

DEPRESSION BABIES: DO MACROECONOMIC EXPERIENCES AFFECT RISK TAKING?*

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We investigate whether individual experiences of macroeconomic shocks affect financial risk taking, as often suggested for the generation that experienced the Great Depression. Using data from the Survey of Consumer Finances from 1960 to 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, invest a lower fraction of their liquid assets in stocks if they participate, and are more pessimistic about future stock returns. Those who have experienced low bond returns are less likely to own bonds. Results are estimated controlling for age, year effects, and household characteristics. More recent return experiences have stronger effects, particularly on younger people. *JEL* Codes: D03, D14, D83, D84, E21, G11.

I. INTRODUCTION

Do personal experiences of economic fluctuations shape individuals' willingness to take risk? For the generation of "Depression babies," it has often been suggested that their experience of a large macroeconomic shock, the Great Depression, had a long-lasting effect on their risk attitudes. In this article, we ask more generally whether people who live through different macroeconomic histories differ in their level of risk taking.

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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, 2008; Alesina and Fuchs-Schündeln 2007; Osili and Paulson 2008).

We examine empirically whether individuals differ in their willingness to take financial risks depending on the macroeconomic history they experienced over the course of their lives. We test whether individuals who experienced low real 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 real bond returns are more wary of participating in the long-term bond market.

A key implication of the experience hypothesis is that differences in the level of risk taking between individuals should be correlated with differences in life-time experiences. For example, after the recessions of the 1970s and early 1980s, young people's stock-market return experience was dominated by recent low returns, whereas older individuals' also had experiences of better returns during the 1950s and 1960s. Hence, we expect relatively low stock market participation rates of young people compared with older people. After boom years, such as the post-war boom until the 1960s, when young people had experiences of high returns but older individuals still had memories of the Great Depression, we expect younger individuals to have high rates of stock market participation relative to older people. A simple scatter-plot of differences in log stock market participation rates between old and young against differences in experienced average stock-market returns (Figure I) confirms this pattern in the raw data. In the main analysis, we test whether these differences persist when we use a broad range of risk-taking proxies,

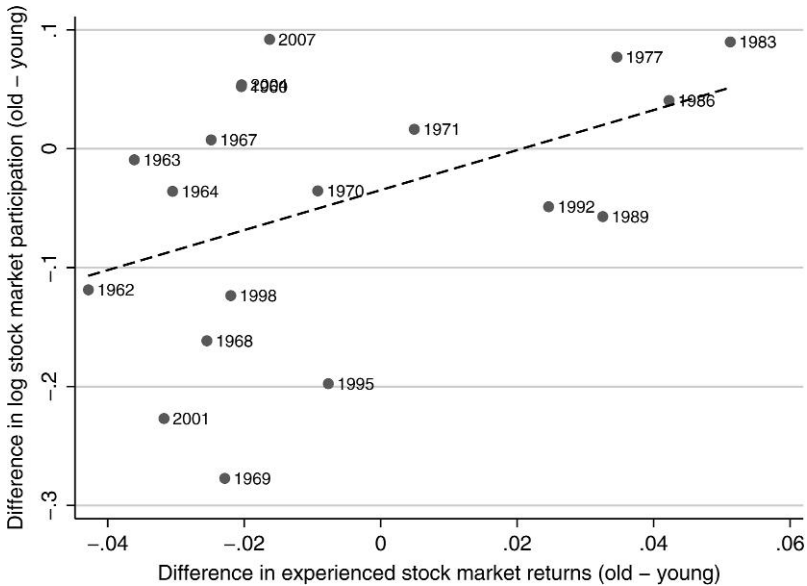


FIGURE I

Differences in Log 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 vertical axis shows the difference in the log participation rates of old (household head age > 60 years) minus young (household head age ≤ 40 years) households. The horizontal axis shows the average real stock market return (S&P 500 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. The 1960 and 2004 observations overlap in the plot.

a more sophisticated weighting scheme for recent and distant experiences, and a wide range of controls for demographics, wealth, retirement savings, income, and other variables.

We use repeated cross-section data on household asset allocation from the Survey of Consumer Finances (SCF) from 1960 to 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. Although 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 personal 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. 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. For all risk-taking measures, the estimated weighting scheme can be represented, to a good approximation, as weights that decline linearly from the most recent year down to 0 in the year of birth. Our estimates imply that young individuals, with short lifetime histories, are particularly strongly influenced by recent data.

We also provide some insight into the channel through which experiences affect risk taking, that is, into the question whether past experiences alter risk preferences or beliefs about future returns. We examine microdata 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 0.5 to 0.6 pp increase in the stock market return expected for next year or, similarly, with a 0.6 to 0.7 pp increase in the return expected on the own portfolio 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 The year dummies also control for potential effects of slow portfolio rebalancing in response to stock-market movements.² As illustrated in Figure I, our identification comes from cross-sectional differences in risk taking and in macroeconomic histories and from changes of those cross-sectional differences over time. The inclusion of age effects allows us to distinguish our results from life cycle effects, such as age-related increases in risk aversion 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 could explain the relation between experienced returns and current risk taking if risk aversion is wealth-dependent. Moreover, differences in wealth are unlikely to explain all four of our risk-taking measures since 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](#)). Finally, to further address concerns about unobserved differences in wealth, we show that our results also hold when retirement account holdings are excluded from the asset holding measures.

Differently from previous work, 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](#); [Campbell 2001](#)). Our identification strategy, in contrast, does not rely on estimating cohort effects. The experience hypothesis predicts a positive relationship between experienced returns and risk taking. Because experienced returns are not

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. In Section III.D. and Online Appendix C, we present simulations of an overlapping-generations model that show directly that slow portfolio rebalancing cannot explain the positive relation between experienced returns and the percent-age allocation to stocks.

collinear with age and time effects, we can control for age and time effects simultaneously.³

The economic magnitude of the experience effect is large, as can be illustrated with the fall of the stock market in 2008. The real return of the Standard & Poor's (S&P) 500 index in 2008 was -36% . Compared with a counterfactual benchmark of 8.2% , which is the (arithmetic) average real return since the beginning of our returns sample (1871), the 2008 downturn lowered the experienced return of a 30-year-old by 3.4 pp, and the experienced return of a 60-year-old by 1.7 pp. According to our estimates, this should lower 30-year-olds' participation rate, everything else equal, by about 7.0 pp (compared with a 45% participation rate for this age in 2007), whereas the effect on the participation rate of 60-year-olds should be only half as big, approximately 3.5 pp (compared with a 65% participation rate in 2007).⁴ Our estimates also imply how long the effects of the crash will last. The 2008 return receives a weight of 7.7% 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 3.9%, and another 20 years later to 1.5%. Hence, after 30 years most of the effect will have faded away.

This example illustrates both key features of our estimated weighting function: individuals are influenced more strongly by recent returns than distant returns, and younger individuals with shorter life histories are more sensitive to recent returns than older individuals are. The example also reveals that the estimated experience effect does not fully coincide with the popular notion that the Great Depression generation was permanently more averse to taking financial risks. According to our estimates, the memory of these events vanishes over time, though it is also the case that effect of extreme events such as the Great Depression (or maybe the 2008 downturn) can last for a long time. In addition, extreme events may have nonlinear effects not captured by our relatively simple weighting scheme.

This article connects to several strands of literature. The literature on reinforcement learning posits that subjects' choice

3. Moreover, because experienced returns vary not only across but within cohorts over time, we can even include an almost full set of cohort dummies and therefore control for any omitted variable that has cohort-level variation. See Online Appendix F.

4. As a note of caution, the hypothetical counterfactual of "no 2008 market crash" holds everything else equal and does not consider general-equilibrium effects on asset prices from changes in stock market participation.

