income we use total family income. All income, wealth, and asset holdings variables are deflated into September 2007 dollars using the consumer price index. 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.[5] Specifically, we require that households have at least $100 of liquid assets outside of retirement accounts and annual family income greater than $100 (both in September 2007 dollars). 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 1983-2007 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. In our main tests, we weight the data using SCF sample weights[6] which undo the overweighting of high-income households and which also adjust for non-response bias. The weighted estimates are representative of the U.S. population.

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

[5] 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.

[6] 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.

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,

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

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 at time t (age_{it}) how many years ago the return was realized (k), and a parameter λ, which controls the shape of the weighting function. We estimate λ from the data.

To illustrate the shape of the weighting function, Figure 2 plots the weights $w_{it}(k, \lambda)$ for three values of λ for a household head who is 50 years old today as a function of how many years before a return was realized, i.e. as a function of k. If $\lambda < 0$, then the weighting function is always 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 $\lambda > 1$).

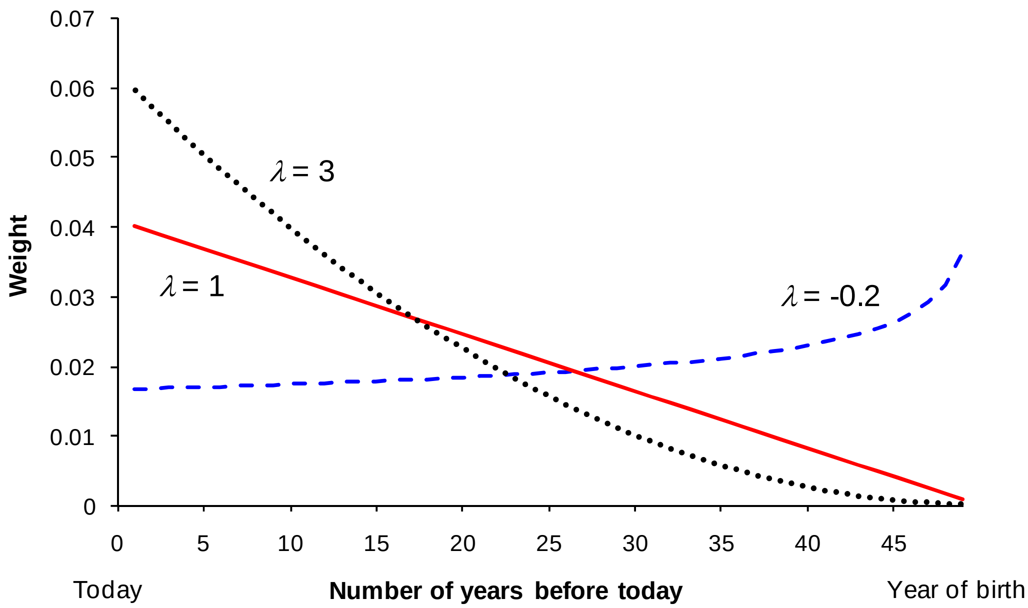


Figure 2: Weights on experienced returns implied by different values of λ for a 50-year old household head.

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, or a step function, 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.[7] We then choose the estimates that resulted in the lowest sum of square (or highest likelihood) as an initial guess for further numerical optimization.

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

[7] 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.)

and social network), then setting the starting point earlier than birth could only improve the explanatory power of weighted average returns compared with our specification. The Supplementary Appendix reports 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. Comparing Panels A and B, we see that stock-market participants tend to be wealthier than the average household. For example, the median holding of liquid assets is $11,642 in the full sample, but $51,883 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 $28,735. The pattern is similar for median income.

As Panel A shows, 38.4% of households participate on average in the stock market in the 1960-2007 period. These rates represent the U.S. population (not the SCF sample) since we apply the SCF sample weights.[9] The bond-market participation rate is similar to the stock-market participation rate. The remaining two risk attitude measures show considerable dispersion across households. The proportion of liquid assets invested in stocks in Panel B has 10th and 90th percentiles of 7.1% and 90.2%. The 10th and 90th percentiles for elicited risk tolerance in Panel A are 1.0 and 3.0, respectively. It is noteworthy that mean elicited risk tolerance is higher for the stock-market participants in Panel B (2.132) than for the full

[9] 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 38.4% of the number of observations in Panel A.

sample in Panel B (1.890) and lies in the middle for bond market participants in Panel C (2.029). 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, setting $\lambda = 1.25$, which is in the ballpark of the estimates of λ that we find later. As Panel A shows, the 10th and 90th percentile for the experienced (real) stock return are 6.4% and 11.6% in the 1960-2007 sample. The 10th and 90th percentile for experienced (real) bond returns are -0.2% and 5.0%. Thus, over our sample period, experienced bond returns are 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 10th and 90th percentile of 4.9% and 5.6% for real stock-market returns, respectively.

III. Results

A. Elicited risk tolerance

We start by relating experienced stock-market returns to elicited risk tolerance. 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 (the number of children and its square, 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 and log liquid assets squared, both interacted with year dummies). $A_{it}(\lambda)$ 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, because $A_{it}(\lambda)$ 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 average difference in fitted probabilities for being in one of the four risk-aversion categories if we set the experienced return to its 10th and 90th percentile, leaving all other variables at their actual sample realizations. To aid in the interpretation of those differences in fitted probabilities, we will compare their magnitude to the unconditional frequencies with which individuals fall into the four elicited risk tolerance categories. As shown in Table II, only few of them fall into the highest risk tolerance category 2, and the highest share of more than 40% is accounted for by category 2.

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 II 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 fitted probability differences for the experienced returns at the 10th and 90th percentile at the bottom.[10] Standard errors robust to misspecification of the likelihood function are shown in parentheses, and are adjusted for multiple imputation in the SCF.[11] Column (i), estimated on the 1983-2007 sample, shows that higher experienced stock-market returns increase the probability that risk tolerance is in the high categories (3 and 4), have little effect on the probability of being in category 2, and decrease the probability that the reported risk tolerance is in the lowest category (category 1). Thus, stock-market returns experienced in the past have a significant and

[10] 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 Supplementary Appendix, Table A.2.

[11] See Section B in the Supplementary Appendix. Clustering by cohort or clustering by year does not have a material effect on our estimates.

positive effect on risk tolerance. As column (ii) shows, adding the liquid assets controls has little effect on the estimates.

The economic magnitudes are sizeable. For example, in column (ii), going from the 10th to the 90th percentile of experienced stock returns implies, on average, a 10.1% percentage points (pp) lower probability of being in the lowest risk tolerance category, and a correspondingly higher probability of being in the higher risk tolerance categories. Compared with an unconditional probability of 36.3% of being in the lowest risk tolerance category, this implied change by 10.1% pp is clearly economically significant.

The estimate of 1.470 (s.e. 0.294) for the weighting parameter λ in column (ii) 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 clearly 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.

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,

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

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 we focus again on average differences in fitted probabilities if the experienced return variable is set to its 10th and 90th percentiles.

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.

Columns (i) and (ii) in Table III report the estimates from our probit model. As shown in Column (ii), the life-time average returns have a positive and highly significant effect on stock-market participation. A change from the 10^{th} to the 90^{th} percentile of experienced stock implies an increase of about 14.6% 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. The fitted probability difference is quite similar in column (i) without the liquid assets controls.

As with the previous measure, elicited risk tolerance, the estimate of 1.698 (s.e. 0.206) 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 II, 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.

