Supplementary Online Appendix

for

Depression Babies:

Do Macroeconomic Experiences Affect Risk-Taking?

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A. Details on Estimation

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

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

and the between-implicate variance of the estimates is,

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

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

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

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

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

For further details see Rubin (1987).

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

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

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

In the case of non-linear least squares,

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

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

B. Coefficients on Control Variables

The tables in the main text omit the coefficients on the control variables, as those are not directly relevant for our analysis. However, since the coefficients may be of general interest and since they illustrate systematic differences in risk-taking between individuals, Table A.1 reports the estimates from the specifications that include liquid asset controls, i.e., from Table II, column (ii), Table III, columns (ii) and (iv), and Table IV, column (ii). The age and year dummy coefficient estimates and the coefficients on liquid assets interacted with the year dummies are not reported due to the large number of coefficients.

As the table shows, non-white race is consistently associated with lower risk taking and higher education with higher risk taking across all risk-taking measures (the signs of the coefficients in the probit models match the signs of the marginal effects), although the effects are weak for the percentage allocated to stocks measure. Being retired has a negative, though weak, effect on all five risk-taking measures. (It is important to keep in mind that age effects are already controlled for.) Having a defined contribution account has a strong positive association with the elicited risk-tolerance measure and the two participation measures, but a negative one with the percentage allocated to stocks in the last two columns. In the latter case, however the percentage of liquid assets invested in defined contribution accounts has a strong positive relationship with the percentage allocated to stocks.

C. Effects of Inertia in Portfolio Rebalancing: Simulations

A potential alternative explanation for the relationship between past stock returns and the percentage of liquid assets allocated to stocks (Table IV) is inertia in rebalancing. Here, we present simulations showing that the time dummies in our regressions absorb the effects of inertia on portfolio allocations. Hence, the experience effects that we document in our regressions cannot be explained by inertia.

We consider a setting with one risky asset (stock) and one risk-free asset, and we construct a panel of overlapping generations. Each generation starts investing at the age of 25, with a risky asset share of 50%, and lives until age 75. It is replaced in the next period with a new generation that starts at age 25. Every year, we draw i.i.d. log stock returns from a normal distribution with a mean of 8% and a standard deviation of 20%. Each generation's risky asset share then evolves according to a partial adjustment model,

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

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

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

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

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

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

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

Table A.2 reports the slope coefficient on the experienced return explanatory variable, corresponding to the coefficient β in our analysis in the main paper. We present results for various parameterizations of adjustment speed ω and weighting parameter λ. Panel A shows results when the regressions do not include time dummies, and Panel B replicates the regressions that we run in the paper, which include time dummies. The first block shows that, with extremely strong inertia (ω =0.10), investors hardly rebalance at all. The second block uses ω = 0.30, which is roughly in line with the degree of portfolio inertia found by Brunnermeier and Nagel (2008) in the Panel Study of Income Dynamics (PSID), though they caution that their estimates are likely to be upward biased due to measurement error. The third block is based on ω = 0.64, which is the adjustment speed coefficient estimated empirically by Campbell, Calvet, and Sodini (2009) from Swedish data with an instrumental variables regression that eliminates bias from measurement error.

As Panel A shows that, when the regression does *not* include time dummies, the slope coefficient on the experienced return variable is positive, and hence goes in the direction of our experience estimates in the paper. In terms of magnitude, however, it requires an empirically implausible degree of inertia (ω =0.10) to get a slope coefficient as big as the one we obtain from the SCF, even without time dummies in the regressions.

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

Why do the regression coefficients in the simulations with time dummies in Panel B turn out to be zero (in the case of initial portfolio shares at age 25 set equal to the cross-sectional mean) or even negative (in the case of initial portfolio shares at age 25 set equal to the target allocation of 50%)? The intuition is easiest to see in the first case. If each generation starts out investing at age 25 with an initial risky asset share equal to its cross-sectional mean among the older generations at that time, then the risky asset shares of all generations end up being always identical, without any cross-sectional variation, and only common time-variation. The common time-variation is completely absorbed by the time dummies in the regressions in Panel B. Hence, there is no variation left to explain for the experienced return variable, which explains its coefficient of exactly zero.