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 higher returns in times of booms than in times of recessions. In terms of experience of the Great Depression, Malmendier and Tate (2005, *forthcoming*) 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 lifetime macroeconomic experiences affect risk taking at the microlevel 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 toward pessimistic beliefs, as suggested by Friedman and Schwartz (1963).

II. DATA AND METHODOLOGY

The key variables for our analysis are 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, data stretching back to the late nineteenth

century. We obtain data on the annual real returns of the S&P 500 stock market index going back to 1871 from Shiller (2005),⁵ 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 Consumer Price Index (CPI) inflation rate from Shiller (2005). Unless otherwise noted, returns are measured in real terms.

II.A. Survey of Consumer Finances

Our source of household-level microdata is the SCF, which provides repeated cross-section observations on asset holdings and various household background characteristics. Our sample has two parts. The first one is the standard SCF from 1983 to 2007, obtained from the Board of Governors of the Federal Reserve System and available every three years. The second source is the precursor of the “modern” SCF, obtained from the Inter-university Consortium for Political and Social Research at the University of Michigan. The precursor surveys start in 1947, partly annually but with some gaps. The data before 1960 contain information on stock holdings in some years, but age is measured in 5- or 10-year brackets, which would make the 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: the 1960, 1962, 1963, 1964, 1967, 1968, 1969, 1970, 1971, and 1977 surveys. We briefly describe the key variables. 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 were 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; or (4) take substantial financial risks expecting to earn substantial returns. We code the answer as an ordinal variable with integer values

5. The S&P index series consists of the S&P Composite index in the early part of the series and the S&P 500 index in the later part. We thank Bob Shiller for providing the data on his Web site.

from 1 to 4, where a value of 4 indicates the highest risk tolerance. For ease of reference, we refer to the measure as “elicited risk tolerance,” although one should not view it as a clean measure of risk tolerance in the Arrow–Pratt sense, distinct from beliefs.⁶ We also note that we cannot interpret the measure in a cardinal sense because individuals may differ in how they interpret the available options quantitatively, for example, “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).⁷ Our analysis uses both elicited risk tolerance and direct measures of asset allocation to ameliorate concerns about the connection between self-reported risk tolerance and actual behavior.

The second measure is a binary variable for stock market participation, available in each survey wave from 1960 to 2007. It indicates whether a household holds more than \$0 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 include stocks held in retirement accounts (e.g., individual retirement accounts [IRAs], Keogh, and 401(k) plans). For 1983 and 1986, we need to impute the stock component of retirement assets from the type of the account or the institution at which they are held and allocation information from 1989. 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 a refined version of the Federal Reserve Board’s conventions in assigning portfolio shares. The Appendix provides the details. Online Appendix F 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 to 2007, with the exception of 1964. It indicates whether a household holds more than \$0 worth of long-term bonds. We define bond holdings as the sum

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

7. A similar financial risk-tolerance measure in the German Socio-Economic Panel strongly predicts financial risk taking, and a related one predicts risky behavior in a lottery field experiment (Dohmen et al. 2010).

of direct holdings of government and corporate bonds, tax-free mutual fund holdings, and, from 1989 onward, the bond share of non-money market mutual funds.

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 to 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). We 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 stock 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, which undo the overweighting of high-income households and also adjust for nonresponse bias.⁸ The weighted estimates are representative of the U.S. population. Note that although it is inefficient to use weighted estimators in place of unweighted estimators when the treatment effect is identical across the different income strata (Deaton 1997; Cameron and Trivedi 2005), the treatment effect in our setting—past return experience—could be heterogeneous. The danger of using the unweighted sample in this case is that the estimated average treatment effect is not representative, a concern that outweighs the loss of efficiency under the (unrealistic) homogenous treatment effect assumption. The robustness checks in Online Appendix F with the unweighted sample show, however, that weighting makes virtually no difference for the parameter estimates and standard errors.

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 nonresponse. Following Poterba and Samwick (2001), we normalize the sample weights so that the sum of the weights in each year is the same.

We also adjust standard errors for multiple imputation. From 1989 onward, the SCF employs a multiple imputation technique to impute missing values from other information in the survey and disguise observations that could potentially reveal the identity of the respondent (see [Kennickell 1998](#)). 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 \(1987\)](#), described in Online Appendix A.

II.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 a young age, perhaps conveyed by parents, might be particularly formative and influence decisions later in life.

Such a flexible estimation faces some hurdles. If we included separate explanatory variables for each past year of return experience back to the year of birth, for example, the large number of coefficients 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 over time. This way, we let the data reveal which weighting scheme best explains households’ risk taking. Specifically, for each household i in year t , we calculate the following weighted average of past asset returns,

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

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

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 $\lambda > 1$).

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 II 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" and U-shaped weights, or a step function. As we discuss in Section III.G, we did not find evidence that nonmonotonicities are important. To the contrary, the weights we obtain with more flexible weighting schemes closely match the decreasing pattern we estimate with our baseline weighting function. Note also that, even if the true weighting patterns is more complex, our restriction

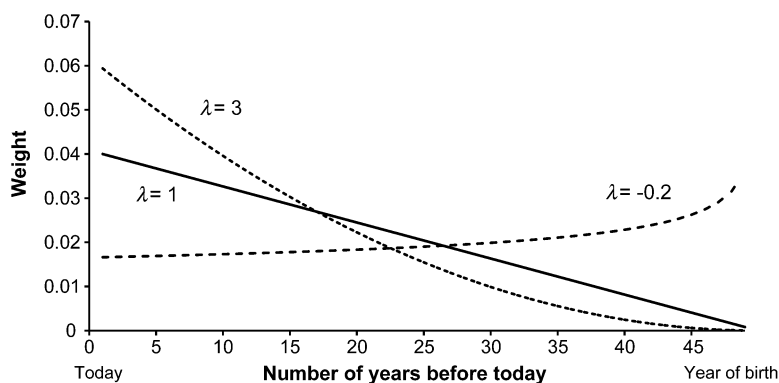


FIGURE II

Weights on Experienced Returns for Different Values of λ for a 50-year-old Household Head

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:

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

$A_{it}(\lambda)$ represents experienced returns and x_{it} is a vector of control variables. We simultaneously estimate β and λ . Because $A_{it}(\lambda)$ is a nonlinear function of the weighting parameter λ , nonlinear estimation methods are required. For regression models with a continuous dependent variable, 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} . 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 Equation (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 $1/(age_{it} - 1)$ times β .

Where we set the starting point for experienced return is of little importance for our results. If setting the starting point at birth is "too early"—individuals are not much influenced by experiences early in their lives—our weighting function will accommodate this with weights that decline relatively fast. If the starting point is "too late"—individuals are also influenced by observations 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 experienced returns compared with our specification. We show in Section III.G that

9. Given a value for the weighting parameter λ , the regression model is linear. (A probit model is still nonlinear due to the nonlinear transformation into probabilities.)

varying the starting point to 10 years before or 10 years after birth has little effect on our results.