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 (iii) of Table III 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. Adding the liquid assets controls in column (iv) slightly increases the coefficient on experienced stock returns. A change from the 10^{th} to the 90^{th} percentile of experienced bond returns is associated with increase of about 15.3% in the probability that a household participates in the bond market. With 1.106, the point estimate for λ is a little lower than in case of stock-market participation, but the pattern of implied weights are only marginally different. 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

Table IV 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,

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

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 and so we can assess economic magnitudes directly by multiplying β with the variation in experienced returns. The control variables are the same as in Tables II and III.

In columns (i) and (ii), experienced returns are measured as real stock returns. As column (i) shows, without the liquid assets controls, the life-time average stock return has only a statistically weak positive effect on the proportion of liquid assets invested in stocks. But with the liquid assets controls added in column (ii), the effect is stronger, both in terms of statistical significance and economic magnitude. The point estimate of 1.476 (s.e. 0.445) implies that a change from the 10^{th} to the 90^{th} percentile of experienced stock returns (5.2%) leads to an increase of about $1.476 \times 5.2\% \approx 7.7$ pp in the allocation to stocks. 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 the Supplementary Appendix.). 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 0.923 (s.e. 0.323), which suggests weights that are declining a roughly linearly. This estimate for λ is approximately of the same magnitude as the λ-estimates in the elicited risk-aversion model in Table II and the stock and bond market participation models in Table III. The similarity of the estimates is noteworthy since elicited risk tolerance is a measure based on a very different approach (survey question versus investment choice) and financial 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. Columns (iii) and (iv) of Table IV repeat the regressions of columns (i) and (ii) 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 about as well as real stock returns. The point estimates for β in column (iv) are slightly higher than in column (ii), 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.

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-taking 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.

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 Table II, column (ii), Table III, columns (ii) and (iv), and Table IV, column (ii) with both experienced real stock returns and experienced real bond returns as explanatory variables. Since an estimation of distinct 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 the earlier specifications that had a single type of return. Table V reports the results. In the first three columns, labeled "Full sample," we use all the available data, as in Tables II and III. In column (iv), where the dependent variable is the percentage share invested in stocks, the sample is restricted to stock market participants, as in Table IV. In column (v) we also explore the share invested in bonds (using only non-retirement assets in the calculation of this share, as bond allocations in retirement accounts are not available), and we restrict the sample to households that participate in stock and bond markets.

For the ordered probit in column (i) and the probit in columns (ii) and (iii) we also report, in addition to the coefficient estimates, the average of the fitted probabilities at the 90th percentile of experienced returns minus the fitted probabilities at the 10th percentile of experienced returns. To save space, we only report this average difference in fitted probabilities for category 1 (low risk tolerance) in case of the elicited risk aversion specification in column (i). The combined spread in fitted probabilities for the other three risk tolerance categories is of the same magnitude, but with opposite sign.

We find that elicited risk tolerance is positively related to experienced stock and bond returns according to the point estimates, but the standard errors are huge and so one cannot draw definitive conclusions from the results. Evidently, the short sample available for this risk-taking measure is not sufficient to disentangle the effects of stock and bond return experiences. Stock market participation, in column (ii), is more strongly related to stock market return experiences than to bond returns, while the opposite is true for the bond market participation measure (fitted probability differences based on percentiles of the experienced return distributions lead to similar conclusions as a comparison of the Probit coefficients). The percentage share allocated to stocks in column (iv) is positively related to experienced stock returns and negatively related to experienced bond returns. For the bond share in column (v) the opposite is true, but the coefficients are smaller, particularly the coefficient on bond returns, and are statistically not significantly different from zero. Taken together, the 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 and magnitude. 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. Unless otherwise noted, all of these additional tests are reported in detail in the Supplementary Appendix, Table A.5. Here we briefly summarize the most important results.

Non-monotonicities in the weighting function. Our weighting function cannot accommodate non-monotonic weighting patterns. To see whether this is a problematic assumption, we experiment with a step function, where the steps are defined over the first, middle, and most recent third of an individual's lifespan. The results are reported in Table A.4 in the Supplementary Appendix, and they indicate that a weighting pattern close to the monotonic weighting pattern implied by our weighting function.

Excluding retirement assets. Allocations to stocks in retirement accounts is probably measured with considerable error since the SCF only provides coarse allocation brackets before 1983 and no allocation information before 1989. To check whether this could influence our results, we repeat our baseline estimations with asset allocation measures and liquid asset controls calculated without retirement account holdings. The estimates are generally very similar to those that we obtained with retirement accounts included. Thus, the choice of whether to include retirement accounts or not is not crucial for our results. Also, running the estimation with retirement accounts included, but excluding the years 1983 and 1986 in which we have to impute the allocation to stocks in retirement accounts has little influence on the estimates.

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.5 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, λ is lower (0.423 instead of 1.698 in the main specification for stock market participation, for example), as observations early in life are now excluded from the weighted-average return, and there is less need to down-weight 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. Setting the starting point before the birth year leads to exactly the opposite pattern: higher point estimates of λ, implying stronger down-weighting of early observations, and higher β coefficients.

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 is not a constant per cohort, but instead varies within each cohort over time as the cohort experiences new return realizations. 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.5, 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 experienced returns pick up some unobserved cohort effect that happens to be correlated with experienced returns. Repeating our baseline specifications with cohort dummies included we find that the point estimates remain similar, with the exception of bond market participation, where the β coefficient drops considerably and standard errors are quite high.

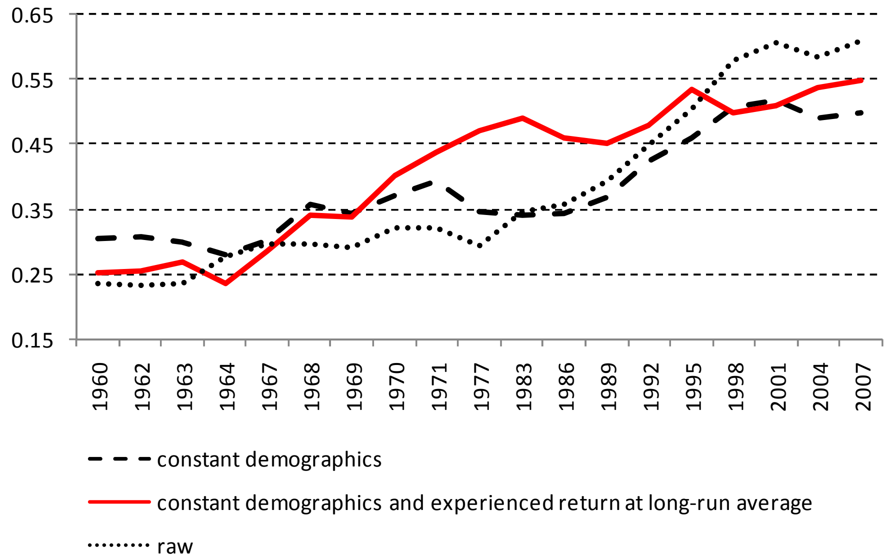
Including Experienced Volatility. We also test whether the experience hypothesis extends to an effect of experienced volatility on households' investment decisions. To calculate experienced volatility, we apply the same weighting function as before, but now estimating the weighted standard deviation 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 the baseline specifications 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 for the percentage allocation to stocks measure. For elicited risk tolerance and stock and bond market participation, the estimated effect is positive, but with relatively high standard errors. Most importantly, the inclusion of experienced volatility has little effect on the coefficient on weighted-average returns. 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.