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

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

D. Interaction of Experience Effects with Sophistication Proxies

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

The results indicate that there is little difference between households with high and low financial sophistication in the strength of experience effects. The interaction terms with the high liquid assets dummy and the college degree dummy never receive a statistically significant coefficient for any of the risk taking measures. Also, in terms of economic magnitudes, there is little difference in the strength of the estimated experience effects as illustrated by the fitted probabilities for the probit models and directly by the coefficients in the regressions with the percentage of liquid asset invested in stocks.

E. Robustness of the Weighting Function

The one-parameter weighting function that we use in our main analysis can take on a variety of shapes, but it cannot accommodate non-montonicity, e.g., a hump-shaped pattern of weights. To check whether

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

such non-monotonicities could be important, we experiment with an alternative approach that uses a step function. We split each individual's life-span into three parts of equal length and compute the average return realized over each one of those three subperiods: recent, middle, and early (e.g., for an individual that is 60 years old in 2007, we calculate average returns from 1987 to 2006 (recent), 1967 to 1986 (middle), and 1947 to 1966 (early). We then regress the risk-taking measures on these three subperiod average returns, using the same controls as those in Table II, column (ii), Table III, columns (ii) and (iv), and Table IV, column (ii). Effectively, this assumes a weighting function that is a step function. A hump shape is now possible: in this case, the regression coefficient on the middle subperiod would take on the highest value. Instead of estimating two parameters (β and λ) we are now estimating three parameters (the three regression coefficients corresponding to the three subperiod average returns).

The results are shown in Table A.4. In each specification, the estimated coefficients show a monotonically declining pattern. The average return of the most recent third of the lifespan always receives a statistically significant coefficient, while the estimated coefficient corresponding to the average return over the earliest third of the lifespan is not significantly different from zero in any of the specification except for bond market participation.

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

We also investigated what happens when we relax the assumption implicit in our weighting function that the return history influencing younger people is shorter than the return history influencing older people. This assumption is implicit both in our baseline approach of starting "experienced returns" at individuals' birth years and in our robustness checks, where we let return experiences start 10 years before or after their birth years (see Section F below). The assumption immediately implies that, at any time, current stock market returns influence younger people more than older people since they are averaging over a shorter horizon. As a result, our weighting function, which we estimate to be declining in time lag, is mechanistically steeper for younger than for older generations.

One alternative assumption – that young and old people respond to equally long return histories *and* use the same weights – is, of course, already addressed in our baseline results. If this were the case, the time dummies in our regression would absorb all the experience effects and we would obtain $\beta = 0$. However, it is possible that older individuals have longer horizons but down-weight distant observations more strongly than younger individuals. To check this alternative, we constructed an additional experienced return variable similar to our original one, with λ set to the baseline point estimates from the main paper, but with "inverted" age (99-age) replacing age in our original weighting function. This additional variable treats, for example, a 74-year old like a 25-year old in our original weighting approach. If older people down-weight distant observations more strongly than younger people, then this additional variable should obtain a positive coefficient in our regressions, possibly driving out our original experienced return variable when we include them both in the estimation. We find that this is not the case. For all risk-taking measures, the inverted experienced return variable receives a *negative* coefficient, and is not or only marginally significant, while the coefficient on the original experienced return variable remains positive and highly significant.

F. Other Robustness Checks

Table A.5 checks the robustness of our results with respect to several changes in methodology. We report the estimates for β and λ in each case. The specifications correspond to Table II, column (ii), Table III, columns (ii) and (iv), and Table IV, column (ii,) of the main paper, i.e., they include the liquid-asset controls. In the probit models, the change in marginal effects is generally close to proportional to the change in the β coefficient compared with our baseline specifications, and so we only report the β coefficients.

