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

Ulrike Malmendier
UC Berkeley and NBER

Stefan Nagel
Stanford University and NBER

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Abstract

We investigate whether individual experiences of macro-economic shocks affect 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 so far report lower willingness to take financial risk, are less likely to participate in the stock market, and if they do, 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. More recent return experiences have stronger effects, but individuals are still influenced by experiences from several decades earlier. The experience effect 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. The average investor's lifetime stock-market experience lines up well with the market's price/earnings ratio, suggesting that experience-driven variation in risk-taking could help explain aggregate stock-market fluctuations.

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I. Introduction

Do personal experiences of economic fluctuations shape individual 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 risk attitudes. In this paper, we ask more generally whether people who live through different macroeconomic histories differ in their level of risk taking.

Standard models in economics assume that individuals are endowed with stable risk preferences, which are 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 their 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' willingness to take financial risks differ depending on the macroeconomic history they experienced over the course of their lives. We test whether individuals who experienced low stock-market returns in their lives so far express a lower willingness to take financial risk, are less likely to participate in the stock market and invest less in stocks. We also test whether individuals who lived through periods of low bond returns are more wary of participating in the long-term bond market. Investments in bonds, even those in default-free government bonds, are risky in real terms because of unexpected inflation. A key implication of the experience hypothesis is that differences in the level of risk taking across individuals are correlated with differences in life-time experiences. For example, after years of low stock-market returns, e.g., after the recessions of the 1970s and early 1980s, the stock-market participation rate of young people should be lower relative to that of old people, who have also experienced better returns in their lives, than after boom years, e.g., in the 1960s, when younger indi-

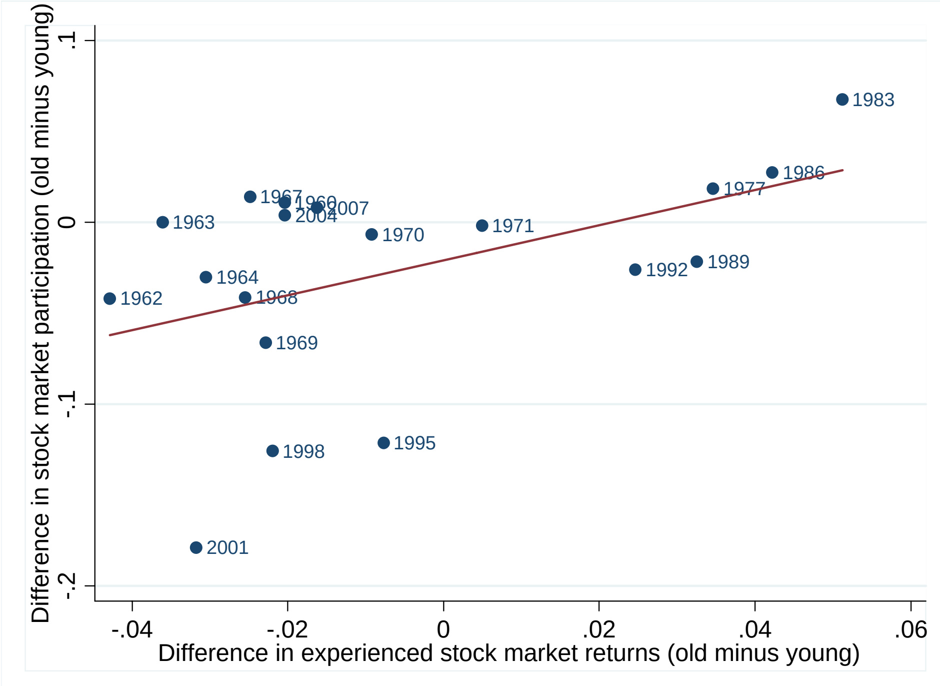

Figure 1: Differences in stock-market participation rates of old and young individuals plotted against differences in experienced stock-market returns. Stock market participation rates are the fraction of households who invest in stocks, including stock mutual funds and stocks held in retirement accounts. 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.

viduals have only experienced high returns in their lives so far, but older individuals still have the memory of the Great Depression and, hence, a worse average experience than young investors. 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. In our main analysis, we test whether these differences persist when we use a broad range of risk-taking proxies, a more sophisticated weighting scheme for recent and distant experiences, and 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) willingness to take financial risk as indicated in a survey question, (ii) stock-market participation, (iii) bond-market participation, and (iv) the proportion of liquid assets invested in stocks. We relate these measures 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- and bond-market returns likely have substantial positive correlation with actual experiences. In our estimation, we allow recent observations and those early in life to carry different weights. That is, we let the data simultaneously determine how individuals weight past observations and how strongly this weighted average of past return observations, which we label "experienced return," affects current risk-taking.

We find that households' risk taking is strongly related to experienced returns. 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. In addition, households with higher experienced bond returns are more likely to participate in the bond market. The estimated weights are similar for all four risk-taking measures: More recent experiences 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. Our estimates imply that young individuals, with short life-time histories, are particularly strongly influenced by recent data. While the precise functional form of declining-weights function varies somewhat across risk measures and specifications, linearly declining weights give very similar estimates and provide a similar fit in all cases. Hence, a simple model of linearly declining weights in experienced returns suffices to significantly improve the prediction of financial risk-taking in stocks and bonds relative to the standard model.

We also provide some insight into the channel through which experiences affect risk-taking, i.e., whether they alter risk preferences or beliefs about future returns. We examine micro data on stock return expectations from the UBS/Gallup survey from 1998 to 2007, again controlling for time effects and age effects. We find that an increase in the experienced stock return by 1 percentage point (pp) is associated with a 0.4 to 0.8 pp increase in the stock return expected for next year. This evidence is consistent with a beliefs channel, though it does not rule out that experiences also affect risk preferences.

All of our estimations control for year effects, age effects, wealth and income. Year effects remove time trends or any aggregate effects, such as time-varying aggregate risk aversion or a mechanical positive relation between recent stock returns and households' stock allocation due to market clearing.[1] As illustrated in Figure 1, our identification comes from cross-sectional differences in risk-taking and in macroeconomic histories, and from correlated changes of those cross-sectional differences over time. Age effects allow us to distinguish our results from life-cycle effects such as increases in risk aversion with age or the absence of labor income in retirement. The wealth and income controls address the concern 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, any remaining unobserved differences in wealth are unlikely to explain all four of our risk-taking measures. Prior literature finds wealth effects for stock-market participation (e.g., Vissing-Jorgensen 2003), but not for the risky asset share of stock-market participants (Brunnermeier and Nagel 2008) or elicited risk tolerance (Sahm 2007). Our results also hold when retirement account holdings are excluded from the asset holding measures.

Our methodology allows us to simultaneously control for age and time effects. Previous work, which has tried to identify cross-cohort differences in risk-taking with cohort-dummy regressions (e.g., Ameriks and Zeldes 2004) faced the problem that cohort effects cannot be separated from age and time effects due to collinearity (see, e.g., Heckman and Robb 1985, and Campbell 2001). Our identification strategy, in contrast, does not rely on estimating cohort effects. The experience hypothesis predicts a positive relationship between the experienced return variable and risk taking. Since experienced returns are not collinear with age and time effects, we can control for age and time effects simultaneously.[2]

The economic magnitude of the experience effect is large, as can be illustrated with the recent fall of the stock market in 2008. The real return of the S&P 500 index in 2008 was -36%. These large nega-

[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.