IV. An Aggregate Perspective

Our estimation focused on focused on cross-sectional differences in risk-taking measures in order to absorb potential confounding macro and equilibrium effects with time dummies. This does not mean that our results only have cross-sectional implications. Differences in experienced returns exist not only between different age groups at a point in time, but also between individuals of the same age at different points in time. This variation over time should, according to our estimates, influence variations in risk-taking in aggregate. Looking at what our estimates could imply for risk-taking in the aggregate is therefore another way to assess the economic significance of our results.

To provide some perspective on this issue, we conduct a simple counterfactual exercise. We take the point estimates from the stock market participation model in Table III, column (ii), and we calculate the fitted probabilities for each household in each survey year if we set all control variables except age, which is left at its actual value, to their full sample averages in the corresponding age group (< 40, 40-49, 50-59, ≥ 60). We label the cross-sectional average of the resulting (counterfactual) fitted probabilities as the "constant demographics" participation rate. Next, we perform a similar calculation, but now with experienced returns set equal to the average stock market return since 1871, the first year in which stock market return data is available from our data source. This counterfactual exercise thus imagines households that consider the full return history, with equal weights for each year, going all the way back from the year prior to the survey year to 1871, instead of focusing on life-time experiences.

(a) Stock market participation rate



(b) Difference in participation rates: Old (age ≥ 60) minus young (age < 40).

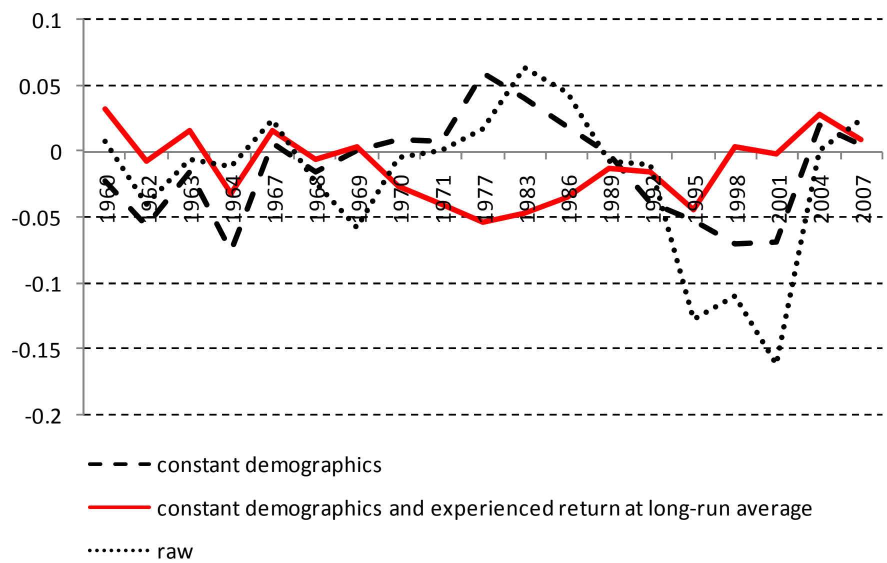


Figure 3: Counterfactual stock market participation rates. Figure (a) shows the average fitted probability from the stock market participation probit model of Table III, column (ii), when all controls, including liquid assets and income are set to their full-sample average within age groups (< 40, 40-49, 50-59, ≥ 60) (dashed line) and when, in addition, the experienced stock market return is set to the average annual return since 1871 until the year prior to the survey year (solid line), compared with the participation rate in the raw data (dotted line). Figure (b) plots the difference in participation rates in these three cases between young (age < 40) and old (age ≥ 60). Observations are weighted with SCF sample weights.

As a note of caution, this counterfactual exercise is simplistic in that it does not consider equilibrium asset-pricing implications of setting demographics and experienced returns to counterfactual values. If these variables influence risk-taking, then changing them would presumably also influence asset prices, which might then also induce changes in stock market participation rates that are not captured in our simple counterfactual exercise. One would need a full equilibrium model to conduct a true counterfactual investigation. However, our simple calculation should at least provide some perspective on the economic magnitudes of changes in risk-taking induced by experienced returns.

Figure 3, Panel (a), presents the results. Comparing the effect of experienced returns (solid line relative to dashed line) with the effect of demographics, liquid assets, and income (dotted line relative to dashed line), it is evident that variations over time in experienced returns lead to changes in stock market participation rates that are at least as big as changes induced by variations in demographics, liquid assets, and income. The biggest impact of experienced return variation appears in the early 1980s, when the participation rate based on the long-term average return would have been more than 10pp higher than with the actual experienced returns. Actual experienced returns were very low at the time, due to the poor real stock market returns in the 1970s.

Panel (b) plots the difference between stock market participation rates of old (age ≥ 60) and young (age < 40) age groups, for raw data (dotted), constant demographics (dashed), as well as constant demographics and experienced returns set to the long-term average since 1871 (solid). This plot provides some perspective on the cross-sectional differences between age groups that our estimation is based on. The raw data plot reveals big differences between participation rates of young and old in the early 1980s, when young households had much lower participation rates than the old age group, and in the late 1990s, when young households had much higher participation rates. Setting experienced returns equal to the long-term average since 1871 completely reverses the big difference in the early 1980s, and, together with constant demographics, eliminates the difference in the late 1990s. The figure only provides an incomplete picture as it shows the difference between only two relatively coarse age groups, but it does provide a rough idea of the substantial magnitude of experienced return effects in the cross-section.

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. Experience-driven variations in aggregate demand for risky assets could then help to explain variation in stock-market valuation levels over time. To check whether the experienced return of the average investor varies in the right way over time that the experienced-induced risky asset demand could potentially explain variation in stock-market valuation levels, we compare this average experienced return with the price-to-earnings (P/E) ratio of the aggregate stock market.

Since experienced returns are identical for individuals of the same age, we calculate experienced stock-market returns for each age from 25 to 74 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). We then average across all age groups and plot the resulting series against the annual price-to-earnings (P/E) ratio from Shiller (2005), which uses a ten-year moving average of earnings in the denominator. We also conducted a similar calculation with wealth-weighted averages of experienced returns and found roughly similar results.

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. 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. Periods of high valuation according to the P/E ratio also are periods when returns going forward tend to be low, as the P/E ratio is known to be negatively related to future stock-market returns. Our findings raise the possibility that these variations in valuation levels and expected returns could be driven by variations in experienced returns of the average investor.

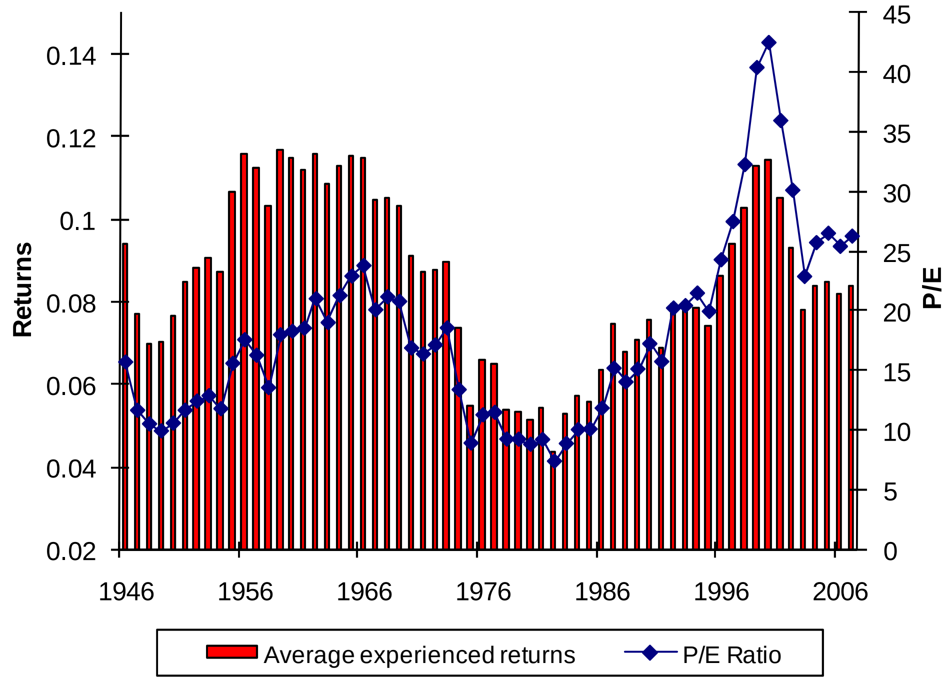


Figure 4: Aggregated experienced real stock returns (λ = 1.25) and equity market valuation 1946-2007.

