Supplementary Appendix

for

Depression Babies:

Do Macroeconomic Experiences Affect Risk-Taking?

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A. Details on SCF Data

For our empirical analysis, we employ both the SCF and its precursor surveys. One challenge in the construction of such a pooled data set over a relatively long periods of time is that the definitions of some data items change over time. Such changes reflect changes in the survey methodology and its level of detail, but also changes in the investment environment that occurred over the last 50 years. In this section, we detail how we dealt with these issues.

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

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

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

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

A fourth issue is that, in 1960, 1963, 1964, 1967, and 1977, asset holding values are not given in a direct dollar number, but instead as a categorical variable, where each category corresponds to a range of values. We assign the midpoint of these ranges as the dollar value. In 1971, we do not have a separate dollar amount of stock holdings, only a combined number for stocks and bonds, and an indicator variable for greater than zero stock holdings. Hence, we only construct the stock-market participation variable but not the stock share of liquid assets for 1971.

B. Details on Estimation

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

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

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

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

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

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

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

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

For further details see Rubin (1987).

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

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

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

In the case of non-linear least squares,

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

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

C. Effects of Inertia in Portfolio Rebalancing: Simulations

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

D. Coefficients on Control Variables

The tables in the main text omit the coefficients on the control variables, as those are not directly relevant for our analysis. However, the coefficients on the control variables may be of general interest, and are also useful to see that the regressions are picking up systematic differences between individuals in their risk attitudes. Table A.2 reports the coefficient estimates for the control variables from the estimations in Table II, column (ii), Table III, columns (ii) and (iv), and Table IV, column (ii), i.e., the specifications that include liquid asset controls. The age and year dummy coefficient estimates and the coefficients on liquid assets interacted with the year dummies are not reported. As the table shows, non-white race and higher education as are most strongly associated with higher elicited risk tolerance and with higher stock and bond market participation. It is noteworthy that the signs of the coefficients of those variables are the same for each one of these three risk-taking measures. For the percentage allocation to

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

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

E. Interaction of Experience Effects with Sophistication Proxies

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

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

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

F. Non-Monotonicities in the Weighting Function

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

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

G. Robustness Checks

Table A.5 checks the robustness of our results with respect to several additional changes in methodology. We report the estimates for β and λ in each case. The specification corresponds to Table II, column (ii), Table III, columns (ii) and (iv), and Table IV, column (ii) of the main paper, i.e., it includes the liquid asset controls.

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

In the second and third blocks, we vary the starting point for the weighting function to 10 years before the birth of the household head and to 10 years after. In the fourth block, we introduce cohort dummies, described in the main text. The bottom block of results in Table A.3 shows tests in which we also include experienced volatility measures along with the experienced returns variable. All estimations and results are described in the main text.

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

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

Table A.2: Control Variable Coefficient Estimates

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

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

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

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

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

Table A.4: Step Function as Alternative Weighting Function

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

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

Table A.5: Methodological Variations

Dependent variable	Elicited risk tolerance	Stock mkt. participation	Bond market participation	% liquid assets in stocks	%liquid assets in stocks
Sample	Full	Full	Full	Stock market participation required	Stock market participation required
Experienced return variable	Real stock returns	Real stock returns	Real bond returns	Real stock returns	Excess returns of stocks over bonds
Retirement assets excluded:					
β	5.900	8.757	10.923	1.402	1.363
	(1.263)	(1.372)	(1.670)	(0.558)	(0.479)
λ	1.780	1.414	1.621	0.495	1.007
	(0.309)	(0.234)	(0.307)	(0.287)	(0.429)
Starting 10 yrs after birth:					
β	3.910	4.994	5.231	0.908	0.999
	(0.834)	(0.969)	(0.956)	(0.308)	(0.293)
λ	0.733	0.434	0.020	0.247	0.554
	(0.224)	(0.169)	(0.190)	(0.223)	(0.288)
Starting 10 yrs before birth:					
β	-9.556	15.657	11.973	3.295	2.211
	(1.946)	(2.704)	(1.781)	(1.122)	(0.605)
λ	2.106	2.062	0.985	1.260	2.263
	(0.430)	(0.277)	(0.297)	(0.350)	(0.544)
Cohort dummies included:					
β	4.366	12.464	2.372	2.107	2.068
	(2.015)	(1.752)	(4.315)	(0.690)	(0.687)
λ	1.470	1.698	1.106	0.923	1.345
	[fixed]	[fixed]	[fixed]	[fixed]	[fixed]
Geometrically averaged returns:					
β	6.348	9.010	10.163	1.672	1.579
	(1.272)	(1.273)	(1.672)	(0.445)	(0.413)
λ	1.445	1.765	1.229	0.981	1.384
	(0.288)	(0.246)	(0.301)	(0.286)	(0.383)

Unweighted:					
β	5.938	10.651	9.661	1.426	1.855
	(1.206)	(1.211)	(1.261)	(0.394)	(0.403)
λ	1.272	1.685	0.766	1.242	1.480
	(0.242)	(0.161)	(0.191)	(0.351)	(0.310)
Experienced volatility included:					
Experienced return	6.685	10.627	7.170	1.691	1.361
	(1.282)	(1.310)	(1.962)	(0.451)	(0.439)
Experienced volatility	6.745	3.842	2.673	-1.620	-0.993
	(3.081)	(1.651)	(1.664)	(0.525)	(0.451)
λ	1.470	1.698	1.106	0.923	1.345
	[fixed]	[fixed]	[fixed]	[fixed]	[fixed]

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