[2] Moreover, since experienced returns vary not only across, but also within cohorts over time, we can include an almost full set of cohort dummies and therefore control for any omitted variable that has cohort-level variation. See Online Appendix E.

tive returns strongly altered investors' life-time average returns, and the effect was strongest for young investors. For example, compared with a counterfactual benchmark of 8.2%, which is the (arithmetic) average real return since begin of our sample period (1871), the 2008 downturn lowered the experienced return of a 30-year old by about 4.0 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.[3] Our estimates also imply how long the effects of the crash will last. The 2008 return receives a weight of 8.9% in the experienced return of a 30-year 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.

Our paper connects to several strands of literature. 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) have changed (Erev and Roth 1998; Camerer and Ho 1999). Kaustia and Knüpfer (2008) provide related evidence that the returns investors experience on their own investments in initial public offerings (IPOs) 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. Greenwood and Nagel (2009) 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- return expectations during the stock-market boom in the late 1990s. Amromin and Sharpe (2009) analyze microdata on stock market return expectations and find that individuals expect

[3] 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.

higher returns in times of booms than in times of recessions. Piazzesi and Schneider (2006) report that after the high-inflation years in the late 1970s, younger individuals expected higher future inflation than older ones. Malmendier and Tate (2005) and (2009) find that corporate managers who are "Depression babies" shy away from external financing. Graham and Narasimhan (2004) find that those who experienced the Great Depression as managers choose a more conservative capital structure with less leverage.

Our evidence that life-time macroeconomic experiences affect risk-taking at the micro-level suggests that movements in the average consumer's macroeconomic experiences could also affect risk-taking in the aggregate, and hence asset prices and the macroeconomy. Along these lines, Cogley and Sargent (2008) propose to explain the equity premium with a model that assumes that the Great Depression created a long-lasting shift towards pessimistic beliefs, as suggested by Friedman and Schwartz (1963).

II. Data and Methodology

The key variables for our analysis are several measures of risk-taking from household microdata as dependent variables and historical stock and bond market returns as explanatory variables. Our analysis requires returns all the way back to birth for every household and, hence, 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)[4], 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

[4] 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.

of Governors of the Federal Reserve System and available every three years. The second source is the precursor of the "modern" SCF, obtained from the Inter-university Consortium for Political and Social Research at the University of Michigan. The precursor surveys start in 1947, partly annually, but with some gaps. 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 Appendix.

Our first risk-attitude measure is individuals' elicited willingness to take financial risk. In the 1983 and 1989-2007 survey waves, respondents 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," although one should not view this measure as a clean measure of risk tolerance (in the Arrow-Pratt sense) distinct from beliefs.[5] 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, though prior literature documents that they predict households' actual allocation to risky assets (Faig and Shum 2006) and differences in risky human capital investments and in wage growth (Shaw 1996).[6] In our analysis, using both elicited risk tolerance and direct measures of asset allocation ameliorates concerns about the connection between self-reported

[5] 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.

[6] A similar financial risk-tolerance measure in the German Socio-Economic Panel strongly predicts financial risk-taking, and a simple risk-taking measure predicts risky behavior in a lottery field experiment (Dohmen et al. 2009).

risk tolerance and actual behavior.

The second measure is a binary variable for stock-market participation, available in each survey wave from 1960-2007. It indicates whether a household holds more than zero dollars worth of 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 1983 and 1986, we need to impute the stock component of retirement assets from the total amount in these accounts. From 1989 to 2004, the SCF offers only coarse information on retirement assets (e.g., mostly stocks, mostly interest bearing, or split), and we follow the conventions of the SCF in assigning portfolio shares. The Appendix provides the details and 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. It indicates whether a household holds more than zero dollars worth of long-term bonds. We define bond holdings as the sum of direct holdings of government bonds and corporate bonds, tax-free mutual fund holdings, and, from 1989 onwards, 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 instruments (e.g., money market funds) in retirement accounts.

Our fourth measure of risk taking is the fraction of liquid assets invested in stocks. The share of directly held stocks plus the equity share of mutual funds can be calculated in all surveys from 1960-2007 other than 1971. Liquid assets are defined as stock holdings plus bonds plus cash and short-term instruments (checking and 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 (CPI-U until 1997 and CPI-U-RS thereafter). 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.[7] 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,[8] 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 base our analysis and interpretations on the weighted estimators for several reasons. While it is inefficient to use weighted estimators in place of unweighted OLS estimators when the treatment effect is identical across the different wealth strata (Deaton 1997, Cameron and Trivedi 2005), the treatment effect in our setting (past return experience) is unlikely to be identical. Rather, the estimated parameter coefficient is best interpreted as some form of average treatment effect (or average parameter) arising from heterogeneous treatment effects. Hence, the danger of using the unweighted sample is that we obtain an unrepresentative average. The advantages of using the sample weights and obtaining a weighted average set of estimated parameters that is representative of the U.S. population (rather than, for example, biased towards the high-income households in the 1983-2007 survey waves) outweigh the loss of consistency under the (unrealistic) homogeneous treatment effect assumption. We compute weighted estimators in our probit models as well as our regression models. For maximum likelihood models, the weighted MLE are consistent and asymptotically normal, but may also not be efficient (Wooldridge 2002, p.595-596; Camerer and Trivedi 2005, p. 828-829). The robustness checks in Online Appendix-Table A.5 with the unweighted sample, however, show that weighting makes virtually no difference for the parameter

[7] 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.

[8] 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.

estimates and standard errors.

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”). Imputed values vary across implicates to represent the sampling uncertainty inherent in the imputation. To adjust the standard errors for this uncertainty, we follow the method of Rubin (1987) which we describe in more detail in the Online Appendix A.

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 influence decisions much later in life. Such a flexible estimation faces some hurdles. If we simply included separate explanatory variables for each past year of return experience (back to the year of birth, for example), the large number of coefficients on those past returns would make it impossible to estimate with any meaningful precision. Moreover, the number of explanatory variables would differ across households depending on their age. To solve both problems, we summarize 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 in time. 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. If $\lambda < 0$, 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 $\lambda > 1$).