The first block of results shows estimates obtained when retirement assets are excluded from the asset holdings variables from 1983 onwards. The estimates for both β and λ are close to those obtained with retirement accounts included. The second block of results removes the years 1983 and 1986 from the sample. In these years, the SCF does not provide information on the allocation to stocks in retirement accounts, and we have to impute the allocation as described in the Appendix of the main paper. Table A.5 shows that this imputation does not have a material effect on our results as the parameter estimates are similar to the baseline estimates if 1983 and 1986 data is removed. Both sets of results show that the question whether retirement accounts should be included or not, and the imprecision with which retirement account allocations are estimated and imputed, are not crucial issues for our empirical results.

The third block shows that similar results are also obtained when the estimation uses solely the "modern" SCF, i.e., when the data prior to 1983 is omitted. The only exception is bond market participation, where the β coefficient flips to a negative sign, and the standard error increases dramatically. Since β is, statistically, close to zero in this case, the estimation of λ breaks down, as λ is not identified when $\beta = 0$. For this reason, we fixed λ at its point estimate from the baseline specification in the main paper. As we discuss in the main paper, this lack of robustness reflects the fact that age dummies absorb almost all of the variation in experienced bond returns in this subsample. If one removes the age dummies (untabulated), then a positive coefficient re-emerges, close in magnitude to the estimate from the baseline specification in the main paper.

The next two blocks vary the starting point for the weighting function to 10 years before the birth of the household head and to 10 years after, respectively. As one would expect, the magnitudes of β and λ vary depending on the starting point. With a starting point 10 years after birth, λ is lower (0.491 instead of 1.325 in the baseline specification for stock market participation, for example), as observations early in life are now excluded from the weighted-average return, and there is less need to down-weight early observations. The point estimates for β are generally lower, too, which partly reflects the fact that the experienced return is now averaged over a shorter sample, and so each return observation receives a higher weight. Setting the starting point before the birth year leads to exactly the opposite pattern: higher point estimates of λ, implying stronger down-weighting of early observations, and higher β coefficients. The results show that, due to the flexibility of the weighting function in putting more or less weight on early observations, our conclusions are not sensitive to the exact choice of the starting point for measuring experienced returns.

The next block of results shows the estimates after including cohort dummies to control for unobserved cohort effects. We add as many cohort dummies as possible up to the point that age, time, and cohort dummies are not perfectly collinear. In this way, the control variables span as much variation as can be spanned by age, time, and cohort effects. This adds about 90 dummy variables to the baseline specifications, and so it is not surprising that standard errors increase considerably, particularly those of λ. With the exception of bond market participation, the point estimates of β are, however, quite close to the baseline specifications. For bond market participation, the coefficient flips sign, and has a huge standard error. Similar to the subsample tests above, removing the age dummies (untabulated) restores a positive coefficient close to the estimate in the baseline specification in the main paper. Evidently, cohort effects, age effects, and experienced return effects are difficult to disentangle for bond market participation.

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

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

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

G. Censoring and Truncation in Regressions with Fraction of Liquid Assets in Stocks

In the main paper, we regress the fraction of liquid assets invested in stocks, y, on experienced returns with the sample restricted to stock-market participants, i.e., to households with a positive fraction invested in stocks ($y > 0$), and we estimate this regression with least squares (within a linear model, up to the non-linear dependence on the weighting parameter λ). Generally, this approach could lead to biased estimates of the conditional expectation $E[y \mid y > 0]$, because this conditional expectation is non-linear. Here we show that alternative approaches that take into account this non-linearity (under strong distributional assumptions), yield quantitatively similar results.