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 average experienced 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 average 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.

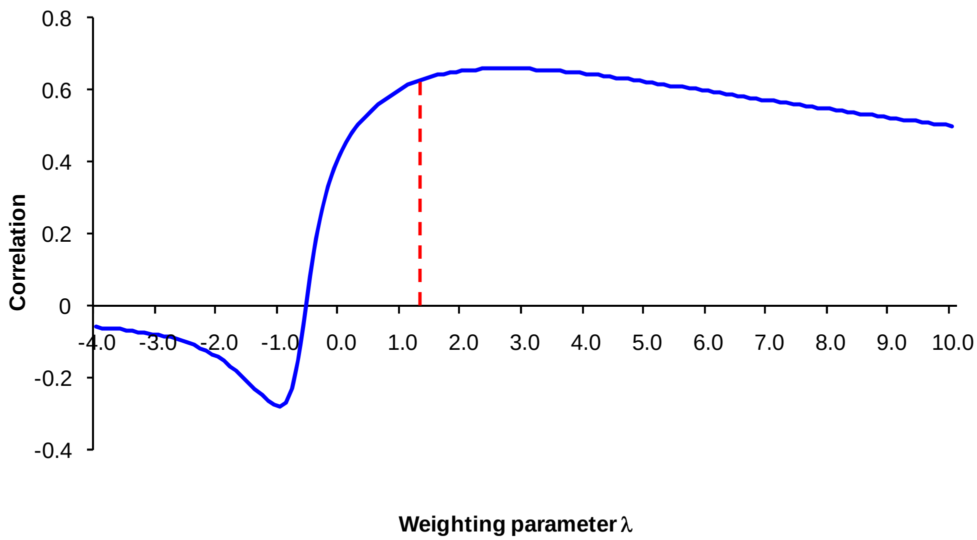


Figure 5: Correlation between experienced real stock returns and P/E ratio for different choices of the weighting parameter λ.

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.

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Table I: Summary Statistics

	10^{th} pctile	Median	90^{th} pctile	Mean	Stddev	#Obs.
Panel A: All households 1960 – 2007						
Liquid assets	727	11,642	172,996	92,047	677,063	43,862
Income	17,049	48,718	109,336	65,764	182,221	43,862
Experienced real stock return ($\lambda = 1.25$)	0.064	0.091	0.116	0.090	0.021	43,862
Experienced real bond return ($\lambda = 1.25$)	-0.002	0.008	0.050	0.018	0.021	43,862
Stock market participation	0	0	1	0.384	0.484	43,862
Bond market participation	0	0	1	0.327	0.469	42,995
Elicited risk tolerance (1983-2007)	1	2	3	1.890	0.831	25,588
Panel B: Stock market participants 1960-2007						
Liquid assets	5,285	51,883	401,400	206,430	1,075,158	21,420
Income	28,370	66,525	158,828	96,813	285,908	21,420
Bond market participation	0	0	1	0.434	0.494	21,179
% Liquid assets in stocks	0.071	0.439	0.902	0.462	0.296	20,601
Elicited risk tolerance (1983-2007)	1	2	3	2.132	0.794	16,131
Panel C: Bond market participants 1960-2007						
Liquid assets	1,936	28,735	315,270	173,404	1,098,734	16,086
Income	24,637	58,783	134,110	84,700	264,119	16,086
Stock market participation	0	1	1	0.526	0.497	16,086
% Liquid assets in stocks	0	0.014	0.709	0.219	0.291	15,389
Elicited risk tolerance (1983-2007)	1	2	3	2.029	0.791	9,940

Notes: Stock returns and bond returns are real returns, deflated with CPI inflation rates. Wealth and income variables are deflated by the CPI into September 2007 dollars. Observations are weighted by SCF sample weights. The bond market participant sample in Panel C excludes the 1964 survey in which bond market participation information is not available.

Table II: Elicited Risk Tolerance

	(i)	(ii)
Experienced stock return coefficient β	5.378	6.619
	(1.208)	(1.283)
Weighting parameter λ	1.719	1.470
	(0.356)	(0.294)
Income controls	Yes	Yes
Liquid assets controls	-	Yes
Demographics controls	Yes	Yes
Age dummies	Yes	Yes
Year dummies	Yes	Yes
Average of fitted prob. at 90th pctile. minus fitted prob. at 10th pctile. of experienced stock return		
Risk tolerance = 1 (low)	-0.096	-0.101
[unconditional freq. = 36.3%]	(0.018)	(0.016)
Risk tolerance = 2	0.022	0.021
[unconditional freq. = 42.6%]	(0.004)	(0.006)
Risk tolerance = 3	0.050	0.052
[unconditional freq. = 16.7%]	(0.012)	(0.012)
Risk tolerance = 4 (high)	0.025	0.027
[unconditional freq. = 4.3%]	(0.009)	(0.010)
#Obs.	25,518	25,518
Pseudo R^2	0.07	0.09

Notes: Ordered probit model estimated with maximum likelihood. Sample period runs from 1983 to 2007 and excludes the 1986 survey (elicited risk tolerance not available). The experienced stock return is calculated from the real return on the S&P500 index. Liquid assets controls are log liquid assets and log liquid assets squared, both interacted with year dummies to allow for year-specific slopes. 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. 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 III: Stock and Bond Market Participation

	Experienced stock returns and stock mkt. participation		Experienced bond returns and bond mkt. participation	
	(i)	(ii)	(iii)	(iv)
Experienced return coefficient β	6.944	10.139	8.936	9.488
	(1.093)	(1.320)	(1.470)	(1.543)
Weighting parameter λ	1.900	1.698	1.323	1.106
	(0.233)	(0.206)	(0.306)	(0.282)
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 of fitted prob. at 90th pctile. minus fitted prob. at 10th pctile. of experienced return	0.128	0.146	0.156	0.153
	(0.023)	(0.022)	(0.027)	(0.026)
#Obs.	43,660	43,660	42,793	42,793
Pseudo R^2	0.20	0.33	0.07	0.12

Notes: Probit model estimated with maximum likelihood. Sample period runs from 1960 to 2007 (excluding 1964 in the case of bond market participation). The experienced stock return is calculated from the real return on the S&P500 index. Liquid assets controls are log liquid assets and log liquid assets squared, both interacted with year dummies to allow for year-specific slopes. 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. 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: Percentage of Liquid Assets Invested in Stocks

	Experienced stock returns		Experienced excess returns of stocks over bonds	
	(i)	(ii)	(iii)	(iv)
Experienced return coefficient β	0.440	1.476	0.688	1.611
	(0.395)	(0.445)	(0.397)	(0.439)
Weighting parameter λ	1.450	0.923	1.185	1.345
	(1.372)	(0.323)	(0.775)	(0.391)
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.	20,247	20,247	20,247	20,247
R^2	0.07	0.10	0.07	0.10

Notes: Model estimated with nonlinear least squares on the sample of stock market participants. Sample period runs from 1960 to 2007, excluding the 1971 survey (percentage allocation not available). Experienced returns stock returns calculated from the real return on the S&P500 index and experienced excess return from the return on the S&P500 index minus the return on long-term U.S. Treasury bonds. Liquid assets controls are log liquid assets and log liquid assets squared, both interacted with year dummies to allow for year-specific slopes. 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. Observations are weighted with SCF sample weights. Standard errors shown in parentheses are robust to heteroskedasticity and adjusted for multiple imputation.