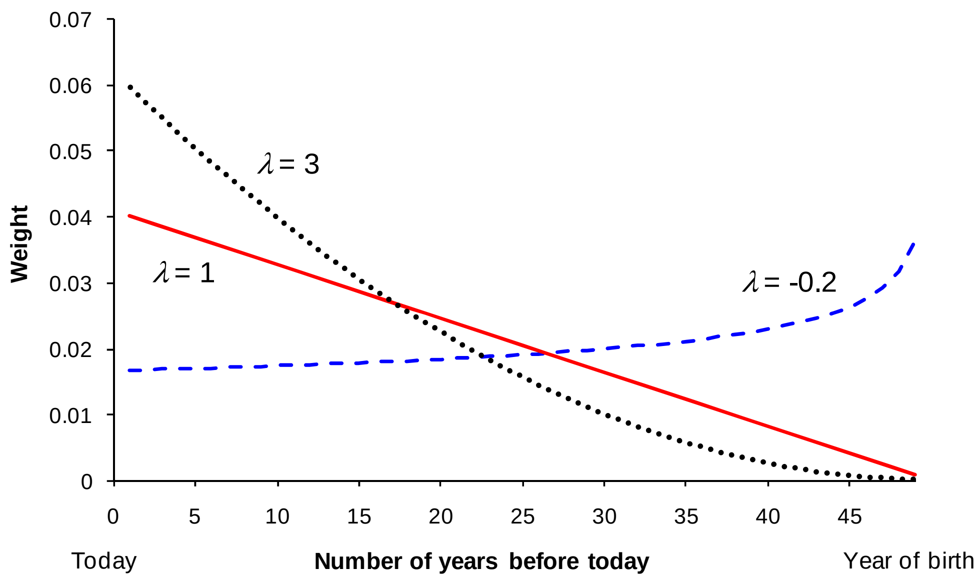

Figure 2: Weights on experienced returns for different values of λ for a 50-year old household head.

To illustrate the shape of the weighting function, we plot the weights $w_{it}(k, \lambda)$ for a 50-year old household head as a function of the time lag k for three values of λ. As Figure 2 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. As discussed in Section III.G, we did not find evidence that interior maxima or non-monotonicities are important. To the contrary, all weighting functions approximate the decreasing pattern we will estimate below. While the true weighting patterns may be more complex, our restriction to a parsimonious one-parameter function biases the estimation against finding any significant effect of experienced returns on risk-taking.

The following generic regression model illustrates how we simultaneously estimate the weights and individuals' sensitivity to experienced returns, calculated with those weights:

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

where $A_{it}(\lambda)$ are experienced returns and x_{it} is a vector of control variables. We simultaneously estimate β and λ. Since $A_{it}(\lambda)$ is a non-linear function of the weighting parameter λ, 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.[9] We use 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}, 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 yields, for a household of that age, the partial effect of a return experienced k years ago on the dependent variable. For example, if $\lambda = 0$, all returns in the household head's history since birth are weighted equally, and their partial effects are all equal to their weight ($1/\text{age}_{it}$) times β.

Where we set the starting point for the experienced return calculation is of little importance for our results. If setting the starting point at birth is "too early" in the sense that individuals are not much influenced by experiences early in their lives, our weighting function can accommodate this with weights that decline relatively fast. If the starting point is "too late" in the sense that individuals are also influenced by observations realized prior to their birth (e.g., through their parents and social network), then setting the starting point earlier than birth could only improve the explanatory power of weighted average returns compared with our specification. We will show in Section III.G, that varying the starting point to 10 years before or 10 years after birth has little effect on our results.

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[9] 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.)

C. Summary Statistics

Table I provides some summary statistics, in Panel A for the full sample, in Panel B for the subsample of stock-market participants, i.e., households that have at least $1 in stocks or mutual funds, and in Panel C for the subsample of 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, with a the median holding of $51,883 in liquid assets rather than $11,642 in the full sample. 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.[10] The bond-market participation rate is similar (32.7%). The remaining two risk-taking measures show considerable dispersion across households. The proportion of liquid assets invested in stocks in Panel B has 10^{th} and 90^{th} percentiles of 7.1% and 90.2%. The 10^{th} and 90^{th} percentiles for elicited risk tolerance in Panel A are 1.0 and 3.0, respectively. Note that mean elicited risk tolerance is higher for the stock-market participants (2.132) than for the full sample (1.890) and lies in the middle for bond market participants (2.029). That is, the elicited risk-tolerance 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 10^{th} and 90^{th} percentile for the experienced (real) stock return are 6.4% and 11.6% in the 1960-2007 sample. The 10^{th} and 90^{th} percentile for experienced (real) bond returns are -0.2%

[10] The 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.

and 5.0%. Thus, over our sample period, experienced bond returns are as volatile in real terms as experienced stock returns. The amount of variation in experienced returns is similar for a range of λ values around 1.25. For example, with $\lambda = 1.00$ and $\lambda = 1.50$, between which most point estimates lie, the differences between the 10th and 90th percentile of real stock-market returns are 4.9 pp and 5.6 pp, 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 SCF risk-tolerance 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

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

where $\Phi(.)$ denotes the cumulative standard normal distribution function, the α_j denote the cutoff points that must be estimated ($\alpha_1 < \alpha_2 < \alpha_3 < \alpha_4 = \infty$), 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 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,[11] both interacted with year dummies to allow year-specific slopes). $A_{it}(\lambda)$ is the experienced 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 and the cutoff points. Since the coefficient vector β does not have a direct economic interpretation, we focus on the difference in fitted probabilities if we set the experienced return to its 10th and 90th percentile, leaving all

[11] We also estimated the model using higher-order polynomials or, alternatively, wealth-decile dummies, with virtually no effect on the estimation results, nor any improvement in fit for our risk-taking measures.

other variables at their actual sample realizations. We calculate this difference for every observation, and then average across the whole sample. To aid in the interpretation of those differences in fitted probabilities, we compare their magnitude to the unconditional frequencies with which individuals fall into the four elicited risk tolerance categories. As shown in brackets in Table II, only few households fall into the highest risk tolerance category 4. 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 time effects without further restrictions. 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 variation in macroeconomic experiences, 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 year dummies absorb all aggregate time effects including variation in average risk aversion. The effect of experienced stock returns is therefore estimated from cross-sectional differences in risk taking and variation of those cross-sectional differences over time, but not from aggregate time-variation. 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).

The inclusion of year dummies also means that the null hypothesis implicit in our approach is that households are influenced in their risk-taking by all historical data and do not place higher weights on observations realized during their life-time than on data realized before they were born. In this case, cross-sectional differences in risk taking would not be correlated with cross-sectional differences in our experienced returns variable, which implies that $\beta = 0$ under the null hypothesis.

Table II presents the results of the ordered probit model, estimated on the 1983-2007 sample. 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.[12] Standard errors, shown in parentheses, are robust to misspecification of the likelihood function and adjusted for multiple imputation in the SCF.[13] Column (i) shows that higher experienced stock-market returns increase the probability having high risk tolerance (3 and 4), have little effect on the probability of being in category 2, and decrease the probability of reporting the lowest risk tolerance (category 1). Thus, stock-market returns experienced in the past have a significant and positive effect on reported risk tolerance. As column (ii) shows, adding the liquid assets controls has little effect on the estimates.

The economic magnitudes are sizeable. Going from the 10th to the 90th percentile of experienced stock returns in column (ii) 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. The implied change is large compared with an unconditional probability of 36.3% of being in the lowest risk tolerance category.

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 tolerance (compare with Figure 2). Of course, there is a substantial standard error around the point estimate, but weights that are increasing with the time lag ($\lambda < 0$) are ruled out. For older individuals, the estimates imply non-negligible weights on returns observed several decades earlier. Apparently, the memory of these early experiences fades away only slowly.

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[12] 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 Online Appendix, Table A.2.
[13] See Section A in the Online Appendix. Clustering by cohort or clustering by year does not have a material effect on our estimates.