Consider the participation equation

$$z^* = x'\gamma + u, \tag{A.9}$$

where participation occurs when $z^* > 0$. (For simplicity of exposition, we suppress the non-linear dependence of one of our explanatory variables, the experienced return, on the weighting parameter λ, but all estimations take this non-linearity into account.) The density of y conditional on participation is determined by

$$y = x'\beta + e, \tag{A.10}$$

where e is drawn from a truncated normal distribution with lower truncation point - $x'\beta$. In the special case with $u = e$ and $\gamma = \beta$, we get a (type I) Tobit model (see, e.g., Wooldridge 2002).

The assumptions $u = e$ and $\gamma = \beta$ are questionable, though, as this assumes that the same mechanism that drives participation also drives the fraction invested in stocks. For example, the level of liquid wealth plays an important role in explaining stock market participation (e.g., in a fixed participation cost model), while it need not play a similar role in explaining the percentage share of stocks conditional on participation. Therefore, to relax this assumption, we also consider an estimator following Cragg (1971), which allows γ and β to be different and which assumes that u and e are independent and u is standard normal. Effectively, Cragg's model is a combination of a truncated regression model with a probit model for the participation equation.

One might also wish to allow for general form of dependence between u and e (as in sample selection models) in addition to the two polar cases in the Tobit and Cragg model, but this is difficult in our application, because convincing identification would require instruments that enter the participation equation, but can be excluded from the equation for the fraction invested in stocks. Such variables are difficult to find for the problem at hand.

We estimate both Tobit and Cragg's model with ML, and in the case of Cragg's model, we impose that λ is identical in the probit and the truncated regression model. Given the estimated parameters, we then calculate fitted values for the conditional expectations $E[y \mid z^* > 0]$ for each household, which in both models follow the same formula

$$E[y \mid z^* > 0] = x'\beta + \sigma_e\, \phi(x'\beta)/\Phi(x'\beta), \quad \text{(A.11)}$$

where $\phi(x'\beta)/\Phi(x'\beta)$ is the inverse Mill's ratio. We calculate the differences between the fitted values at the 90th and 10th percentiles of experienced returns, and we report the average differences, as in our analysis in the main paper. We also calculate the R^2 conditional on participation as the squared correlation between the observed value of y and the fitted $E[y \mid z^* > 0]$ in the sample of participants.

Table A.6 presents the results, with experienced returns calculated from real stock returns. Tobit estimates are shown in columns (i) and (ii), and estimates for Cragg's model in columns (iii) and (iv). The number of observations in Table A.6 is lower than in the stock market participation probit estimation in Table III of the main paper, because the pre-1983 SCF sometimes provides only an indicator for stock-market participation, but not the percentage of liquid assets invested in stocks. With both models, we obtain estimates of λ that are fairly close to those we obtained in the main paper in Tables III and IV. As the fitted value differences for experienced returns at the 90th and 10th percentile reported in the Table show, the estimated effect of experienced return on the percentage share of stocks is positive with both models, and the magnitude of the difference is very similar to the magnitude obtained in Table IV in the main paper. Overall, the results seem to be robust with respect to censoring or truncation, and they do not seem sensitive to the assumption made about the dependence between u and e, as we obtain similar results in the polar cases of $u = e$ and independence of u and e.