Table V: Using Stock and Bond Returns Jointly

Dependent variable	Elicited risk tolerance	Stock mkt. participation	Bond market participation	% liquid assets in stocks	% liquid assets in bonds
Sample	Full	Full	Full	Stock market participation required	Stock and bond market participation required
Experienced stock return coeff. β_{stock}	3.422	9.050	0.829	1.565	-0.882
	(2.519)	(1.388)	(1.220)	(0.450)	(0.576)
Weighting parameter for stocks λ_{stock}	1.470	1.698	1.698	0.923	0.923
	[fixed]	[fixed]	[fixed]	[fixed]	[fixed]
Average of fitted prob. at 90^{th} pctile. minus fitted prob. at 10^{th} pctile. of experienced stock return	-0.052	0.131	0.016		
	(0.035)	(0.023)	(0.024)		
Probability of	lowest risk tolerance	participation	participation		
Experienced bond return coeff. β_{bond}	8.026	6.490	9.238	-0.997	0.087
	(5.373)	(1.780)	(1.529)	(0.582)	(0.606)
Weighting parameter for bonds λ_{bond}	1.106	1.106	1.106	1.106	1.106
	[fixed]	[fixed]	[fixed]	[fixed]	[fixed]
Average of fitted prob. at 90^{th} pctile. minus fitted prob. at 10^{th} pctile. of experienced bond return	-0.141	0.085	0.149		
	(0.087)	(0.024)	(0.026)		
Probability of	lowest risk tolerance	participation	participation		

Notes: Models and controls as in Table II, column (ii), Table III, columns (ii) and (iv), and Table IV, column (ii), but with experienced real stock and bond returns jointly included as explanatory variables and λ parameters fixed at the values obtained in those earlier regressions. 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. Observations are weighted with SCF sample weights. Standard errors shown in parentheses are robust to heteroskedasticity/misspecification of the likelihood function and adjusted for multiple imputation.

Supplementary Appendix

for

Depression Babies:

Do Macroeconomic Experiences Affect Risk-Taking?

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September 2009

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 50 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 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).

A third problem concerns assets held in retirement accounts. In the "old" SCF, 1977 and earlier, the SCF did not ask respondents to separate financial assets held in retirement accounts from other financial assets. Retirement accounts were also far less important at the time than later in the sample, as IRA and 401(k) defined contribution plans did not exist yet. In 2004 and 2007, the SCF has detailed information on the percentage allocation of retirement account assets to stocks. From 1989-2001 onwards, the SCF reports separately assets held in retirement accounts with some information on the allocation of these assets. We follow the convention used by the Federal Reserve Board to interpret an allocation of IRAs of "mostly stocks" as 100% stocks, "mostly interest bearing" as no stocks, and "split between stocks and bonds" or "split between stocks and money market accounts" as 50% stocks, and "split between stocks and bonds and money market accounts" as 30% stocks. For 401(k)-type plans there is only one common "split category", for which we assume 50% stocks. In 1983 and 1986, only the total amount in IRA and 401(k)-type plans is available, but no allocation information. To impute the allocations, we first compute the fraction of households in 1989 with IRA but no 401(k)-type account, that have the IRA at least partly invested in stock, as well as the fraction of those with IRA and 401(k) that have the IRA at least partly invested in stocks. We calculate similar proportions for 401(k)-type account holders, i.e, how many of them are at least partly invested in stocks depending on whether they also own an IRA or not. We then take these four percentages and apply them to 1983 and 1986 data by grouping households in those years into four categories depending on whether they own an IRA and/or 401(k)-type account, and we randomly assign households to be stockholders in their IRA and/or 401(k) so that we match these 1989 percentages. For those that we assign to be stockholders, we assume that they invest 75% of their IRA and/or 401(k) in stocks (the average retirement account allocation to stocks in the 1989 survey for households that have greater than zero holdings in IRA or 401(k) accounts).

A fourth issue is that, in 1960, 1963, 1964, 1967, 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. 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:

$$\bar{b} = \frac{1}{M}\sum_{m=1}^{M} b_m \, . \qquad \text{(A.1)}$$

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

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

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

$$\bar{V} = \frac{1}{M}\sum_{m=1}^{M} V_m \qquad \text{(A.3)}$$

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. Effects of Inertia in Portfolio Rebalancing: Simulations

Inertia in rebalancing might seem as a potential alternative explanation for why past stock market returns are related to the risky asset share in Table IV in the main paper. Here we present simulations showing that the time dummies in our regressions absorb the effects of inertia on portfolio allocations, and hence the experience effects that we document in our regressions cannot be explained by inertia.

We construct a panel of overlapping generations, where each generation starts investing at the age of 25, with a risky asset share of 50% and lives until age 75. Every year, we draw IID log stock market returns from a normal distribution with mean of 8% and standard deviation of 20%. Each generation's risky asset share then evolves according to a partial adjustment model,

$$\alpha_{t+1} = \omega \alpha^{d}{}_{t+1} + (1-\omega)\alpha^{p}{}_{t+1} \tag{A.7}$$

where α_{t+1}^{d} represents the desired portfolio share that the household would have under perfect and instantaneous rebalancing, and α_{t+1}^{p} represents the passive portfolio share, which evolves according to

$$\alpha_{t+1}^{p} = \frac{\alpha_t (1 + r_{t+1})}{1 + \alpha_t r_{t+1}} \tag{A.8}$$

where r_{t+1} represents the (simple, not log) stock market return in year t+1. Thus, the passive share represents the risky asset share that the household would have in year t+1 if any changes in portfolio allocations due to realized stock market returns are not rebalanced, all riskfree asset returns are paid out as cash flows from the portfolio, and no new cash flows enter the portfolio. By eliminating all other influences on the risky asset share other than that of realized stock market returns, we influence of inertia on the risky asset share. The parameter ω in equation (A.7) controls the speed of adjustment. A value of 1.0 would imply instantaneous adjustment, a value of 0 would imply no adjustment at all.

We set the desired portfolio share α_{t+1}^{d} equal to 50%. The exact value of α_{t+1}^{d} is not important. Results are similar for a wide range of values around 50%. A generation dies once it has reached the age of 75 and it is replaced in the next period with a new generation of investors that starts at age 25. In our baseline simulations, a new generation starts with a portfolio share equal to α_{t+1}^{d} .= 50%. As an alternative, we also run simulations where the initial portfolio share at age 25 is set equal to the cross-sectional mean of the portfolio shares of all the other generations in the same year. Thus, in this latter case, the young do the same as "everyone else" at that time, rather than starting out with their target allocation.