B. Stock-market Participation

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

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

The binary indicator y_{it} equals 1 if the stock holdings of household i at time t are positive. We are interested in the effect of experienced returns, $A_{it}(\lambda)$, on the probability of stock-market participation. The vector x_{it} includes the same income and demographics controls as in the ordered probit model above. Liquid-asset controls are particularly important in this context since a standard model with fixed per-period participation costs predicts that stock-market participation is increasing in liquid assets (Vissing-Jorgensen 2003), and experienced 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 experienced returns have a positive and highly significant effect on stock-market participation after controlling for liquid assets. The effect of stock-market return experience on stock-market participation is large: A change from the 10^{th} to the 90^{th} percentile of experienced stock implies a 14.6 pp increase in the probability that a household participates in the stock market. The fitted probability difference is quite similar in column (i) without the liquid assets controls.

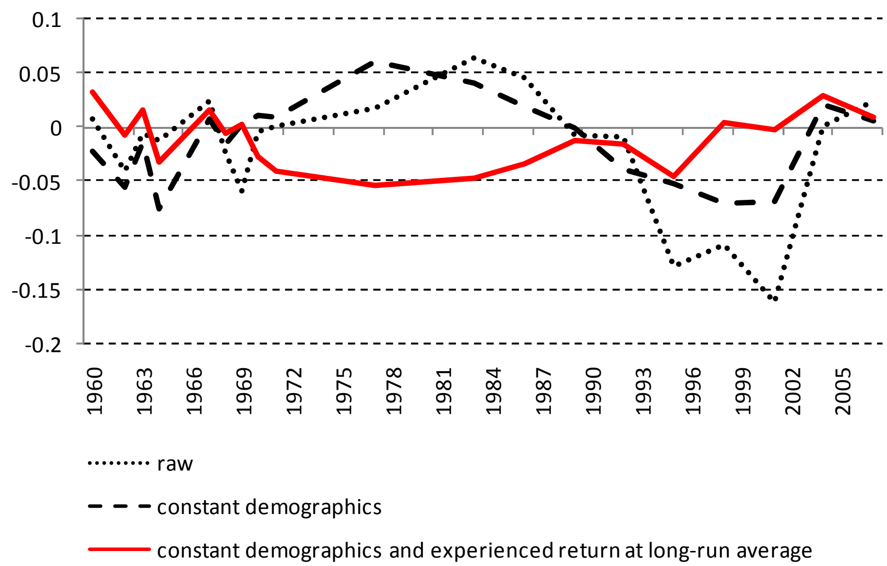
As with the previous measure, elicited risk tolerance, the estimate of 1.698 (s.e. 0.206) for the weighting parameter λ implies that households' stock-market participation decisions are affected by returns many years in the past, but rules out weights that are increasing with the time lag ($\lambda < 0$). The weighting parameter is remarkably similar to the estimate from the elicited risk-tolerance model in Table II, even though the latter one is based on a self-assessment by the respondent and the former is based on asset holdings. Yet, a significant part of the variation in both risk-taking measures can be traced to variation in experienced real stock-market returns, with roughly similar weights on the history of past returns.

To provide additional perspective on the economic magnitude of the experience effect, we conduct a simple counterfactual exercise. We compare the actual participation rates to those predicted if households always accounted for the full time-series of past returns, without overweighting life-time returns. We calculate the counterfactual in two steps. First, we take the point estimates from column (ii), and we calculate the fitted participation probabilities for each household in each survey year when all control variables, except age and year dummies, are set to their full sample averages in four age groups (< 40, 40-49, 50-59, ≥ 60). We label this (counterfactual) participation rates obtained the "constant demographics" rate. Second, we re-calculate the fitted probabilies, holding not only the control variables constant over time, but also substituting experienced returns with the average stock-market return since 1871. 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 the first available year in our returns data set, without placing higher weight on life-time experiences.

Figure 3 presents the results. Panel (a) plots the stock market participation rates of the old (age ≥ 60) minus the participation rate of the young (age < 40) age group. The raw data (dotted line) as well as the constant-demographics plot (dashed line) 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 (solid line) completely reverses the big difference in the early 1980s, and, together with constant demographics, eliminates the difference in the late 1990s. Panel (b) plots the overall participation rates for the whole sample. Comparing the effect of experienced returns (solid line relative to dashed line) with the effect of time-varying demographics, liquid assets, and income (dashed line relative to dotted line), it is evident that return experiences affect stock-market participation at least as much as variations in demographics controls. The biggest impact of experienced returns appears in the early 1980s, when the participation rate based on the long-term average return since 1871 would have been more than 10 pp higher than with the actual experienced returns. Experienced returns were very low at the time, due to the poor real stock-market returns in the 1970s.

The counterfactual exercise for the overall participation rate is simplistic in that it does not consider equilibrium asset-pricing implications of changing demographics and experienced returns to counterfactual values. If these variables influence risk-taking, they presumably also influence asset prices and, hence, also stock market participation. However, our simple calculations provide some indication of the economic magnitudes of changes in aggregate risk-taking induced by experienced returns.

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



(b) Overall stock market participation rate

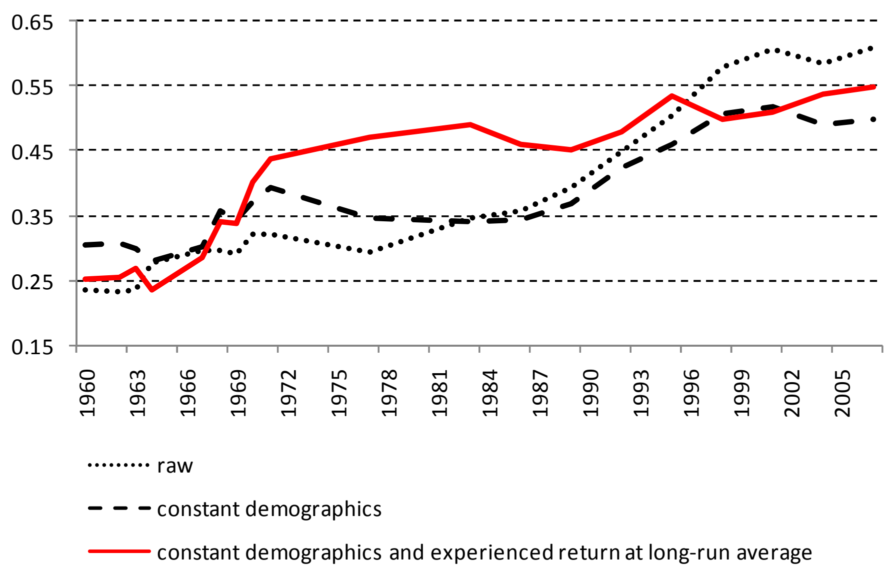


Figure 3: Counterfactual stock market participation rates. Figure (a) shows the difference in average fitted stock market participation probabilities between young (age < 40) and old (age ≥ 60) (old minus young) from the stock market participation probit model of Table III, column (ii), when all controls, 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 average fitted participation probabilities in the whole sample. Observations are weighted with SCF sample weights.