II.C. Summary Statistics

Table I provides some summary statistics, in Panel A for the full sample; Panel B for the subsample of stock-market

TABLE I
SUMMARY STATISTICS

	10 th pct	Median	90 th pct	Mean	Std. dev.	#Obs.
<i>Panel A: All households</i>						
Liquid assets	0	6,382	144,639	80,248	652,585	51,204
Income	11,883	43,419	105,339	60,511	178,088	51,204
Experienced real stock return ($\lambda = 1.50$)	0.062	0.092	0.119	0.091	0.022	51,204
Experienced real bond return ($\lambda = 1.50$)	-0.002	0.006	0.051	0.018	0.022	51,204
Stock market participation	0	0	1	0.342	0.474	51,204
Bond market participation	0	0	1	0.376	0.484	49,866
Elicited risk tolerance (1983–2007)	1	2	3	1.826	0.841	28,732
<i>Panel B: Stock market participants</i>						
Liquid assets	4,974	51,567	409,723	210,070	1,108,027	22,541
Income	28,339	67,799	164,596	99,759	297,869	22,541
Bond market participation	0	1	1	0.681	0.466	22,293
Fraction of liquid assets in stocks	0.071	0.451	0.900	0.466	0.295	21,669
Elicited risk tolerance (1983–2007)	1	2	3	2.103	0.801	17,049
<i>Panel C: Bond market participants</i>						
Liquid assets	2,332	31,842	322,119	169,981	1,027,384	22,553
Income	26,113	61,926	143,552	89,119	275,068	22,553
Stock market participation	0	1	1	0.628	0.483	22,553
Fraction of liquid assets in stocks	0	0.157	0.740	0.266	0.294	21,556
Elicited risk tolerance (1983–2007)	1	2	3	2.010	0.804	15,954

Notes. The sample period is 1960–2007. Stock returns and bond returns are real returns, deflated with Consumer Price Index (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. Elicited risk tolerance is not available in the 1986 survey pct, percentile.

participants, that is, households that have at least \$1 in stocks; and Panel C for the subsample of bond-market participants, that is, households that have at least \$1 invested in bonds, all in September 2007 dollars. Comparing Panels A and B, we see that stock market participants tend to be wealthier than the average household, with a median holding of \$51,567 in liquid assets rather than \$6,382 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 \$31,842. The pattern is similar for median income.

As Panel A shows, 34.2% of households participate on average in the stock market during 1960–2007. These rates represent the U.S. population (not the SCF sample) because we apply the SCF sample weights.¹⁰ The bond market participation rate is quite similar (37.6%). The remaining two risk-taking measures show considerable dispersion across households: The proportion of liquid assets invested in stocks in Panel B has 10th and 90th percentiles of 7.1% and 90.0%; elicited risk tolerance in Panel A has 10th and 90th percentiles of 1.0 and 3.0. Note that mean elicited risk tolerance is higher for the stock market participants (2.103) than for the full sample (1.826) and lies in the middle for bond market participants (2.010). That is, elicited risk tolerance is indeed correlated with households' actual risk taking as revealed by their participation choices.

Our main question of interest is whether the variation in risk taking across households is related to experienced stock and bond returns. To get a sense of the variation in experienced returns, we calculate the weighted average returns $A_{it}(\lambda)$ from Equation (1) for both stock and bond returns, setting $\lambda = 1.50$, which is in the ballpark of the estimates we find later. As Panel A shows, the 10th and 90th percentiles for the experienced (real) stock returns are 6.2% and 11.9%, and the 10th and 90th percentiles for experienced (real) bond returns are 0% and 5.1%. Thus, during our sample period, experienced bond returns are about as volatile in real terms as experienced stock returns. The variation is similar for a range of λ values around 1.50. For example, with $\lambda = 1.00$, the difference between the 10th and 90th percentile of real stock market returns is 5.0 pp.

10. The unweighted proportion of stock holders in the SCF is higher because high-income households are oversampled. This explains why Panel B has more than 27.5% of the number of observations in Panel A.

III. RESULTS

III.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

$$(3) \quad P(y_{it} \leq j | x_{it}, A_{it}(\lambda)) = \Phi(\alpha_j - \beta A_{it}(\lambda) - \gamma' x_{it}) \quad j \in \{1, 2, \dots, 4\},$$

where $\Phi(\cdot)$ 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 that includes income controls (log income, log income squared), household characteristics (the number of children and its square, the percentage of liquid assets invested in defined contribution plans or IRAs, dummies for retirement, completed high school education, completed college education, marital status, race, having a defined benefit pension plan, and having a defined contribution pension plan or IRA), 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, $\Phi(\cdot)$ does not map a linear function of explanatory variables into the response probability P , because $A_{it}(\lambda)$ is a nonlinear 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. Because 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 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 the lower part of Table II,

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

TABLE II
ELICITED RISK TOLERANCE

	(i)	(ii)
Experienced stock return coefficient β	4.533 (1.106)	6.692 (1.180)
Weighting parameter λ	1.834 (0.452)	1.433 (0.280)
Income controls	Yes	Yes
Liquid assets controls	–	Yes
Household characteristics	Yes	Yes
Age dummies	Yes	Yes
Year dummies	Yes	Yes
Average of fitted prob. at 90 th pct. minus fitted prob. at 10 th pct. of experienced stock return		
Risk tolerance = 1 (low)	–0.088 (0.020)	–0.103 (0.016)
[unconditional freq. = 0.413]		
Risk tolerance = 2	0.025 (0.001)	0.029 (0.003)
[unconditional freq. = 0.391]		
Risk tolerance = 3	0.040 (0.011)	0.047 (0.010)
[unconditional freq. = 0.153]		
Risk tolerance = 4 (high)	0.023 (0.009)	0.027 (0.009)
[unconditional freq. = 0.043]		
#Obs.	28,571	28,571
Pseudo R^2	0.09	0.10

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&P 500 index. Liquid assets controls are log liquid assets and log liquid assets squared, both interacted with year dummies to allow for year-specific slopes. Household characteristics include the number of children and number of children squared, the percentage of liquid assets invested in defined contribution pension plans and IRAs, as well as dummies for marital status, retirement, race, education, for having a defined benefit pension plan, and for having a defined contribution pension plan or IRA. 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 pct, percentile.

few households fall into the highest risk tolerance category 4. The highest share of more than 40% is accounted for by category 1.

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 nonseparability of cohort, age, and time effects. 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. Suppose, for example, that risk tolerance is time-varying for reasons other than the experience effect. In this case, past stock returns and current risk tolerance could be mechanically correlated: stock prices rise when investors become more risk tolerant and drop when investors' risk tolerance falls. This concern is addressed by our identification strategy. The year dummies absorb all aggregate time effects, including variation in average risk tolerance. The effect of experienced stock returns is estimated from cross-sectional differences in risk taking and variation of those cross-sectional differences over time, but not from aggregate time variation. Year dummies also absorb all other unobserved aggregate factors that might affect stock and bond prices and, hence, simultaneously change past returns and current aggregate allocation to stocks and bonds through market clearing.

The inclusion of year dummies also means that, under the null hypothesis, the weights placed on past returns do not depend on the current age of the person. This would be true, for example, if all individuals observed the same historical data set and formed their beliefs in the same way, without over-weighting lifetime experiences. In this case, cross-sectional differences in risk taking would not be correlated with cross-sectional differences in experienced returns, that is, $\beta = 0$ 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 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 of having high risk tolerance (2, 3, and 4), and decrease the probability of reporting the lowest risk

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.1.

13. See Section A in the Online Appendix. Clustering by cohort or by year does not have a material effect on our estimates.

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 somewhat strengthens the effect.

The economic magnitudes are sizable. Going from the 10th to the 90th percentile of experienced stock returns in column (ii) implies, on average, a 10.3 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 41.3% of being in the lowest risk-tolerance category.

The estimate of 1.433 (s.e. 0.280) 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 II). 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 nonnegligible weights on returns observed several decades earlier. Apparently, the memory of these early experiences fades away only slowly.

III.B. Stock Market Participation

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

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

The binary indicator y_{it} equals 1 if household i has any stock holdings at time t . 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 controls and household characteristics as in the ordered probit model. Liquid asset controls are particularly important in this context because a standard model with fixed 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 the 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 economic magnitude is large: a change from the 10th to the 90th percentile of experienced stock returns implies a 10.2 pp increase in the probability of stock market participation. The fitted probability difference is quite similar in column (i) without the liquid assets controls.