In addition to the portfolio share histories of the overlapping generations, we also keep track of their return experience histories. Each period, we calculate the experienced return as in the main analysis of the paper according to equation (1), with the starting point set at birth (i.e., 25 years before the generation reaches the investing age), and given a specific value of the weighting parameter λ.

We simulate return and portfolio histories for 50,075 years, of which we discard the first 75, which are needed to initialize the overlapping generations along with the return history. With the remaining 50,000 cross-sections we then run pooled OLS regressions, similar to those in our main analysis in the paper, of the risky asset share on experienced returns.

Table A.1 reports the slope coefficient on the experienced return explanatory variable, corresponding to the coefficient β in our analysis in the main paper. We present results for various parameterizations of our simulations. The different columns vary the weighting parameter λ that is used to calculate the experienced returns. Panel A shows results when the regressions do not include time dummies, and Panel B replicates the regressions that we run in the paper, which include time dummies. The three blocks in each panel differ in the adjustment speed coefficient ϕ. The first block with ϕ =0.10 shows what happens with extremely strong inertia. With an adjustment coefficient that low, investors rebalance very little. The second block, with ϕ = 0.30 is roughly in line with the degree of portfolio inertia found by Brunnermeier and Nagel (2008) in the Panel Study of Income Dynamics (PSID), but they caution that their estimates are likely to be upward biased due to measurement error. The third block of results is based on ϕ = 0.64, which is the adjustment speed coefficient estimated empirically by Campbell, Calvet, and Sodini (2009) from Swedish data with an instrumental variables regression that eliminates bias from measurement error.

As Panel A shows, when the regression does *not* include time dummies, the slope coefficient on the experienced return variable is positive, and hence goes in the direction of our estimates in the paper. In terms of magnitude, however, it is also apparent that even without time dummies in the regressions, it would require an empirically implausible degree of inertia to get a slope coefficient as big as the one we obtain from the SCF. Only with an adjustment speed of 0.10, the coefficients get close to those that we estimate from the SCF.

However, our regressions in the paper include time dummies, so the appropriate comparison is Panel B. The striking result in this panel is that the slope coefficient is either zero or *negative* for the whole range of λ from 0.0 to 3.0. These simulation results show that inertia cannot explain the positive slope coefficient on experienced returns that we are finding in the SCF data. In fact, the inertia effect is likely to work against us by *weakening* the effect of experienced returns. Adjusted for inertia effects, the true regression coefficient on experienced returns might even be higher than the estimate we report in the paper.

It may be useful to explain the intuition for why the regression coefficient in the simulations with time dummies in Panel B turns out to be zero (in the case of initial portfolio shares at age 25 equal to the cross-sectional mean) or even negative (in the case of initial portfolio shares at age 25 equal to 50%).

This is easiest to see in the first case. If each generation starts out investing at age 25 with the initial risky asset share equal to the cross-sectional mean of the risky asset share of the older generations at that time, then the risky asset shares of all generations end up being always identical, without any cross-sectional variation, but only common time-variation. This common time-variation is completely absorbed by the time dummies in the regressions in Panel B. Hence, there is no variation left to explain for the experienced return variable, which explains its coefficient of exactly zero.

In the second case, where new generations start out with their target portfolio share of 50%, the situation is a little more complicated. It is still the case that most of the variation over time in the risky asset shares of different generations is common time variation, as they move up and down together from year to year with realized stock market returns. The magnitude of the changes in portfolio shares, $\Delta\alpha_t = \alpha_t - a_{t-1}$, are not completely identical for different generations, however, because the levels a_t are not the same for all generations, and so a given return realization leads to somewhat different $\Delta\alpha_t$. The time dummies therefore do not completely absorb all variation in risky asset shares caused by inertia. As it turns out, though, the remaining variation in risky asset shares is actually *negatively* correlated with experienced returns for empirically relevant parameter values. This effect is driven by differences between young generations and the older generations. Consider a new generation of investors that starts investing in year t at age 25 with a portfolio share of 50%. Their risky asset share relative to the cross-sectional mean is $0.50 - \bar{\alpha}_t$, where $\bar{\alpha}_t$ denotes the cross-sectional mean of risky asset shares across all generations that are alive and in their investing age in year t. The cross-sectionally de-meaned experienced return of the young is $A_{25,t} - \bar{A}_t$, where $A_{25,t}$ is a weighted average of the returns from year t-24 to year t and $\bar{A}_t$ is the cross-sectional mean of experienced returns across all generations in year t. Thus, the coefficient in a regression with time dummies of risky asset shares on experienced returns depends on the correlation between $0.50 - \bar{\alpha}_t$ and $A_{25,t} - \bar{A}_t$. Unless the portfolio inertia is extremely strong and/or the weighting parameter λ very high,[1] $\bar{\alpha}_t$ is more strongly positively correlated with $A_{25,t}$ (which depends on the last 25 years of returns) than with $\bar{A}_t$ (which depends on a longer history). As a result, $0.50 - \bar{\alpha}_t$ and $A_{25,t} - \bar{A}_t$ .are negatively correlated. In other words, the young typically have risky asset shares *below* the cross-sectional mean in times when their experienced returns are *above* the cross-sectional mean, and vice versa. Since the regressions with time dummies effectively de-mean dependent and explanatory variables cross-sectionally, these regressions pick up this negative correlation. This explains the negative coefficients seen in Panel B of Table A.1.

Summing up, we conclude that inertia in rebalancing cannot explain the positive relationship between experienced returns and risky asset shares that we find empirically in the SCF data. Most of the variation in portfolio shares created by inertia in portfolio rebalancing is common time-variation that is absorbed by time dummies in the regressions. If anything, our simulations show that inertia in portfolio rebalancing should make it more difficult to detect a positive relation between experienced returns and portfolio shares in our regressions with time dummies.

D. 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.2 reports the coefficient estimates for the control variables from the estimations in Table II, column (ii), Table III, columns (ii) and (iv), and Table IV, column (ii), i.e., the specifications that include liquid asset controls. The age and year dummy coefficient estimates and the coefficients on liquid assets interacted with the year dummies are not reported. As the table shows, non-white race and higher education as are most strongly associated with higher elicited risk tolerance and with higher stock and bond market participation. It is noteworthy that the signs of the coefficients of those variables are the same for each one of these three risk-taking measures. For the percentage allocation to

[1] For $\phi = 0.30$, for example, $\lambda > 10$ is needed to generate a positive correlation. For $\lambda = 1.0$, $\phi < 0.01$ is needed to generate a positive correlation. None of these parameter combinations are empirically plausible.

stocks, however, none of the control variables except the log income and log income squared have any statistically significant relationship with the dependent variable.

E. Interaction of Experience Effects with Sophistication Proxies

In Table A.3 we explore how the strength of the experience effect varies with investor sophistication. We use a dummy for a level of liquid assets above the cross-sectional median in a given year and a dummy for completion of a college degree as sophistication proxies and interact them with the experienced return variable. The weighting parameter in each specification is fixed at the value obtained in the main analysis, as reported in Table II, column (ii), Table III, columns (ii) and (iv), and Table IV, column (ii).

The evidence from the liquid assets dummy interaction is mixed. For elicited risk tolerance the coefficient on the interaction term is close to zero, while for stock market participation and the percentage allocation to stock measures the interaction term implies a significant lowering of the coefficient on experienced returns, albeit clearly not strong enough to eliminate the experienced return effect among the high wealth households. In contrast, for bond market participation the interaction coefficient is positive and significant.