C. Bond-market Participation

As our third measure of risk taking, we turn to investment in long-term bonds. We test how participation in bond markets is related to experienced (real) returns on long-term government bonds. We estimate the same probit model as the one we used for stock-market participation. Column (iii) of Table III shows that 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 bond returns. A change from the 10th to the 90th percentile of experienced bond returns is associated with increase of about 15.3 pp 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 is only marginally different. Thus, bond-market participation and stock-market participation both show positive correlation with the returns that individuals' experienced over their life-times 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 controls for fixed costs of stock-market participation since it conditions on participating. We use the following non-linear regression model:

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

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. Hence, 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.

As column (i) shows, without the liquid assets controls, the experienced stock return has only a statistically weak positive effect on the proportion of liquid assets invested in stocks. When the liquid assets controls are added in column (ii), the effect is stronger, both statistically and economically. 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 pp) leads to an increase of about 1.476×5.2 pp ≈ 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 risky asset share (see Curcuru, Heaton, Lucas, and Moore (2009), and Brunnermeier and Nagel (2008). The control variable coefficients reported in Online Appendix B confirm this finding. Thus, experienced stock-market returns emerge as a major influence on households' willingness to bear stock-market risk.

The point estimate for λ in column (ii), 0.923 (s.e. 0.323), suggests weights that decline roughly linearly. The estimate is still of similar magnitude as the λ-estimates in the elicited risk-tolerance model in Table II and the stock and bond market participation models in Table III. The similarity is noteworthy since elicited risk tolerance is 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 supports our interpretation that all measures 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. From the perspective of an investor choosing between stocks and bonds, the experience hypothesis predicts that she will increase her investment in stocks relative to bonds only if stocks performed better than bonds over her life-time so far. 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 as well as real stock returns. The point estimate for β are slightly higher. The results are also similar if we restrict the sample to households participating both in stock and bond markets, who can presumably change their stock and bond allocations relatively flexibly, with participation cost already sunk.

One possible concern is that the positive relation between experienced returns and the percentage allocation to stocks is explained by slow portfolio rebalancing of households in response to stock market movements, as documented, for example, in Brunnermeier and Nagel (2008) and Campbell, Calvet, and Sodini (2009) . However, we illustrate that this is not the case using simulations of an overlapping-generations model where agents are slow to rebalance (Online Appendix C). In regressions on the simulated data similar to those in Table IV, experienced returns do not receive a positive coefficient. The key is the inclusion of time dummies. Without time dummies, there is indeed a mechanical positive relationship between experienced returns and the portfolio share of stocks. But when time dummies are included, the regression thus focuses on cross-sectional variation and the positive relationship disappears.

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

As an additional test of the experience hypothesis, we compare the relative predictive power of experienced stock and bond returns for all of our risk-taking measures. We relate each measure 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.

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 (as bond allocations in retirement accounts are not available) and restricting the sample to households that participate in both stock and bond markets. For the probit models in columns (i) to (iii) we also report the average of the fitted probabilities at the 90^{th} minus the 10^{th} percentile of experienced returns, in column (i) for category 1 (low risk tolerance).

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 too large to draw definitive conclusions. Evidently, the short sample available for this risk-taking measure is not sufficient to disentangle the effects of stock and bond 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. The percentage share allocated to stocks in column (iv) is positively related to experienced stock returns and (insignificantly) 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.

The results 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 roles of stock and bond returns also provides some hints on the question whether life-time experiences 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 risk-taking in stocks, while bond returns should matter most for risk-taking in bonds. In a simple preference-based story, instead, individuals' relative risk aversion depends on past experiences of stock and bond returns and, hence, there are no 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. Experience Effects on Stock Market Return Expectations

In an effort to further disentangle the roles of beliefs and risk preferences, we investigate how past stock return experiences relate to expectations about future stock returns. We use the UBS/Gallup survey on stock return expectations of households, obtained from the Roper Center at the University of Connecticut. Details on the data set are provided at the end of the Appendix. Using these data, Vissing-Jorgensen (2003) finds time-varying differences in expectations between different age groups. Young people have the highest stock return expectations, particularly around the time of the stock market peak in 2000. We test whether this pattern reflects a positive effect of experienced returns on expectations. We use two types of expectations: The stock market return expected over the next 12 months, and the return respondents expect to earn on their own portfolios over the next 12 months.

Unfortunately, the UBS/Gallup survey covers a much shorter time period than the SCF, 1998 to 2007, mostly monthly, but with a few exceptions. The short time span makes it difficult to statistically disentangle the effect of experienced returns from age effects. To reduce the burden on the estimation, we work with the weighting parameters obtained in the baseline specifications for stock market participation (λ = 0.923, Table III) or percentage allocation to stocks (λ = 1.698, Table IV). We regress stock return expectations on experienced returns, where experienced returns are calculated for each individual, given λ and the individuals age, using real stock market returns up to the end of the year preceding the survey year, in the same way as in our previous analysis of risk-taking measures. We weight each observation with sample weights provided by the UBS/Gallup survey. As in our earlier analysis of SCF data, we focus on individuals with age ranging from 25 to 74.

Table VI presents the results. Columns (i) and (ii) use the expected stock-market return over the next 12 months as dependent variable. This variable is only available from 1998 to 2003. Despite the very short sample, the estimate for the coefficient on experienced returns in column (i) of 0.801 is more than two standard errors away from zero. With λ = 1.698 in column (ii), the point estimate is about half as big, and only marginally significant. The magnitudes of the point estimates are substantial. They imply that a 1 pp higher experienced return translates into 0.4-0.8 pp higher expected return.

Columns (iii) and (iv) repeat this analysis with the expected return on the respondent's own portfolio as the dependent variable. The benefit of using this variable is a substantially longer sample, extending until 2007. The downside is that it does not separate expectations from risk preferences as cleanly. It is perceivable that a highly risk averse investor chooses a portfolio with a low level of risk and hence expects a low return, while a risk tolerant individual chooses a high-risk portfolio and expects a high return. Thus, differences in people's expectations about their own future portfolio return could partly stem from differences in risk preferences. However, the point estimates for the coefficient on experienced returns are very similar to those in columns (i) and (ii), suggesting that there is not much room for a strong confounding effect of risk preferences. Due to the larger sample, standard errors become considerably smaller.

The findings from expectations data lend further support to the view that experienced returns affect beliefs about future asset returns. This does not rule out that life-time return experiences could affect risk preferences as well, but it shows that, at a minimum, the beliefs channel accounts for an important part of the experience effects.

G. Methodological Variations and Robustness Checks

We check the robustness of our results to several further variations in methodology. All of these (and more) additional tests are reported in detail in Sections D, E, and F of the Online Appendix.

Financial sophistication. We interact experienced return with two financial-sophistication proxies: a dummy for high levels of liquid assets and dummy for completed college education. The results do not show a clear tendency of experience to matter more or less with higher financial sophistication.

Non-monotonicities in the weighting function. To check whether our monotonic weighting function is misspecified, 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, reported in Online Appendix E, indicate a pattern of weights that closely resembles the monotonic weights produced by our weighting function.