As with the previous measure, elicited risk tolerance, the estimate of 1.325 (s.e. 0.209) for the weighting parameter λ in our baseline specification in column (ii) 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 stock returns, with roughly similar weights on the history of past returns for both measures.

To provide additional perspective on the economic magnitude of the experience effect, we conduct a simple counterfactual exercise.¹⁴ We compare the actual (raw) and fitted participation rates from the probit model in column (ii) with counterfactual participation rates that are based on the same point estimates from column (ii), but with the average real stock market return since 1871 replacing the experienced return. This counterfactual exercise thus imagines households considering the full return history, with equal weights for each year, going all the way back from the year prior to the survey to the first year in our returns data, instead of over-weighting their lifetime experiences.

Figure III presents the results. Panel A illustrates counterfactual participation rates in the cross-section by plotting the stock market participation rates of the old (age > 60 years) minus the participation rate of the young (age ≤ 40 years). The dotted line is based on actual participation rates in the raw data, and the dashed line shows the fitted values from the probit model with actual experienced returns. Both series exhibit the biggest deviations from their overall sample averages in the early 1980s, when young households were less likely to participate than those in the old age group, and in the late 1990s, when young households had much higher participation rates. These are also the periods

14. We thank an anonymous referee for suggesting this analysis.

TABLE III
STOCK AND BOND MARKET PARTICIPATION

	Experienced stock returns and stock market participation		Experienced bond returns and bond market participation	
	(i)	(ii)	(iii)	(iv)
Experienced return coefficient β	6.963 (1.149)	10.627 (1.403)	10.809 (1.446)	8.433 (1.680)
Weighting parameter λ	1.924 (0.267)	1.325 (0.209)	1.176 (0.218)	1.282 (0.367)
Income controls	Yes	Yes	Yes	Yes
Liquid assets controls	–	Yes	–	Yes
Household characteristics	Yes	Yes	Yes	Yes
Age dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Average of fitted prob. at 90 th pctl. minus fitted prob. at 10 th pctl. of experienced return	0.092 (0.019)	0.102 (0.017)	0.161 (0.022)	0.114 (0.023)
#Obs.	51,013	51,013	49,678	49,678
Pseudo R^2	0.40	0.49	0.27	0.33

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 in columns (i) and (ii) is calculated from the real return on the S&P 500 index. The experienced bond return in columns (iii) and (iv) is calculated from the real 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. Household characteristics include the number of children and number of children squared, the percentage of liquid assets invested in defined contribution pension plans and IRAs, as well as dummies for marital status, retirement, race, education, having a defined benefit pension plan, and having a defined contribution pension plan or IRA. 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.

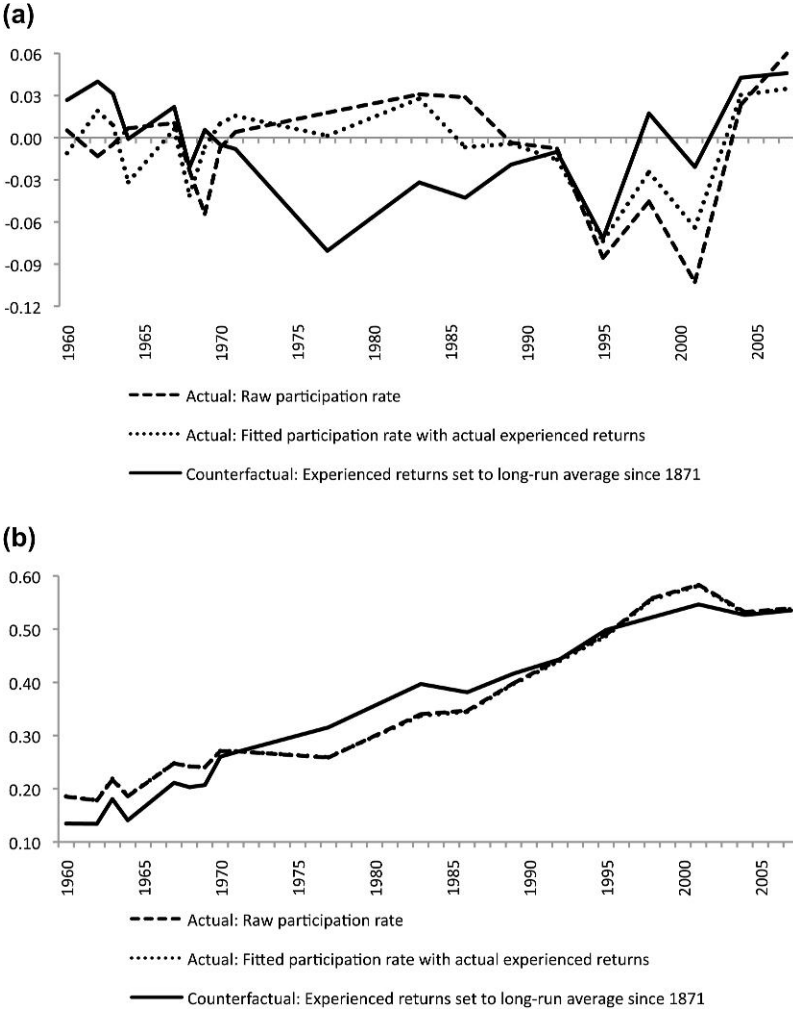


FIGURE III
Counterfactual Stock Market Participation Rates

Panel A shows the difference in average fitted stock market participation probabilities between young (age ≤ 40) and old (age > 60) (old minus young) from the probit model of Table III, column (ii), (dashed line), compared with the counterfactual difference in average fitted probabilities when the experienced stock market return is set to the average annual return since 1871 until the year prior to the survey year (solid line), and the actual participation rate in the raw data (dotted line). Panel B plots the average fitted and actual participation probabilities in the whole sample. Observations are weighted with SCF sample weights.

when experienced returns are estimated to have their biggest impact: setting experienced returns, counterfactually, equal to the long-term average since 1871, as shown by the solid line, completely reverses the young–old difference in the early 1980s, and mostly eliminates the differences between young and old in the late 1990s. Overall, the counterfactual and actual fitted participation rate differences between old and young deviate by up to 8 pp, which illustrates the economic significance of the experience effect.

Panel B plots the overall participation rates for the whole sample (rather than differences between old and young). In this plot, the actual and the fitted participation rates (dotted and dashed lines) exactly overlap due to the inclusion of year fixed effects. The counterfactual participation rate (solid line), however, is often substantially different, particularly following the boom years in the 1960s and 1990s and after the recession years of the late 1970s and early 1980s. The gap between actual and counterfactual participation rates reaches up to 7 pp, suggesting that return experiences may have a considerable effect on overall stock market participation rates.

As a caveat, note that the counterfactual exercise for the overall participation rate is simplistic in that it does not consider equilibrium asset-pricing implications of setting experienced returns to counterfactual values. If return experiences influence risk taking, they presumably also influence asset prices, which could feed back into stock market participation rates. These simple calculations provide a rough indication of the economic magnitudes of changes in aggregate risk taking induced by experienced returns.

III.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 decreases the coefficient on experienced bond returns. A change from the 10th to the 90th percentile of

experienced bond returns is associated with an increase of about 11.4 pp in the probability that a household participates in the bond market. The point estimate for λ is 1.282, almost the same as in the case of stock market participation in column (ii). Thus, bond market participation and stock market participation both show a positive correlation with the returns that individuals experienced over their lifetimes in those markets.