The evidence from the college degree dummy interaction in the lower part of the table provides a clearer picture. Here the coefficient on the interaction dummy is consistently positive for all risk-taking measures. The magnitude of the coefficient is relatively small, though, and not significantly different from zero. Thus, on balance the evidence does not indicate that there is a consistently weaker or stronger experience effect on risk-taking among financially more sophisticated households.

F. Non-Monotonicities in the Weighting Function

The one-parameter weighting function that we use in our main analysis can take on a variety of shapes, but it cannot accommodate non-montonicity, e.g., a hump-shaped pattern of weights. To check whether such non-monotonicities could be important, we experiment with an alternative approach that uses a step function. We split each individuals life-span into three parts of equal length and compute the average return realized over each one of those three subperiods: recent, middle, and early (e.g., for an individual that is 60 years old in 2007, we calculate average returns from 1987 to 2006 (recent), 1967 to 1986 (middle), and 1947 to 1966 (early). We then regress the risk-taking measures on these three subperiod average returns, using the same controls as those in Table II, column (ii), Table III, columns (ii) and (iv), and Table IV, column (ii). Effectively, this assumes a weighting function that is a step function. A hump shape is now possible: in this case, the regression coefficient on the middle subperiod would take on the highest value. Instead of estimating two parameters (β and λ) we are now estimating three parameters (the three regression coefficients corresponding to the three subperiod average returns).

The results are shown in Table A.4. For each of the risk-taking measures except those based on the percentage allocation to stocks, the estimated coefficients show a monotonically declining pattern, with the average return of the most recent third of the lifespan receiving a statistically significant coefficient, while the estimated coefficient corresponding to the average return over the earliest third of the lifespan is not significantly different from zero. For the regressions with percentage allocation to stocks as the dependent variable, the coefficient on the middle third has a slightly higher point estimate than the coefficient on the most recent third, but from the relatively high standard errors one can see that this is not statistically reliable evidence in favor of non-mononpremonicity.

As an additional test, we also added a control variable for the average return experienced during the first 20 years of life. This addresses the concern that non-monotonicities could arise because individuals place particularly high weight on early experiences (the “formative” years hypothesis) or, alternatively, that our weighting function, due to its functional form restriction places too much weight on the early years. In the latter case, one would expect a negative coefficient on the control variable. The results (not tabulated) show that the coefficient on the average returns from the first 20 years of life is close to zero for all risk-taking measures and never statistically significant. The estimates of β and λ also hardly change at all. Overall, the results do not indicate that our assumption of a monotonic weighting function is in conflict with the data.

G. Robustness Checks

Table A.5 checks the robustness of our results with respect to several additional changes in methodology. We report the estimates for β and λ in each case. The specification corresponds to Table II, column (ii), Table III, columns (ii) and (iv), and Table IV, column (ii) of the main paper, i.e., it includes the liquid asset controls. In the probit models, the change in marginal effects is generally similar to those in the β coefficient compared with our baseline specifications, unless otherwise noted, and so we only report the β coefficients.

The first block of results shows estimates obtained when retirement assets are excluded from the asset holdings variables from 1983 onwards. The estimates for both β and λ are close to those that we obtained with retirement accounts included. This shows that the question whether retirement accounts should be included or not, and the imprecision with which retirement account allocations are estimated and imputed are not crucial issues for our empirical results.

The second block of results removes the years 1983 and 1986 from the sample. In these years, the SCF does not provide information on the allocation to stocks in retirement accounts, and we have to impute the allocation as described in Section A of this Appendix. As Table A.5 shows, however, this imputation does not have a material effect on our results as the parameter estimates are still similar to the baseline estimates if 1983 and 1986 data is removed.

The third block shows that similar results are also obtained when the estimation focuses solely on the “modern” SCF, i.e., the data prior to 1983 is omitted. The only exception is bond market participation, where the β coefficient drops considerably compared with the baseline specification.

The next two blocks vary the starting point for the weighting function to 10 years before the birth of the household head and to 10 years after, as described in the main text. In the following block, we introduce cohort dummies, also described in the main text.

The bottom block of results in Table A.5 shows tests in which we also include experienced volatility measures along with the experienced returns variable.

Table A.1: Simulated Regression Coefficients on Experienced Returns in Overlapping Generations Model with Inertia in Portfolio Rebalancing

Adjustment Speed	Initial share	Weighting parameter λ 0	0.5	1	1.5	2	2.5	3
		Panel A: Regression without time dummies						
0.10	0.50	1.49	1.86	1.94	1.95	1.93	1.87	1.81
	Mean	1.89	2.25	2.28	2.24	2.17	2.07	1.99
0.30	0.50	0.45	0.59	0.63	0.65	0.67	0.68	0.67
	Mean	0.48	0.62	0.67	0.68	0.70	0.70	0.71
0.64	0.50	0.12	0.16	0.18	0.19	0.19	0.19	0.20
	Mean	0.12	0.16	0.18	0.19	0.19	0.20	0.20
		Panel B: Regression with time dummies						
0.10	0.50	-0.69	-1.11	-1.05	-0.82	-0.58	-0.36	-0.18
	Mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.30	0.50	-0.07	-0.16	-0.19	-0.20	-0.19	-0.17	-0.15
	Mean	-0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.64	0.50	-0.01	-0.01	-0.02	-0.02	-0.02	-0.02	-0.02
	Mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table A.2: Control Variable Coefficient Estimates

Dependent variable	Elicited risk tolerance	Stock market. participation	Bond market participation	% liquid assets in stocks	%liquid assets in stocks
Sample	Full	Full	Full	Stock market participation required	Stock market participation required
Experienced return variable	Real stock returns	Real stock returns	Real bond returns	Real stock returns	Excess returns of stocks over bonds
African American	-0.056	-0.130	-0.175	-0.028	-0.027
	(0.034)	(0.044)	(0.041)	(0.012)	(0.012)
Hispanic	-0.122	-0.271	-0.515	-0.020	-0.019
	(0.054)	(0.056)	(0.065)	(0.018)	(0.018)
Other non-White	-0.068	-0.321	-0.357	-0.018	-0.017
	(0.051)	(0.064)	(0.062)	(0.016)	(0.016)
Non-White (pre-1983)	-	-0.322	-0.039	0.062	0.063
	-	(0.057)	(0.047)	(0.034)	(0.034)
High School completed	0.242	0.358	0.151	0.006	0.003
	(0.037)	(0.025)	(0.024)	(0.011)	(0.011)
College degree	0.190	0.197	0.038	0.016	0.016
	(0.020)	(0.021)	(0.020)	(0.006)	(0.006)
Married	-0.043	0.026	0.080	-0.021	-0.021
	(0.023)	(0.024)	(0.022)	(0.007)	(0.007)
Retired	-0.076	-0.134	0.019	-0.001	-0.003
	(0.034)	(0.036)	(0.033)	(0.011)	(0.011)
#Children	-0.071	0.006	0.221	0.005	0.004
	(0.019)	(0.017)	(0.017)	(0.005)	(0.005)
#Children^2	0.008	-0.001	-0.033	0.000	0.000
	(0.005)	(0.004)	(0.004)	(0.001)	(0.001)
Log Income	0.096	-0.621	0.269	-0.057	-0.061
	(0.175)	(0.147)	(0.109)	(0.046)	(0.046)
(Log Income)^2	0.002	0.037	-0.011	0.002	0.002
	(0.008)	(0.007)	(0.005)	(0.002)	(0.002)
Has defined benefit plan	-0.006	0.007	0.198	0.002	0.001
	(0.019)	(0.025)	(0.023)	(0.006)	(0.006)

Notes: Coefficients on control variables in Tables II, column (ii), Table III, columns (ii) and (iv), and Table IV, column (ii). Year dummies, age dummies, and liquid assets and liquid assets squared interacted with year dummies are included in the regressions, but coefficients not shown in the table. Estimations in the columns labeled “Full sample” use all available data; estimations in the last two columns use either the sample of stock market participants or the sample of bond market participants. Observations are weighted with SCF sample weights. Standard errors shown in parentheses are robust to heteroskedasticity/misspecification of the likelihood function and adjusted for multiple imputation.