Excluding retirement assets. The allocation to stocks in retirement accounts is probably measured with considerable error since the SCF only provides coarse allocation brackets before 2004 and no allocation information before 1989, which necessitated an imputation of retirement allocations in 1983 and 1986. Repeating our baseline estimations with retirement account holdings completely excluded, we find that the estimates are generally very similar to our baseline estimates. Also, running the estimation with retirement accounts included, but excluding the years with imputed retirement allocations (1983 and 1986) 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 do not matter much, our weighting function should approximately adapt to this with a relatively high value of λ. Consistent with this intuition, we find that our results do not change much if we set the starting point at 10 years after or at 10 years before birth.

Including cohort dummies. Our main explanatory variable, life-time weighted average return, is not a constant per cohort, but instead varies over time as the cohort experiences new return realizations. This allows us to also include as many cohort dummies in our specifications as possible up to the point that age, time, and cohort dummies are not perfectly collinear in order to control for unobserved cohort effects. 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.

Experienced Volatility. We also test whether experienced volatility affects households' risk-taking decisions. We calculate experienced volatility using the same weighting function as before, but now applied to the standard deviation of returns. To limit the demands on the estimation, we fix the weighting parameter for both experienced return and experienced volatility at the point estimate for λ obtained in the baseline specifications. We do not find a consistent effect of experienced volatility on risk-taking. Experienced volatility tends to be negatively associated with percentage allocation to stocks. For the other three measures, the estimated effect is positive but of smaller magnitude than the experienced return effect and has relatively large standard errors. Most importantly, the inclusion of experienced volatility has little effect on the coefficient on experienced returns. It is possible that experience of extreme events affects risk-taking more strongly than experience of risk measured by standard deviations. But the rare nature of extreme events, combined with the difficulty in deciding what constitutes an extreme event, means that their effects are difficult to investigate empirically within our framework. We leave an investigation of extreme events to future work.

IV. An Aggregate Perspective

Our estimation has focused on cross-sectional differences in risk-taking measures in order to absorb potential confounding macro and market-clearing 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 given point in time but at different points in time, and the time variation should influence risk-taking in the aggregate. The population-wide time-variation in risk-taking could, in turn, help explain the puzzling fluctuations in valuation ratios like the price/earnings (P/E) ratio, which appear to reflect fluctuations in expected returns (rather than variation in expected cash flows).

A full investigation of the asset-price effects of macroeconomic experiences is beyond the scope of this paper, but we carry out a plausibility check. For the experience effect to be plausible, the time series of experienced return of the average investor should line up with the time series of the price/earnings ratio of the aggregate stock market. Periods of high experienced returns (and hence high risk-taking due to low risk aversion and/or optimism) should coincide with periods of high price/earnings ratios.

We calculate experienced stock-market returns for each age from 25 to 74 in each year from 1946 to 2007 based on a weighting parameter of $\lambda = 1.25$, which is roughly the average parameter estimate across all specifications with liquid asset controls in Tables II-IV. We then average the experienced returns across all ages in each year and plot the resulting average experienced returns series against the annual price-to-earnings (P/E) ratio of the S&P 500 index from Shiller (2005).[14] We also conducted a similar calculation with liquid assets-weighted averages of experienced returns and found similar results.

[14] Shiller's P/E series uses a ten-year moving average of earnings in the denominator

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, and the line shows the P/E ratio. The two series are highly positively correlated. Periods of high equity-market valuations and low subsequent returns (the 1960s and 1990s) coincide with periods when investors have high experienced stock-market returns. Periods of low valuation and high subsequent returns (1940s and early 1980s) coincide with investors having low experienced stock-market returns. While this is not a definitive proof that variations in P/E ratios and expected returns are driven by experience effects, it underscores that a theory of experience-induced variation in risk-taking is at least a plausible explanation.

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 *micro-data*, where we exploit cross-sectional differences between investors' risk-taking measures. We do not use aggregate data in

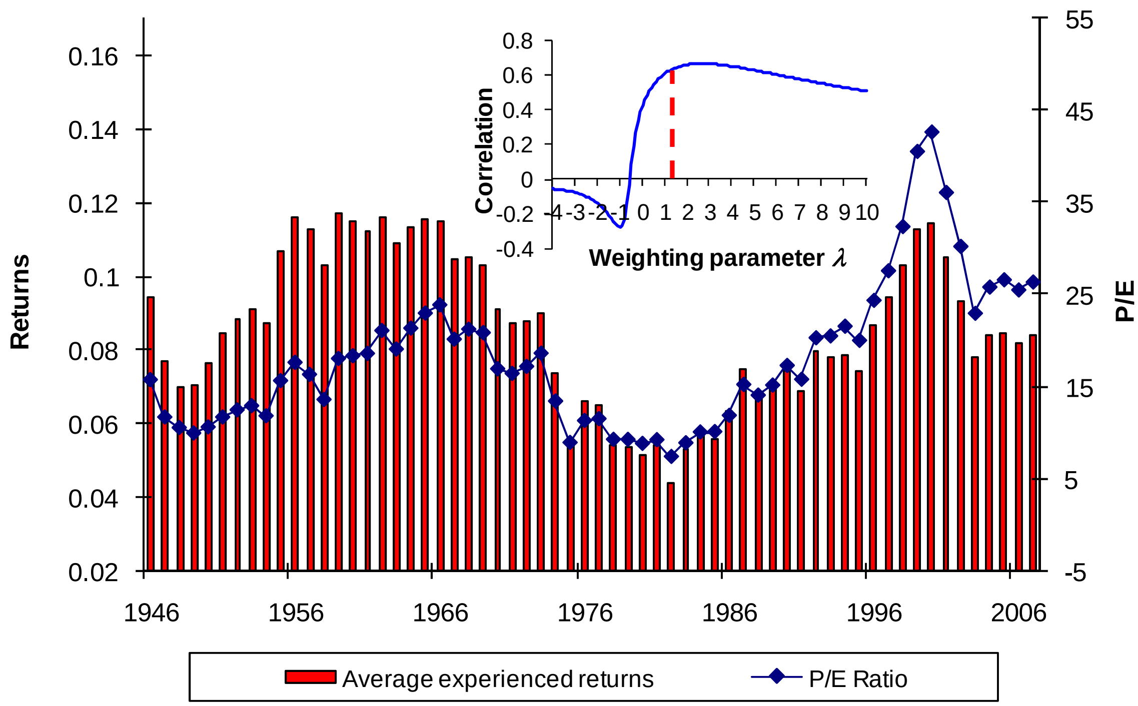


Figure 4: Average experienced real stock returns (λ = 1.25) and price-to-earnings ratio 1946-2007. The average experienced return series is calculated by averaging experienced returns across all ages at a given point in time. The small inset figure shows the correlation between the average experienced return series and the P/E ratio if the weighting parameter is varied from -4.0 to 10.0. The correlation for λ = 1.25 is indicated by the dashed line.

the estimation, and λ is not chosen to match movements in the P/E ratio over time. The weighting parameter estimated from the micro-data could, for example, have turned out to be negative, which would mean that investors place more weight on returns experienced early in life than 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 demonstrated by the small inset graph in Figure 4. It plots 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 micro-data estimates of λ had turned out differently. The value of $\lambda = 1.25$ is close to the value that yields the maximum correlation. 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.

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.