Similarly to the stock market results, the bond market results are strong in the full sample, both in terms of statistical and in terms economic magnitude. However, the bond results are less robust to variations in methodology. For example, if we restrict the sample to the 1983–2007 subperiod, or if we introduce cohort dummies, the standard error of β becomes about three times as big as in Table III, and the coefficient becomes insignificantly negative (see Online Appendix F). The root of this lack of robustness is that the cross-sectional differences between young and old in experienced bond returns are much more persistent than those in experienced stock returns. Before 1986, there was hardly any difference in the bond return experiences of different age groups. But as a consequence of the persistent decline in inflation in the later part of the 1980s, young individuals always had higher experienced bond returns than older individuals from 1986 to 2007, with only small changes from year to year in the slope and shape of this experienced return profile across ages. Thus, if the sample is restricted to 1983–2007, the variation in experienced returns is almost completely absorbed by age dummies, making it impossible to distinguish experience and age effects. If we omit age dummies in the 1983–2007 subsample, or in the specification with cohort dummies, a strong experienced bond return effect reemerges with coefficients estimates close to those in Table III.

III.D. *Fraction of Liquid Assets Invested in Stocks*

Table IV shows the estimated effect of experienced stock returns on the fraction of liquid assets that households invest in stocks. This measure controls for fixed costs of stock market participation because it conditions on participating. We use the following nonlinear regression model:

$$(5) \quad y_{it} = \alpha + \beta A_{it}(\lambda) + \gamma' x_{it} + \varepsilon_{it},$$

where y_{it} refers to the fraction of liquid assets invested in stocks. The model is nonlinear because the experienced stock return, $A_{it}(\lambda)$, is a nonlinear function of λ . We estimate the model with nonlinear least squares.¹⁵ 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 a statistically significant positive effect on the percentage invested in stocks. When the liquid assets controls are added in column (ii), the effect is even stronger, both statistically and economically. The point estimate of 1.668 (s.e. 0.395) implies that a change from the 10th to the 90th percentile of experienced stock returns leads to an increase of about 7.9 pp in the allocation to stocks. This finding is remarkable because 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 Brunnermeier and Nagel 2008; Curcuru et al. 2009). The control variable coefficients reported in Online Appendix B confirm this finding. With the exception of the controls for participation in a defined contribution plan and for the percentage of liquid assets invested in defined contribution accounts, none of the controls has a strong effect. 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), 1.166 (s.e. 0.299), suggests weights that decline roughly linearly. The estimate is 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 because elicited risk tolerance is based on a very different approach (survey question about risk attitude versus investment choice) and because financial market participation and choice of the risky asset share conditional on participation are possibly quite distinct decisions. The similarity of the estimates suggests that our weighting

15. Online Appendix G discusses potential concerns arising from censoring or truncation and shows that estimation with tobit or a truncated regression/probit model following Cragg (1971) yields quantitatively similar results.

TABLE IV
FRACTION OF LIQUID ASSETS INVESTED IN STOCKS

	Experienced stock returns		Experienced excess returns of stocks over bonds	
	(i)	(ii)	(iii)	(iv)
Experienced return coefficient β	0.972 (0.362)	1.668 (0.395)	1.076 (0.391)	1.734 (0.423)
Weighting parameter λ	1.299 (0.520)	1.166 (0.299)	1.736 (0.622)	1.831 (0.428)
Income controls	Yes	Yes	Yes	Yes
Liquid assets controls	–	Yes	–	Yes
Household characteristics	Yes	Yes	Yes	Yes
Age dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Average of fitted allocation stocks at 90th ptile. minus fitted allocation at 10th ptile. of experienced return	0.048 (0.018)	0.079 (0.019)	0.083 (0.030)	0.134 (0.033)
#Obs.	21,611	21,611	21,611	21,611
R^2	0.12	0.16	0.12	0.16

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 (allocation to stocks not available). Experienced stock returns are calculated from the real return on the S&P 500 index, experienced excess return from the return on the S&P 500 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. Household characteristics include the number of children and number of children squared, the percentage of liquid assets invested in defined contribution pension plans and IRAs, as well as dummies for marital status, retirement, race, education, having a defined benefit pension plan, and having a defined contribution pension plan or IRA. Observations are weighted with SCF sample weights. Standard errors, shown in parentheses, are robust to heteroskedasticity and adjusted for multiple imputation.

function captures a general pattern of how historical experiences influence financial risk taking.

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 lifetime 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 households' allocation to stocks as well as real stock returns. The point estimates for β are slightly higher, and a spread between the 10th and 90th percentile of experienced returns generates a substantially larger effect on the fraction invested in stocks, for example, 13.4 pp in column (iv). The results are also similar if we restrict the sample to households participating both in stock and bond markets (untabulated), that is, to those who can presumably change their stock and bond allocations relatively flexibly because their participation costs in both markets are already sunk.

One possible concern is that the positive relation between experienced returns and the percentage allocation to stocks could reflect 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). We show that this is not the case using simulations of an overlapping-generations model in which 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 reason 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. When time dummies are included, the regression focuses on cross-sectional variation and the mechanical positive relationship disappears.

III.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 rerun 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. Because an estimation of distinct weighting parameters for both stock and bond returns within the same model would be too demanding on the data to 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 and restrict the sample to households that participate in bond markets. To aid the interpretation of the results, we report the average of the fitted probabilities for category 1 (low risk tolerance) at the 90th minus those at the 10th percentile of experienced returns in column (i), analogous differences in fitted probabilities for participation in columns (ii) and (iii), and differences in fitted portfolio shares in columns (iv) and (v).

We find that elicited risk tolerance, in column (i), is positively related to experienced stock and bond returns according to the point estimates, but the standard errors are too high to draw definitive conclusions. Evidently, the sample available for this risk-taking measure is too small to disentangle the effects of stock and bond experiences. Stock market participation, in column (ii), is strongly related to stock market return experiences, but not to bond returns, whereas the opposite is true for bond market participation. The percentage share allocated to stocks in column (iv) is positively related to experienced stock returns and (insignificantly) negatively to experienced bond returns. For the bond share in column (v) the opposite is true: experienced stock returns have a negative effect, and experienced bond returns have a positive effect.

The results help further address concerns about unobserved wealth effects, that is, the alternative interpretation that the correlation of return experiences with unobserved wealth components, coupled with wealth-dependent risk aversion, explains our results. To the extent that both experienced stock

TABLE V
USING STOCK AND BOND RETURNS JOINTLY

Dependent variable	Elicited risk tolerance	Stock market participation	Bond market participation	Fraction of liquid assets in stocks	Fraction of liquid assets in bonds
Sample	Full	Full	Full	Stock market participants	Bond market participants
	(i)	(ii)	(iii)	(iv)	(v)
Experienced stock return coeff. β_{stock}	4.670 (2.042)	10.564 (1.405)	-1.149 (1.244)	1.765 (0.410)	-1.381 (0.361)
Weighting parameter for stocks λ_{stock}	1.433 [fixed]	1.325 [fixed]	1.325 [fixed]	1.166 [fixed]	1.166 [fixed]
Average of fitted values at 90 th pct. minus fitted values at 10 th pct. of experienced stock return...	0.072 (0.029)	0.101 (0.016)	-0.015 (0.016)	0.103 (0.024)	-0.085 (0.022)
...where fitted value refers to	probability of not being in lowest risk tolerance category	probability of stock market participation	probability of bond market participation	fraction of liquid assets in stocks	fraction of liquid assets in bonds

TABLE V
(CONTINUED)

Dependent variable	Elicited risk tolerance	Stock market participation	Bond market participation	Fraction of liquid assets in stocks	Fraction of liquid assets in bonds
Sample	Full	Full	Full	Stock market participants	Bond market participants
	(i)	(ii)	(iii)	(iv)	(v)
Experienced bond return coeff. β_{bond}	5.413 (4.420)	0.944 (1.904)	8.562 (1.579)	-0.748 (0.572)	0.970 (0.487)
Weighting parameter for bonds λ_{bond}	1.282 [fixed]	1.282 [fixed]	1.282 [fixed]	1.282 [fixed]	1.282 [fixed]
Average of fitted values at 90 th pctile, minus fitted values at 10 th pctile, of experienced bond return...	0.101 (0.079)	0.009 (0.018)	0.115 (0.021)	-0.036 (0.028)	0.046 (0.023)
...where fitted value refers to	probability of not being in lowest risk tolerance category	probability of stock market participation	probability of bond market participation	fraction of liquid assets in stocks	fraction of liquid assets in bonds