Table A.1: Control Variable Coefficient Estimates

Dependent variable	Elicited risk tolerance	Stock market participation	Bond market participation	% liquid assets in stocks	%liquid assets in stocks
Sample	Full	Full	Full	Stock market participants	Stock market participants
Experienced return variable	Real stock returns	Real stock returns	Real bond returns	Real stock returns	Excess returns of stocks over bonds
Log Income	0.026	-0.530	-0.017	-0.033	-0.036
	(0.135)	(0.150)	(0.007)	(0.063)	(0.040)
(Log Income)^2	0.005	0.032	0.119	0.001	0.001
	(0.006)	(0.007)	(0.023)	(0.003)	(0.002)
High School completed	0.219	0.345	0.119	0.002	0.000
	(0.033)	(0.026)	(0.023)	(0.012)	(0.010)
College degree	0.184	0.215	0.002	0.014	0.014
	(0.019)	(0.024)	(0.023)	(0.007)	(0.006)
African-American	-0.039	-0.185	-0.071	-0.020	-0.020
	(0.030)	(0.052)	(0.048)	(0.015)	(0.013)
Hispanic	-0.145	-0.216	-0.266	-0.013	-0.013
	(0.047)	(0.066)	(0.053)	(0.015)	(0.017)
Other non-white	-0.091	-0.175	-0.243	-0.018	-0.017
	(0.048)	(0.075)	(0.069)	(0.011)	(0.016)
Non-white (pre-1983)		-0.318	-0.049	0.073	0.075
		(0.055)	(0.046)	(0.030)	(0.033)
Married	-0.061	0.002	0.062	-0.016	-0.015
	(0.021)	(0.024)	(0.023)	(0.006)	(0.007)
Retired	-0.098	-0.032	-0.022	-0.006	-0.006
	(0.032)	(0.040)	(0.035)	(0.011)	(0.011)
#Children	-0.064	0.007	0.179	0.002	0.002
	(0.017)	(0.017)	(0.017)	(0.006)	(0.005)
#Children^2	0.007	0.000	-0.028	0.000	0.000
	(0.004)	(0.004)	(0.004)	(0.001)	(0.001)
Has defined benefit plan	0.021	0.032	0.153	0.011	0.010
	(0.019)	(0.028)	(0.030)	(0.008)	(0.006)
Has defined contribution account	0.160	1.560	1.203	-0.197	-0.197
	(0.031)	(0.044)	(0.045)	(0.012)	(0.011)
% of liq. assets in DC accounts	-0.050	0.086	0.249	0.262	0.262
	(0.035)	(0.059)	(0.063)	(0.016)	(0.011)

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

Table A.2: Simulated Regression Coefficients on Experienced Returns in Overlapping Generations Model with Inertia in Portfolio Rebalancing

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

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

Dependent variable	Elicited risk tolerance	Stock market participation	Bond market participation	% liquid assets in stocks	%liquid assets in stocks
Sample	Full	Full	Full	Stock market participants	Stock market participants
Experienced return variable	Real stock returns	Real stock returns	Real bond returns	Real stock returns	Excess returns of stocks over bonds
Level of liquid assets					
Experienced return	6.263	11.003	9.502	1.618	1.793
	(1.192)	(1.398)	(1.726)	(0.406)	(0.451)
Experienced return × $I_{\text{Liquid assets > median}}$	0.931	-0.779	-2.002	0.065	-0.068
	(0.365)	(0.345)	(1.024)	(0.135)	(0.215)
Weighting parameter λ	1.433	1.325	1.282	1.166	1.831
	[fixed]	[fixed]	[fixed]	[fixed]	[fixed]
Average of fitted prob. at 90th pctile. minus fitted prob. at 10th pctile. of experienced return… liquid assets ≤ median	0.098	0.105	0.128		
	(0.016)	(0.016)	(0.023)		
liquid assets > median	0.112	0.098	0.101		
	(0.016)	(0.016)	(0.022)		
…where probability refers to	not being in lowest risk tolerance category	stock market participation	bond market participation		
College degree					
Experienced return	6.068	9.847	9.034	1.386	1.802
	(1.289)	(1.470)	(1.624)	(0.435)	(0.447)
Experienced return × $I_{\text{College degree}}$	1.222	1.467	-1.113	0.396	-0.084
	(0.863)	(0.956)	(0.902)	(0.264)	(0.190)
Weighting parameter λ	1.433	1.325	1.282	1.166	1.831
	[fixed]	[fixed]	[fixed]	[fixed]	[fixed]
Average of fitted prob. at 90th pctile. minus fitted prob. at 10th pctile. of experienced return… without college degree	0.094	0.094	0.122		
	(0.018)	(0.017)	(0.022)		
with college degree	0.112	0.108	0.107		
	(0.017)	(0.017)	(0.022)		
…where probability refers to	not being in lowest risk tolerance category	stock market participation	bond market participation		