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 higher tolerance of financial risk, are more likely to participate in the stock market, and allocate a higher proportion of their liquid assets to stock. Individuals who have experienced high real bond returns are more likely to participate in the bond market. We find that individuals put more weight on recent returns than on more distant realizations, but experiences several decades ago still have some impact on current risk-taking of older households. The magnitudes of the effects are economically important. For example, an increase of 5 percentage points in the level of experienced real stock returns is associated with an increase in the probability of stock market participation of about 15 percentage points, and an increase in the percentage of liquid assets allocated to stocks of about 7 percentage points. Our results are consistent with the view that economic events experienced over the course of one's life have a more significant impact on risk taking than historical facts learned from summary information in books and other sources.

We also offer some evidence that experience influences risk taking, at least partly, through a beliefs channel, as opposed to an effect on risk preferences. We show that higher experienced stock returns are associated with more optimistic beliefs about future stock returns. This suggest that the experience effects could be the result of individuals' attempts to learn from their experiences, albeit not by using all "available" historical data, as in standard rational and boundedly rational learning models, but by focusing on their life-time experiences. Consistent with this view, we show in follow-up work, Malmendier and Nagel (2009), that inflation expectations are influenced by individuals' inflation experiences in similar ways as risk-taking and stock return expectations are 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						
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						
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						
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: The sample period is 1960-2007. 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, and Elicited risk tolerance is not available in the 1986 survey.

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. The 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 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. The 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 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. The sample period runs from 1960 to 2007, excluding the 1971 survey (percentage allocation not available). Experienced stock returns are calculated from the real return on the S&P500 index, 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 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 mkt. 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 90th pctile. minus fitted prob. at 10th pctile. of experienced stock return	-0.052	0.131	0.016		
	(0.035)	(0.023)	(0.024)		
Probability of	lowest risk tol. category	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 90th pctile. minus fitted prob. at 10th pctile. of experienced bond return	-0.141	0.085	0.149		
	(0.087)	(0.024)	(0.026)		
Probability of	lowest risk tol. category	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 misspecification of the likelihood function/heteroskedasticity and adjusted for multiple imputation.

Table VI: Explaining Stock Market Return Expectations with Experienced Returns

	Expected stock market return over the next 12 months (1998 – 2003)		Expected return on own portfolio over the next 12 months (1998 – 2007)	
	(i)	(ii)	(iii)	(iv)
Experienced stock return coefficient β	0.801	0.393	0.800	0.480
	(0.386)	(0.215)	(0.244)	(0.125)
Weighting parameter λ	0.923	1.698	0.923	1.698
	[fixed]	[fixed]	[fixed]	[fixed]
Age dummies	Yes	Yes	Yes	Yes
Year-month dummies	Yes	Yes	Yes	Yes
#Obs.	40,145	40,145	72,631	72,631
R^2	0.08	0.08	0.06	0.06

Notes: Dependent variable is the expected return over the next 12 months from the UBS/Gallup survey. Estimation is done with least squares, weighted with sample weights. The λ parameter is fixed at the values obtained in column (ii) of Tables III and IV. The experienced stock return is calculated from the real return on the S&P500 index. Standard errors shown in parentheses are robust to heteroskedasticity.

Appendix: Details on Data

For our empirical analysis, we employ both the "modern" SCF, obtained from the Board of Governors of the Federal Reserve System, and its precursor surveys obtained from the ICPSR at the University of Michigan. A major challenge in the construction of such a pooled data set stretching over several decades is that the definitions of some data items as well as the construction of the sample change over time. The changes reflect changes in the survey methodology and the level of detail, but also changes in the investment environment over the last 50 years. This Appendix details how we dealt with these issues.

One problem concerns the construction of the stock-market participation indicator 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 fund and tax-free mutual fund holdings 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 count the total holding of mutual funds as stock holdings. 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 Board, 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, instead, this number is almost 50%. Hence, the coding imprecision due to this missing information in the early years of our data set 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 1983 and 1986 retirement account assets are reported separately, but no direct allocation information is available. We can however approximate the allocation in the 1983 wave using data on the type of retirement savings plan and the institution at which the account is held.[15] For thrift accounts, we treat stock savings plans and profit sharing plans as 100% stock, annuity plans as 100% bonds, and other types of plans as split equally between bonds and cash. For IRA accounts, we allocate accounts held at brokerage companies, the employer, or investment management companies as 100% stock, and those held at insurance companies as 100% in bonds, and accounts held at banks and other institutions as 100% cash. The 1986 survey did not collect this information, but the 1986 sample is a re-interview of households interviewed in 1983, and so we can link the 1986 data with the allocation information in 1983. We assume that each household's percentage allocation in thrift and IRA accounts in 1986 is the same as in 1983. For couples that separated, we apply the same allocation to both households. For households that did not own IRA or thrift accounts in 1983, we assume that thrift accounts are split equally between stocks and bonds and IRA are fully invested in cash. From 1989 to 2001, the SCF provides rough allocation categories in retirement accounts. An allocation in IRAs of "mostly" stocks, or bonds, or cash is interpreted as 100% allocation to the respective asset class, an allocation that is "split between stocks and bonds" or between "stocks and cash" is treated as an equal split between the two categories, and a "split between stocks, bonds and cash" as an equal split between three

[15] See Carroll (2002) for a similar approach.

asset classes. For thrift and 401(k)-type plans, the survey only distinguishes "stocks" and "interest-bearing" assets, and we allocate 50% to stocks and 50% to bonds if holdings are "split" between these two categories.[16] In 2004 and 2007, the SCF has detailed information on the percentage allocation of retirement account assets to stocks, but no information on the allocation of the remainder between cash and bonds. For the non-stock portion of IRA, we assume that it is split equally between cash and bonds if the stock portion is zero, and invested in cash otherwise. This is assumption is consistent with the predominant allocation pattern in the earlier waves of the SCF. For other accounts, which are mostly 401(k)-type accounts, we assume as in the earlier years that the non-equity portion is in bonds.

A fourth issue is that the 1960, 1963, 1964, 1967, and 1977 surveys do not provide the dollar amount of stock and bond holdings, but only 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. Therefore, we can only calculate indicator variables for greater than zero stock holdings and for greater than zero bond holdings in 1971, but not the percentage of liquid assets allocated to stocks.

Finally, we also briefly describe the UBS/Gallup data on stock return expectations obtained from the Roper Center at the University of Connecticut. We work with the responses to the following two questions: (a) "What overall rate of return do you expect to get on your portfolio in the next twelve months?" (b) "Thinking about the stock market more generally, what overall rate of return do you think the stock market will provide investors during the coming twelve months?". The data set covers the period from May 1998 to October 2007. In 1998, data is available in May, September, and November. In the following years the data is available every month, with the exception of January 1999 and January 2006, and with roughly 1,000 respondents per month. Coverage of question (b) on market-wide returns stops after April 2004. Our approach in handling the data closely follows Vissing-Jorgensen (2003). In 1998 and 1999, return expectations of less than 1% are recorded as a categorical variable, without stating the percentage amount, and we set those responses to 0%. We eliminate observations with expected returns higher than 95% or lower than -95%.

[16] Aggregate data from the Employee Benefits Research Institute shows that most of the non-stock portion of 401(k)-account balances is invested in bond funds and guaranteed investment contracts, not in cash. See, e.g., Holden and VanDerhei (2003.