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 with the γ parameters fixed at the point estimates obtained in those earlier regressions. The experienced stock return is calculated from the real return on the S&P 500 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.

returns and experienced bond returns are positively correlated with past wealth shocks, this alternative story cannot explain why stock returns have a strong positive influence on stock investments, and bond returns do not, and why bond returns have a strong positive influence on bond investments, and stock returns do not. Even if one takes the (less plausible) view that experienced bond returns are negatively correlated with past wealth shocks¹⁶ and that bond market participation also reflects *lower* rather than higher risk taking, this story could explain the coefficients on experienced bond returns in the bond market participation (positive) and risky asset-share regressions (negative), but would also predict that stock returns should come in significantly negative in the bond market participation model and that bond returns have a negative coefficient in the stock market participation regression, which is not the case.

Disentangling the roles of stock and bond returns also provides some first hints on the question of whether lifetime experiences affect preferences or beliefs. The additional 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, whereas bond returns should matter most for risk taking in bonds. A simple preference-based story, instead, in which individuals' relative risk aversion depends on past experiences of stock and bond returns, would not predict differential effects of stock and bond returns. 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.

III.F. Experience Effects on Stock Market Return Expectations

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

16. This view is less plausible because, for example, the highest experienced (real) bond returns in our sample are recorded for young individuals in the 1990s at a time when the economy was booming.

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 timespan 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 ($\lambda = 1.325$, Table III) and for the percentage allocation to stocks ($\lambda = 1.166$, Table IV). We regress stock return expectations on experienced returns, where experienced returns are calculated for each individual, given λ and the individual's 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. We weight each observation with sample weights provided by the UBS/Gallup survey. As in our earlier analysis of SCF data, we focus on 25- to 74-year-old individuals.

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 0.616 is almost two standard errors away from 0. With $\lambda = 1.325$ in column (ii), the point estimate is a little smaller, but the standard error is also smaller. The magnitudes of the point estimates are substantial. They imply that a 1 pp higher experienced return translates into 0.5–0.6 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: A highly risk averse investor may choose a low-risk portfolio and hence expects a low return, whereas a risk-tolerant investor chooses a high-risk portfolio and expects a high return. Thus, differences

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	0.616 (0.311)	0.528 (0.275)	0.654 (0.189)	0.584 (0.164)
Weighting parameter λ	1.166 [fixed]	1.325 [fixed]	1.166 [fixed]	1.325 [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 reported by individual respondents in the UBS/Gallup survey. Estimation is done with least squares, weighted with sample weights. The λ parameters are fixed at the point estimates obtained in column (ii) of Tables III and IV. The experienced stock return is calculated from the real return on the S&P 500 index. Standard errors, shown in parentheses, are robust to heteroskedasticity.

in people's expectations about their own future portfolio return could partly stem from differences in risk preferences. However, the coefficient estimates for experienced returns are very similar to those in columns (i) and (ii), suggesting that there is not much room for a strong confound. 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 return experiences affect risk preferences as well. But it shows that, at a minimum, the beliefs channel accounts for an important part of the experience effects.

III.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 a dummy for completed college education. The results do not provide any indication that the experience effects are significantly weaker for financially more sophisticated households.

Nonmonotonicities 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 because 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 foregoing analyses, the starting point for lifetime 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, lifetime 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 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 below 0 and standard errors become very 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 the percentage allocation to stocks, but the effect is not statistically significant. For the other three measures, the estimated effect is positive but of smaller magnitude than the experienced return effect and also not statistically significant. Most important, the inclusion of experienced volatility has little effect on the experienced return coefficient. 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 hard 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, absorbing potentially confounding macro and market-clearing effects with time dummies. This does not mean that our results have only cross-sectional implications. Differences in experienced returns exist not only between different age groups at a given point in time but also between different points in time. This time variation should influence risk taking in the aggregate, which, in turn, could help explain the puzzling phenomenon that periods of high risky asset prices, as measured, for example, by the price/earnings (P/E) ratio, are often followed by low subsequent returns (see, e.g., [Campbell and Shiller 1988](#)).

A full investigation of the asset-price effects of macroeconomic experiences is beyond the scope of this article, but we carry out a plausibility check. For the experience effect to be plausible, the time series of experienced stock returns of the average investor should line up with the time series of the P/E ratio of the aggregate stock market. Periods of high experienced returns (and hence high risk taking) should coincide with periods of high P/E ratios. The average experienced return series is calculated as a weighted average of experienced returns across all age groups (from age 25 to age 74) at a given point in time, where the weight is the percentage share of aggregate liquid assets held by the age group, on average, in all SCF waves from 1960 to 2007. The small inset figure shows the correlation between the average experienced return series and the P/E ratio if the weighting parameter λ is varied from -4.0 to 10.0 . The correlation for $\lambda = 1.50$ is indicated by the dashed line.

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 $\lambda = 1.50$, 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. Because individuals with higher liquid asset holdings are likely to have more influence on asset prices, we weight the experienced returns of each age by the proportion of aggregate liquid assets that is held by individuals of that age, on average, in all SCF waves from 1960 to 2007. We plot the resulting average experienced returns series against the annual P/E ratio of the S&P 500 index from Shiller (2005).

Figure IV 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.

Note that this correlation does not arise mechanically from the well-known positive correlation between P/E ratios and past returns. We do not use aggregate data in the estimation of the weighting parameter λ , nor do we choose λ to match movements in the P/E ratio over time. Rather, we estimate λ from *microdata*,

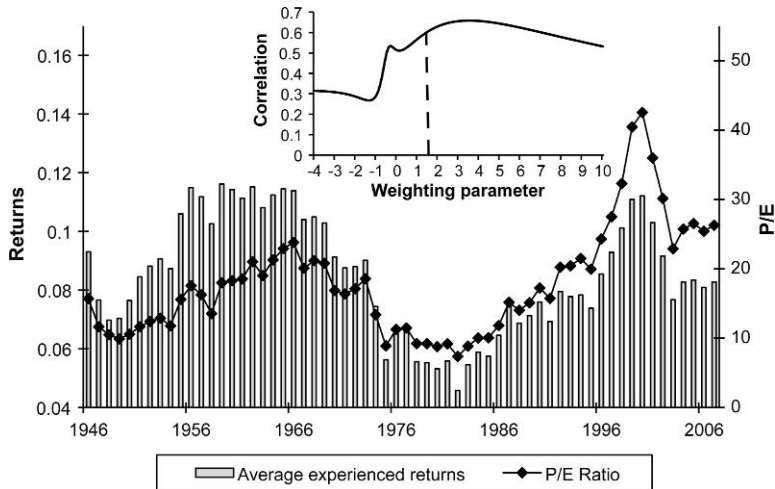


FIGURE IV

Average Experienced Real Stock Returns ($\lambda = 1.50$) and P/E Ratio of the S&P 500 Index 1946–2007

The P/E ratio is an updated series from Shiller (2005), which is calculated with a 10-year moving average of trailing earnings of firms in the S&P 500 index in the denominator. The small inset figure plots the correlation of the average experienced return series and the P/E ratio series if the weighting parameter λ is varied.

exploiting cross-sectional differences in risk taking. Our estimate of λ 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, average experienced returns would have a low correlation with recent stock market returns, and the time pattern of the bars in Figure IV would look very different. This point is demonstrated by the small inset graph in Figure IV. 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 could easily have been smaller if the micro-data estimates of λ had turned out differently. In fact, our micro-data estimates of $\lambda \approx 1.50$ are not far off the value that produces the maximum correlation ($\lambda \approx 3.00$) in the sense that they produce very similar weights (see Figure II).