(Table A.3 continued)

Notes: Models and controls as in Table II, column (ii), Table III, columns (ii) and (iv), and Table IV, column (ii), of the main paper, but with experienced real returns interacted with a dummy for households that have liquid assets higher than the median in a given year in the upper block of results, and for households with completed college education in the lower block of results. The λ parameter is fixed at the value obtained in the regressions in the main paper that did not include the interaction term. The experienced stock return is calculated from the real return on the S&P500 index. The experienced bond return is calculated from the real return on long-term U.S. Treasury bonds. Estimations in the columns labeled "Full sample" use all available data; estimations in the last two columns use the sample of stock market participants. Observations are weighted with SCF sample weights. Standard errors, shown in parentheses, are robust to heteroskedasticity/misspecification of the likelihood function and adjusted for multiple imputation.

Table A.4: Step Function as Alternative Weighting Function

Dependent variable	Elicited risk tolerance	Stock market. participation	Bond market participation	% liquid assets in stocks	% liquid assets in stocks
Sample	Full	Full	Full	Stock market participation required	Stock market participation required
Experienced return variable	Real stock returns	Real stock returns	Real bond returns	Real stock returns	Excess returns of stocks over bonds
Average return recent third of lifespan	3.800	3.899	4.670	0.683	0.577
	(0.868)	(0.795)	(1.021)	(0.247)	(0.278)
Average return middle third of lifespan	2.028	2.337	2.108	0.551	0.413
	(0.451)	(0.470)	(0.512)	(0.136)	(0.122)
Average return early third of lifespan	0.601	0.580	0.889	0.121	-0.054
	(0.338)	(0.346)	(0.369)	(0.097)	(0.088)

Notes: Control variables as in Table II, column (ii), Table III, columns (ii) and (iv), and Table IV, column (ii), of the main paper. The average stock return is calculated from the real return on the S&P500 index. The average bond return is calculated from the real return on long-term U.S. Treasury bonds. Estimations in the columns labeled "Full sample" use all available data; estimations in the last two columns use either the sample of stock market participants or the sample of bond market participants. Observations are weighted with SCF sample weights. Standard errors, shown in parentheses, are robust to heteroskedasticity/misspecification of the likelihood function and adjusted for multiple imputation.

Table A.5: Methodological Variations

Dependent variable	Elicited risk tolerance	Stock mkt. participation	Bond market participation	% liquid assets in stocks	%liquid assets in stocks
Sample	Full	Full	Full	Stock market participation required	Stock market participation required
Experienced return variable	Real stock returns	Real stock returns	Real bond returns	Real stock returns	Excess returns of stocks over bonds
Retirement assets excluded					
β	5.787	9.347	11.391	1.689	1.752
	(1.172)	(1.382)	(1.676)	(0.535)	(0.452)
λ	1.680	1.358	1.641	0.419	0.910
	(0.323)	(0.221)	(0.297)	(0.216)	(0.316)
Years with imputed retirement account allocations excluded (1983 and 1986)					
β	3.930	11.836	9.440	1.585	1.310
	(2.056)	(1.786)	(1.915)	(0.558)	(0.513)
λ	1.137	1.194	1.758	1.042	1.665
	(0.476)	(0.186)	(0.476)	(0.335)	(0.573)
Old SCF (prior to 1983) excluded					
β	-	9.528	-3.731	1.766	2.334
		(1.834)	(3.454)	(0.429)	(0.549)
λ	-	1.072	1.282	1.511	2.081
		(0.274)	[fixed]	(0.364)	(0.583)
Starting 10 yrs after birth					
β	3.836	5.635	5.747	0.991	1.221
	(0.769)	(0.831)	(1.225)	(0.240)	(0.289)
λ	0.667	0.491	0.827	0.567	0.868
	(0.213)	(0.150)	(0.304)	(0.227)	(0.283)
Starting 10 yrs before birth					
β	9.605	14.955	11.265	2.522	2.230
	(1.780)	(2.014)	(2.139)	(0.651)	(0.564)
λ	2.123	2.023	2.010	1.604	2.771
	(0.407)	(0.185)	(0.521)	(0.410)	(0.584)