Supplementary Online Appendix

for

Depression Babies:

Do Macroeconomic Experiences Affect Risk-Taking?

Ulrike Malmendier
UC Berkeley and NBER

Stefan Nagel
Stanford University and NBER

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A. Details on Estimation

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

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

and the between-implicate variance of the estimates is,

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

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

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

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

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

For further details see Rubin (1987).

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

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

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

In the case of non-linear least squares,

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

where $g(b)$ now denotes the gradient vector of the regression function with respect to the parameter vector, and ε is the regression residual.

B. 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. The estimates also illustrate that the regressions are picking up systematic differences in risk-taking between individuals. Table A.1 reports the coefficient estimates for the control variables from the specifications that include liquid asset controls, i.e., in Table II, column (ii), Table III, columns (ii) and (iv), and Table IV, column (ii). The age and year dummy coefficient estimates and the coefficients on liquid assets interacted with the year dummies are not reported due to the large number of coefficients. 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 (the signs of the coefficients in the probit models match the signs of the marginal effects). 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 stocks, however, none of the control variables except the log income and log income squared have any statistically significant relationship with the dependent variable.

C. Effects of Inertia in Portfolio Rebalancing: Simulations

A potential alternative explanation for the relationship between past stock returns and risky asset share in Table IV is inertia in rebalancing. Here we present simulations showing that the time dummies in our regressions absorb the effects of inertia on portfolio allocations. 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 it lives until age 75. Every year, we draw i.i.d. log stock market returns from a normal distribution with a mean of 8% and a 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^d_{t+1} represents the desired portfolio share that the household would have under perfect and instantaneous rebalancing, and α^p_{t+1} represents the passive portfolio share, which evolves according to

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

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 if no changes in allocations due to realized stock returns were rebalanced, all risk-free asset returns were paid out as cash flows from the portfolio, and no new cash flows entered the portfolio. By eliminating all other influences on the risky asset share, we maximize the impact of inertia. 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^d_{t+1} equal to 50%. The exact value of α^d_{t+1} is not important.

Results are similar for a wide range of values around 50%. A generation dies at the age of 75 and is replaced in the next period with a new generation that starts at age 25. In our baseline simulations, a new generation starts with a portfolio share equal to α_{t+1}^{d} = 50%. We also run alternative simulations where we set the initial portfolio share equal to the cross-sectional mean of the portfolio shares of all other generations that are in investing age in the same year. 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 history, we also keep track of the return experience history of each generation. 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. The first 75, which are needed to initialize the overlapping generations along with the return history, and are then discarded. 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.2 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 adjustment speed ω and weighting parameter λ. 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 first block shows what happens with extremely strong inertia (ω =0.10). With an adjustment coefficient that low, investors hardly rebalance at all. The second block uses ω = 0.30, which is roughly in line with the degree of portfolio inertia found by Brunnermeier and Nagel (2008) in the Panel Study of Income Dynamics (PSID), though they caution that their estimates are likely to be upward biased due to measurement error. The third block is based on ω = 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 experience 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 one reported in the paper.

Why do the regression coefficients in the simulations with time dummies in Panel B turn out to be zero (in the case of initial portfolio shares at age 25 set equal to the cross-sectional mean) or even negative (in the case of initial portfolio shares at age 25 set equal to 50%)? The intuition 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 its cross-sectional mean 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. The 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 more complicated. Most of the variation in the risky asset shares of different generations is still common time variation, as portfolios move up and down together from year to year with realized stock-market returns. The magnitude of the changes in portfolio shares, $\Delta\alpha_t = \alpha_t - a_{t-1}$, however, are not identical for different generations because the levels a_t are not the same for all generations. Thus, a given return realization leads to somewhat different $\Delta\alpha_t$. The time dummies therefore do not absorb all variation in risky asset shares caused by inertia. It turns out, though, that the remaining variation 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 older generations that are alive and in their investing age in year t. The cross-sectionally demeaned 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

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

result, 0.50 - $\overline{\alpha}_t$ and $A_{25,t}$ - $\overline{A}_t$ .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.

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. 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. 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 proxies for financial sophistication 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 results are mixed. For elicited risk tolerance the coefficient on the interaction term is close to zero. For stock market participation and the percentage allocation to stock, it is significantly negative, 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 is more consistent. Here, the coefficient on the interaction dummy is always positive, though insignificant and 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.

E. 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 individual's 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. The average return of the most recent third of the lifespan receives 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 the relatively high standard errors indicate that this is not statistically reliable evidence in favor of non-monotonicity.

As an additional test, we add 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 places too much weight on the early years, due to its functional form restriction. 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.

F. Other Robustness Checks

Table A.5 checks the robustness of our results with respect to several changes in methodology. We report the estimates for β and λ in each case. The specifications correspond to Table II, column (ii), Table III, columns (ii) and (iv), and Table IV, column (ii,) of the main paper, i.e., include the liquid-asset controls. In the probit models, the change in marginal effects is generally close to proportional to the change in the β coefficient compared with our baseline specifications, 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 obtained with retirement accounts included. 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. Both sets of results show 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 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, respectively. As one would expect, 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 is now averaged over are shorter sample, and so each return observation receives a higher weight. 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. The results show that due to the flexibility of the weighting function in putting more or less weight on early observations, our conclusions are not sensitive to the exact choice of the starting point for measuring experienced returns.

The next block of results shows the estimates that we obtain when we include cohort dummies in the specifications to control for unobserved cohort effects. We add 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 adds about 90 dummy variables to the baseline specifications, and so it is not surprising that standard errors increase considerably, particularly those of λ. With the exception of bond market participation, the point estimates of β are, however, quite close to those from the baseline specifications. For bond market participation, the coefficient still has the right sign, but it is no longer statistically significantly different from zero. Overall, the evidence suggests that unobserved cohort effects cannot explain our findings.

In the next two blocks, experienced returns are calculated with geometric averaging instead of arithmetic averaging or with observations not weighted with the SCF sample weights. None of those methodological changes has any significant effect on the estimates.

This is followed by β estimates that we obtain when we set $\lambda = 1$. These results show that one can approximate the experienced returns quite well with $\lambda = 1$ in place of the earlier estimates of λ.

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, as described in the main text.

Table A.1: 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 (the latter two also 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.2: 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.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					
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					
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 for households that have liquid assets higher than the median in a given year in the upper half, and for households with completed college education in the lower half. 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	5.553	6.419	0.779	0.999
	(0.834)	(0.814)	(1.160)	(0.253)	(0.293)
λ	0.733	0.738	0.745	0.423	0.554
	(0.224)	(0.157)	(0.232)	(0.286)	(0.288)
Starting 10 yrs before birth					
β	9.556	13.894	12.822	2.406	2.211
	(1.946)	(1.843)	(1.957)	(0.775)	(0.605)
λ	2.106	2.602	1.683	1.278	2.263
	(0.430)	(0.291)	(0.355)	(0.402)	(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 λ = 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 unless otherwise indicated. Standard errors, shown in parentheses, are robust to heteroskedasticity/misspecification of the likelihood function and adjusted for multiple imputation.