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 the aggregate demand for risky assets. Our results thus suggest the possibility that personally experienced risky asset returns affect asset prices by inducing 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 many years ago still have some impact on current risk taking. The magnitudes of the effects are economically important. For example, an increase of 5 pp in the level of experienced real stock returns is associated with an increase in the probability of stock market participation of about 10 pp, and, for stock market participants, an increase in the percentage of liquid assets allocated to stocks of about 7 pp.

We also offer some evidence that experience influences risk taking, at least partly, by affecting beliefs rather than risk preferences. We show that higher experienced stock returns are associated with more optimistic beliefs about future stock returns. This suggests 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 or even boundedly rational learning models, but by focusing on their lifetime experiences. Consistent with this view, [Malmendier and Nagel \(2009\)](#) show that inflation expectations are influenced by individuals' inflation experiences in similar ways as risk taking and stock return expectations are influenced by individuals' return experiences.

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 Inter-university

Consortium for Political and Social Research 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 past 50 years. This Appendix details how we dealt with these issues. At the end, we also discuss the expectations data from the UBS/Gallup survey.

One issue in the “old” SCF data is a change in the sampling unit from “spending unit” in the surveys prior to 1964 to “family unit” from 1964 onward. A “family unit” can be made up of two or more spending units that are related by blood and share the same dwelling. To ensure comparability across years, we use identifiers provided in the pre-1964 data to aggregate related secondary spending units with their primary spending unit.

Another issue in the “old” SCF data 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 use the mid-point of these ranges as the dollar value. In 1971, we do not even have a separate dollar amount of stock holdings, only a combined number for stocks and bonds. Therefore, we can only calculate indicator variables for positive stock holdings and for positive bond holdings in 1971, but not the percentage of liquid assets allocated to stocks or bonds.

One problem in the data prior to 1989 concerns the split of mutual fund holdings into stock funds and bond funds. Information on the equity portion of mutual fund holdings is not available 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, the household and nonprofit sector held about \$631 billion of corporate equities directly in 1977, 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 nonprofit 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.) One item that one could potentially also include among bonds is the cash value of life insurance. We have chosen to exclude this item because the cash value information is not available prior to 1983 and is notoriously badly measured in subsequent surveys (see [Avery and Elliehausen 1990](#)).

Another issue concerns assets held in retirement accounts. The “old” SCF prior to 1983 did not ask respondents explicitly 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 IRAs and 401(k) defined contribution plans did not yet exist. Starting in 1983, retirement account assets are reported separately, but direct information on the allocation to stocks, bonds, and cash of these accounts is not available until 1989. From 1989 to 2001, the SCF provides rough allocation categories in retirement accounts, and from 2004 onward the exact equity share in percent.

For thrift-type accounts and defined contribution plans we can distinguish “mostly in stocks,” “split,” and “mostly in interest-bearing assets.” We follow the practice of the Federal Reserve Board and designate “split” to mean “equally split between stocks and bonds,” and “mostly” to mean 100% stocks or bonds, respectively.¹⁷ (We refine the calculation further as described shortly.) In 2004 and 2007, the SCF offers the exact percentage allocated to stocks, and we allocate the remainder to bonds.

For IRAs from 1989 to 2001, we can distinguish allocations of “mostly” stocks, or bonds, or cash, which we interpret as 100% allocation to the respective asset class, again with the further adjustment described shortly. 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” is treated as an equal split between three asset classes. In 2004 and 2007, the SCF has detailed information on the percentage allocation of IRA assets to stocks but no information on the allocation of the remainder between cash and bonds.

17. Aggregate data from the Employee Benefits Research Institute show that most of the nonstock portion of 401(k) account balances is invested in bond funds and guaranteed investment contracts, not in cash. See, for example, [Holden and VanDerhei \(2003\)](#).

For the nonstock portion of IRAs, we impute the holdings of bonds and cash from 2001 data as follows: we observe the institution at which the account is held (e.g., brokerage, insurance company, etc.). For each type of institution, we calculate in 2001 the frequency with which the nonstock portion is fully in cash, fully in bonds, or split between cash and bonds. We then randomly assign allocations of the nonstock portion in 2004 and 2007 conditional on the type of institution at which the account is held so that they reproduce these 2001 conditional frequencies.

A further refinement of the allocation calculations is required because the wording of the allocation questions changed in 2004, which reduces the comparability with earlier surveys. In 2004 and later, the survey asks whether “all” of the account is invested in stocks, and if not, what the percentage invested in stocks is. In contrast, earlier surveys ask whether the account is “mostly” in stocks. As a result, the proportion of account holders answering with “yes” to the “mostly” question in 1989–2001 is much higher than the proportion of those answering with “yes” to the “all” question in 2004 and 2007. Presumably, most individuals with allocations of roughly 70% and more to the asset in question would respond with “yes” to the “mostly” question. In 2004 and 2007, the number of responses with percentage allocations of 70%–99% is generally about half of the number of responses with “all” in stocks. Thus, probably about a third of the “mostly” responses in 1989–2001 come from households with less than 100% allocation to stocks. To adjust for this and improve comparability with 2004 and 2007, we randomly adjust a third of the “mostly” responses in 1989–2001 to have only 80% allocated to the “mostly” asset and 20% split among the remaining asset classes.

To address the missing retirement account allocations in 1983 and 1986, we refine an approach used by [Carroll \(2002\)](#) and exploit information on account types or the institution at which accounts are held, and information on the distribution of allocations in 1989. In the 1989–2007 surveys, allocations differ substantially between account types and institutions, so this method should provide a useful approximation. For thrift-type accounts and defined contribution plans, we observe the type of account (e.g., thrift savings plan, stock ownership plan, etc.). For each account type we calculate the frequency with which the account is allocated “mostly” to stocks, “mostly” to bonds, or “split” in 1989, or not eligible for inclusion into liquid assets according to Federal Reserve conventions (e.g., certain types of plans that do not allow

borrowing and emergency withdrawals are not included), and then we randomly assign allocations in 1983, conditional on the 1983 account type, that are consistent with these conditional frequencies in 1989. For IRAs, we perform a similar imputation, but with allocation category frequencies conditioned on the type of institution at which the account is held. For both thrift-type/defined contribution accounts and IRAs we also apply the adjustment of “mostly” responses as described. The 1986 survey did not collect the information on account type and institutions at which the account is held, but the 1986 sample is a reinterview of households interviewed in 1983, so we use households’ imputed 1983 allocation as a proxy. For couples that separated between 1983 and 1986, we apply the same allocation to both households. If only one of the two (thrift-type/defined contribution and IRA) allocations is available, we use the available one as a proxy for the other, consistent with a strong positive correlation between the two in 1989. If none is available, we randomly assign an allocation consistent with the unconditional frequencies of the allocation categories in 1989. It is also not clear to what extent defined contribution plan assets are captured in 1986. There is no separate survey question for this item in 1986, but unlike in 1983, the wording of the 1986 question asking for thrift-type account assets does not explicitly ask respondents to exclude defined contribution pension assets, so it is possible that some respondents included those. For households that had thrift-type/defined contribution plan assets in 1983 but do not report any in 1986, we carry forward the 1983 amount compounded by 10% per year.

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: (1) “What overall rate of return do you expect to get on your portfolio in the next 12 months?” and (2) “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 are available in May, September, and November. In the following years the data are available every month, with the exception of January 1999 and January 2006, and with roughly 1,000 respondents per month. Coverage of question (2) on marketwide 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%.