Table A.3: Interaction of Experience Effect with Sophistication Proxies

Dependent variable	Elicited risk tolerance	Stock market. participation	Bond market participation	% liquid assets in stocks	% liquid assets in stocks
Sample	Full	Full	Full	Stock market participation required	Stock market participation required
Experienced return variable	Real stock returns	Real stock returns	Real bond returns	Real stock returns	Excess returns of stocks over bonds
High liquid assets dummy					
Experienced return	6.664	11.296	8.366	1.900	2.443
	(1.286)	(1.307)	(1.476)	(0.443)	(0.440)
Experienced return × $I_{\text{Liquid assets > median}}$	0.070	-2.119	3.710	-0.687	-1.123
	(0.286)	(0.340)	(0.766)	(0.094)	(0.152)
Weighting parameter λ	1.470	1.698	1.106	0.923	1.345
	[fixed]	[fixed]	[fixed]	[fixed]	[fixed]
College degree dummy					
Experienced return	6.024	10.057	9.063	1.187	1.477
	(1.419)	(1.377)	(1.537)	(0.491)	(0.464)
Experienced return × $I_{\text{College degree}}$	1.034	0.759	0.762	0.452	0.136
	(0.917)	(0.830)	(0.850)	(0.315)	(0.209)
Weighting parameter λ	1.470	1.698	1.106	0.923	1.345
	[fixed]	[fixed]	[fixed]	[fixed]	[fixed]

Notes: Models and controls as in Table II, column (ii), Table III, columns (ii) and (iv), and Table IV, column (ii) of the main paper, but with experienced real returns interacted with a dummy that equals one for households that have liquid assets higher than the median in a given year. The λ parameter is fixed at the value obtained in the earlier regressions that did not include the interaction term. 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 either the sample of stock market participants or the sample of bond market participants. Observations are weighted with SCF sample weights. Standard errors shown in parentheses are robust to heteroskedasticity/misspecification of the likelihood function and adjusted for multiple imputation.

Table A.4: Step Function as Alternative Weighting Function

Dependent variable	Elicited risk tolerance	Stock market. participation	Bond market participation	% liquid assets in stocks	% liquid assets in stocks
Sample	Full	Full	Full	Stock market participation required	Stock market participation required
Experienced return variable	Real stock returns	Real stock returns	Real bond returns	Real stock returns	Excess returns of stocks over bonds
Average return recent third of lifespan	4.557	4.011	5.535	0.450	0.450
	(0.942)	(0.792)	(0.915)	(0.268)	(0.291)
Average return middle third of lifespan	2.253	1.975	2.687	0.506	0.467
	(0.495)	(0.456)	(0.485)	(0.151)	(0.132)
Average return early third of lifespan	0.701	-0.061	1.317	0.120	0.010
	(0.366)	(0.320)	(0.366)	(0.103)	(0.086)

Notes: Control variables as in Table II, column (ii), Table III, columns (ii) and (iv), and Table IV, column (ii) of the main paper. The average stock return is calculated from the real return on the S&P500 index. The average 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 either the sample of stock market participants or the sample of bond market participants. Observations are weighted with SCF sample weights. Standard errors shown in parentheses are robust to heteroskedasticity/misspecification of the likelihood function and adjusted for multiple imputation.

Table A.5: Methodological Variations

Dependent variable	Elicited risk tolerance	Stock mkt. participation	Bond market participation	% liquid assets in stocks	%liquid assets in stocks
Sample	Full	Full	Full	Stock market participation required	Stock market participation required
Experienced return variable	Real stock returns	Real stock returns	Real bond returns	Real stock returns	Excess returns of stocks over bonds
Retirement assets excluded:					
β	5.900	8.757	10.923	1.402	1.363
	(1.263)	(1.372)	(1.670)	(0.558)	(0.479)
λ	1.780	1.414	1.621	0.495	1.007
	(0.309)	(0.234)	(0.307)	(0.287)	(0.429)
Years with imputed retirement account allocations excluded (1983 and 1986)					
β	4.602	10.818	10.928	1.127	1.154
	(2.245)	(1.589)	(1.655)	(0.605)	(0.517)
λ	1.198	1.700	1.322	0.849	1.140
	(0.450)	(0.226)	(0.294)	(0.455)	(0.540)
Old SCF (prior to 1983) excluded					
β	-	11.856	1.632	1.739	2.542
		(1.795)	(2.502)	(0.492)	(0.631)
λ	-	1.052	-0.252	1.380	2.006
		(0.190)	(0.937)	(0.405)	(0.626)
Starting 10 yrs after birth:					
β	3.910	4.994	5.231	0.908	0.999
	(0.834)	(0.969)	(0.956)	(0.308)	(0.293)
λ	0.733	0.434	0.020	0.247	0.554
	(0.224)	(0.169)	(0.190)	(0.223)	(0.288)
Starting 10 yrs before birth:					
β	-9.556	15.657	11.973	3.295	2.211
	(1.946)	(2.704)	(1.781)	(1.122)	(0.605)
λ	2.106	2.062	0.985	1.260	2.263
	(0.430)	(0.277)	(0.297)	(0.350)	(0.544)

(Table A.5 continued)

Cohort dummies included:					
β	3.865	13.277	3.459	2.800	2.051
	(1.851)	(2.059)	(2.850)	(0.993)	(0.716)
λ	2.410	1.359	2.814	0.261	1.142
	(1.577)	(0.286)	(1.226)	(0.329)	(0.715)
Geometrically averaged returns:					
β	6.348	9.010	10.163	1.672	1.579
	(1.272)	(1.273)	(1.672)	(0.445)	(0.413)
λ	1.445	1.765	1.229	0.981	1.384
	(0.288)	(0.246)	(0.301)	(0.286)	(0.383)
Unweighted:					
β	5.938	10.651	9.661	1.426	1.855
	(1.206)	(1.211)	(1.261)	(0.394)	(0.403)
λ	1.272	1.685	0.766	1.242	1.480
	(0.242)	(0.161)	(0.191)	(0.351)	(0.310)
Approximation with $\lambda = 1$					
β	6.184	9.134	9.297	1.472	1.437
	(1.313)	(1.402)	(1.423)	(0.446)	(0.406)
λ	1.00	1.00	1.00	1.00	1.00
	[fixed]	[fixed]	[fixed]	[fixed]	[fixed]
Experienced volatility included:					
Experienced return	6.685	10.627	7.170	1.691	1.361
	(1.282)	(1.310)	(1.962)	(0.451)	(0.439)
Experienced volatility	6.745	3.842	2.673	-1.620	-0.993
	(3.081)	(1.651)	(1.664)	(0.525)	(0.451)
λ	1.470	1.698	1.106	0.923	1.345
	[fixed]	[fixed]	[fixed]	[fixed]	[fixed]

Notes: Control variables as in Table II, column (ii), Table III, columns (ii) and (iv), and Table IV, column (ii) of the main paper. Observations are weighted with SCF sample weights. Standard errors shown in parentheses are robust to heteroskedasticity/misspecification of the likelihood function and adjusted for multiple imputation.