(Table A.5 continued)

Cohort dummies included					
β	3.789	11.188	-2.860	1.746	1.343
	(1.722)	(2.052)	(4.319)	(0.857)	(0.658)
λ	2.511	1.545	1.282	0.480	1.264
	(2.233)	(0.358)	[fixed]	(0.622)	(1.090)
Geometrically averaged returns					
β	6.480	9.956	8.800	1.739	1.629
	(1.170)	(1.346)	(1.796)	(0.393)	(0.403)
λ	1.415	1.417	1.333	1.246	1.871
	(0.273)	(0.210)	(0.386)	(0.287)	(0.429)
Unweighted					
β	5.535	10.343	9.226	1.791	2.061
	(1.120)	(1.280)	(1.531)	(0.360)	(0.384)
λ	1.371	1.428	1.254	1.315	1.866
	(0.274)	(0.180)	(0.411)	(0.259)	(0.319)
Approximation with $\lambda = 1$					
β	6.314	10.481	7.924	1.643	1.234
	(1.196)	(1.422)	(1.473)	(0.397)	(0.370)
λ	1.00	1.00	1.00	1.00	1.00
	[fixed]	[fixed]	[fixed]	[fixed]	[fixed]
Experienced volatility included					
Experienced return	6.690	10.641	5.672	1.732	1.645
	(1.179)	(1.391)	(2.044)	(0.399)	(0.420)
Experienced volatility	4.715	0.397	3.281	-0.982	-0.396
	(2.843)	(1.739)	(1.715)	(0.562)	(0.434)
λ	1.433	1.325	1.282	1.166	1.831
	[fixed]	[fixed]	[fixed]	[fixed]	[fixed]

Notes: Control variables as in Table II, column (ii), Table III, columns (ii) and (iv), and Table IV, column (ii), of the main paper. Estimations in the columns labeled “Full sample” use all available data; estimations in the last two columns use either the sample of stock market participants or the sample of bond market participants. Observations are weighted with SCF sample weights unless otherwise indicated. Standard errors, shown in parentheses, are robust to heteroskedasticity/misspecification of the likelihood function and adjusted for multiple imputation.

Table A.6: Fraction of Liquid Assets Invested in Stocks, Tobit and Cragg Models

	Tobit		Cragg	
	(i)	(ii)	(iii)	(iv)
Experienced return coefficient β	3.105	3.971	1.434	2.309
	(0.463)	(0.513)	(0.651)	(0.748)
Weighting parameter λ	1.823	0.575	1.783	0.841
	(0.263)	(0.177)	(0.185)	(0.146)
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 stock share at 90th pctile. minus fitted stock share at 10th pctile. of experienced return conditional on stock market participation	0.065	0.062	0.054	0.066
	(0.013)	(0.011)	(0.028)	(0.027)
#Obs.	42,607	42,607	42,607	42,607
R^2 conditional on stock market participation	0.03	0.06	0.07	0.12

Notes: Model estimated with Tobit in columns (i) and (ii), and a model following Cragg (1971), in columns (iii) and (iv). The sample period runs from 1960 to 2007, excluding the 1971 survey (percentage allocation not available). Experienced stock returns are calculated from the real return on the S&P500 index. 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 heteroskedasticity and adjusted for multiple imputation. The reported R^2 is the squared correlation between fitted conditional expected stock shares and the actual percentage invested in stocks in the whole sample including stock market participants and non-participants.