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REFERENCES

- Alesina, Alberto, and Nicola Fuchs-Schündeln, "Good-bye Lenin (or Not?): The Effect of Communism on People's Preferences," *American Economic Review*, 97 (2007), 1507–1528.
- Ameriks, John, and Stephen Zeldes, "How Do Household Portfolio Shares Vary with Age?" Columbia University Working Paper, 2004.
- Amromin, Gene, and Stephen A. Sharpe, "Expectations of Risk and Return among Household Investors: Are Their Sharpe Ratios Countercyclical?" Board of Governors of the Federal Reserve System Working Paper, 2009.
- Avery, Robert B., and Gregory E. Elliehausen, "1983 Survey of Consumer Finances: Technical Manual and Codebook," Board of Governors of the Federal Reserve System Working Paper, 1990.
- Brunnermeier, Markus, and Stefan Nagel, "Do Wealth Fluctuations Generate Time-Varying Risk Aversion? Micro-Evidence on Individuals' Asset Allocation," *American Economic Review*, 98 (2008), 713–736.
- Camerer, Colin, and Teck Ho, "Experience-Weighted Attraction Learning in Normal Form Games," *Econometrica*, 67 (1999), 827–874.
- Cameron, A. Colin, and Pravin K. Trivedi, *Microeconometrics: Methods and Applications* (New York: Cambridge University Press, 2005).
- Campbell, John Y., "A Comment on James Poterba's 'Demographic Structure and Asset Returns,'" *Review of Economics and Statistics*, 83 (2001), 585–588.
- Campbell, John Y., Laurent E. Calvet, and Paolo Sodini, "Fight or Flight? Portfolio Rebalancing By Individual Investors," *Quarterly Journal of Economics*, 124 (2009), 301–348.
- Campbell, John Y., and Robert J. Shiller, "Stock Prices, Earnings, and Expected Dividends," *Journal of Finance*, 43 (1988), 661–676.
- Carroll, Christopher D., "Portfolios of the Rich," in *Household Portfolios*, ed. Luigi Giuso, Michael Haliassos, and Tullio Jappelli, (Cambridge, MA: MIT Press, 2002).
- Choi, James J., David Laibson, Brigitte C. Madrian, and Andrew Metrick, "Reinforcement Learning and Savings Behavior," *Journal of Finance*, 64 (2009), 2515–2534.
- Cogley, Timothy, and Thomas J. Sargent, "The Market Price of Risk and the Equity Premium: A Legacy of the Great Depression?," *Journal of Monetary Economics*, 55 (2008), 454–476.
- Cragg, John G., "Some Statistical Models for Limited Dependent Variables with Application to the Demand for Durable Goods," *Econometrica*, 39 (1971), 829–844.
- Curcuru, Stephanie, John Heaton, Deborah Lucas, and Damien Moore, "Heterogeneity and Portfolio Choice: Theory and Evidence," in *Handbook of Financial Econometrics*, ed. Yacine Ait-Sahalia and Lars P. Hansen, (Amsterdam: North-Holland, 2009).
- Deaton, Angus, *The Analysis of Household Surveys: A Microeconometric Approach to Development Policy*, (Baltimore, MD: Johns Hopkins University Press, 1997).

- Dohmen, Thomas, Falk, Armin, Huffman, David, Sunde, Uwe, Schupp, Jürgen, and Gert G. Wagner, "Individual Risk Attitudes: Measurement, Determinants and Behavioral Consequences," *Journal of the European Economic Association*, (2010), forthcoming.
- Erev, Ido, and Alvin E. Roth, "Predicting How People Play Games: Reinforcement Learning in Experimental Games with Unique, Mixed Strategy Equilibria," *American Economic Review*, 88 (1998), 848–881.
- Faig, Miquel, and Pauline Shum, "What Explains Household Stock Holdings?" *Journal of Banking and Finance*, 30 (2006), 2579–2597.
- Friedman, Milton, and Anna J. Schwartz, *A Monetary History of the United States, 1867–1960*, (Princeton, NJ: Princeton University Press, 1963).
- Graham, John R., and Krishnamoorthy Narasimhan, "Corporate Survival and Managerial Experiences during the Great Depression," Duke University Working Paper, 2004.
- Greenwood, Robin, and Stefan Nagel, "Inexperienced Investors and Bubbles," *Journal of Financial Economics*, 93 (2009), 239–258.
- Guiso, Luigi, Paola Sapienza, and Luigi Zingales, "The Role of Social Capital in Financial Development," *American Economic Review*, 94 (2004), 526–556.
- , "Trusting the Stock Market," *Journal of Finance*, 63 (2008), 2557–2600.
- Hertwig, Ralph, Greg Barron, Elke U. Weber, and Ido Erev, "Decisions from Experience and the Effect of Rare Events in Risky Choice," *Psychological Science*, 15 (2004), 534–539.
- Holden, Sarah, and Jack VanDerhei, "401(k) Plan Asset Allocation, Account Balances, and Loan Activity in 2001," Employee Benefit Research Institute Issue Brief No. 255, 2003.
- Kaustia, Markku, and Samuli Knüpfer, "Do Investors Overweight Personal Experience? Evidence from IPO Subscriptions," *Journal of Finance*, 63 (2008), 2679–2702.
- Kennickell, Arthur B., "Multiple Imputation in the Survey of Consumer Finances," Board of Governors of the Federal Reserve System Working Paper, 1998.
- Malmendier, Ulrike, and Stefan Nagel, "Learning from Inflation Experiences," Stanford University and UC Berkeley Working Paper, 2009.
- Malmendier, Ulrike, and Geoffrey Tate, "CEO Overconfidence and Corporate Investment," *Journal of Finance*, 60 (2005), 2661–2700.
- Malmendier, Ulrike, Geoffrey Tate, and Jonathan Yan, "Overconfidence and Early-life Experiences: The Impact of Managerial Traits on Corporate Financial Policies," *Journal of Finance*, forthcoming.
- Nisbett, Richard E., and Lee D. Ross, *Human Inference: Strategies and Shortcomings of Social Judgment*, (Englewood Cliffs, NJ: Prentice Hall, 1980).
- Osili, Una Okonkwo, and Anna L. Paulson, "Institutions and Financial Development: Evidence from International Migrants in the United States," *Review of Economics and Statistics*, 90 (2008), 498–517.
- Poterba, James M., and Andrew Samwick, "Household Portfolio Allocations over the Life-Cycle," in *Aging Issues in the U.S. and Japan*, ed. Seiritsu Ogura, Toshiaki Tachibanaki, and David A. Wise, (Chicago: University of Chicago Press, 2001).
- Rubin, Donald B., *Multiple Imputation for Nonresponse in Surveys*, (New York: Wiley, 1987).
- Sahm, Claudia R., "Stability of Risk Preference," Federal Reserve Board of Governors Working Paper, 2007.
- Shaw, Kathryn L., "An Empirical Analysis of Risk Aversion and Income Growth," *Journal of Labor Economics*, 14 (1996), 626–653.
- Shiller, Robert J., *Irrational Exuberance*, 2nd ed., (Princeton, NJ: Princeton University Press, 2005).
- Vissing-Jørgensen, Annette, "Perspectives on Behavioral Finance: Does 'Irrationality' Disappear with Wealth? Evidence from Expectations and Actions," in *NBER Macroeconomics Annual*, ed. Mark Gertler and Kenneth Rogoff, (Cambridge, MA: MIT Press, 2003).
- Weber, Elke U., Ulf Böckenholt, Denis J. Hilton, and Brian Wallace, "Determinants of Diagnostic Hypothesis Generation: Effects of Information, Base Rates, and Experience," *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 19 (1993), 1151–1164.