APPENDIX of "Do Wealth Fluctuations Generate Time-varying Risk Aversion? Micro-Evidence on Individuals' Asset Allocation"

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We use data from the PSID to investigate how households' portfolio allocations change in response to wealth fluctuations. Persistent habits, consumption commitments, and subsistence levels can generate time-varying risk aversion with the consequence that when the level of liquid wealth changes, the proportion a household invests in risky assets should also change in the same direction. In contrast, our analysis shows that the share of liquid assets that households invest in risky assets is not affected by wealth changes. Instead, one of the major drivers of households' portfolio allocation seems to be inertia: households rebalance only very slowly following inflows and outflows or capital gains and losses. (JEL D1, D5, E21, G11, G12)

APPENDIX

A.1. Model with Internal Habit

The analysis in Section I.A can easily be extended to models with internal habit, where the habit depends on past consumption as in Constantinides (1990) in a continuous-time setting. Specifically, let the habit, X_t, follow the difference equation:

$$X_{t+1} - X_t = bC_t - aX_t. \tag{A.1}$$

Define

$$C_t^* \equiv (C_t - X_t)\,\frac{R_f + a}{R_f - b + a}, \tag{A.2}$$

and

$$W_t^* \equiv W_t - (1 + R_f)\,\frac{X_t}{R_f - b + a}. \tag{A.3}$$

W_t^* reflects the excess wealth that is not needed to finance future discounted habit, where the habit grows at a rate of b and depreciates at a rate of a. Note that the value of X_{t+1} is known at time t. Now assume that the investor at time t invests, after time t consumption, a fraction α_t^* of wealth in excess of $\frac{X_{t+1}}{R_f-b+a}$ into the risky asset, and the rest in the riskless asset. This surplus portfolio yields a return $R^*_{p,t+1} \equiv \alpha_t^*\,(R_t - R_f) + R_f$. The remaining $\frac{X_{t+1}}{R_f-b+a}$ dollars are invested in the riskless asset. The dynamic budget constraint becomes

$$W_{t+1} = \left(1 + R^*_{p,t+1}\right)(W_t - C_t - \frac{X_{t+1}}{R_f - b + a}) + (1 + R_f)\,\frac{X_{t+1}}{R_f - b + a}. \tag{A.4}$$

Substituting in the definitions of surplus wealth and consumption and multiplying terms we get

$$W^*_{t+1} = \left(1 + R^*_{p,t+1}\right)(W^*_t - C^*_t). \tag{A.5}$$

Using the definition of C^*_t the optimization problem now is

$$\max E_t \sum_{\tau=0}^{\infty} \delta^\tau \frac{\left(C^*_{t+\tau}\right)^{1-\gamma}}{1-\gamma} \left(\frac{R_f - b + a}{R_f + a}\right)^{1-\gamma}, \tag{A.6}$$

which is equivalent to

$$\max E_t \sum_{\tau=0}^{\infty} \delta^\tau \frac{\left(C^*_{t+\tau}\right)^{1-\gamma}}{1-\gamma}, \tag{A.7}$$

so the problem again maps into a power utility problem. The portfolio share now is

$$\alpha_t = \alpha^* \left(1 - \frac{X_{t+1}}{(W_t - C_t)(R_f + a - b)}\right). \tag{A.8}$$

Approximating $\alpha^* \approx 1$, as in the main text, we get

$$\alpha_t = 1 - \frac{X_{t+1}}{(W_t - C_t)(R_f + a - b)}. \tag{A.9}$$

Log-linearizing and, in an abuse of notation, slightly changing our definitions to $x_t \equiv \log(X_t/(R_f + a - b))$, $w_t \equiv \log(W_t - C_t)$, we have

$$\alpha_t = 1 - \exp(x_{t+1} - w_t) \tag{A.10}$$

$$\approx \kappa - \rho(x_{t+1} - w_t), \tag{A.11}$$

which implies

$$\Delta\alpha_t = -\rho\Delta x_{t+1} + \rho\Delta w_t. \tag{A.12}$$

Note that $\Delta x_{t+1} = \Delta \log(X_{t+1}) = \log(1 + bC_t - aX_t)$. Therefore, as long as b and a are close to zero, which means that the habit reacts sluggishly to past consumption, we can approximate

$$\Delta\alpha_t \approx \rho\Delta w_t. \tag{A.13}$$

as we do in Section B. Of course, if the habit reacts faster, then it is possible that the effects of Δx_{t+1} and Δw_t offset, and our tests don't pick up the time-varying risk aversion induced by the habit. So our tests should be viewed as tests for low frequency movements in relative risk aversion.

A.2. Numerical Solution of a Model with Anticipated Income

To illustrate the effects of anticipated income on portfolio choice, we numerically solve a three-period version of our model, in which the household receives, with some positive probability, a large payment (e.g., an inheritance) in the second period. The household starts with an initial wealth of $W_0 = 50$ in liquid assets and chooses consumption (C_1, C_2) and the risky asset share (α_1, α_2) at time $t = 1, 2$. For simplicity, the household is assumed to have no labor income or other assets. At $t = 3$, the household is assumed to consume the entire remaining wealth. At $t = 2$, the household receives a payment B, with probability $p_B = 0.8$. Hence, the expected value of this payment to the household at $t = 1$ is $E_1[B] = p_B B$. We further set $\log(1 + R_t) \sim \mathcal{N}(\mu, \sigma^2)$, $\log(1 + R_f) = 0.04$, $\mu = 0.09$, $\sigma = 0.15$, $\gamma = 4$, and $\delta = 0.9$.

We solve the model by backward induction using a standard approach. We first solve the second period problem as a function of beginning of second period wealth. For a given level of beginning of second period wealth (before second period consumption but after returns from the first to the second period are realized), we perform a grid search over values of C_2 and α_2 to find the combination that maximizes expected utility, where we use numerical integration to evaluate expected utility. In this way we obtain maximized expected utility, i.e., the value function, as a function of beginning of second period wealth on a discretely spaced grid. We interpolate the value function between grid points and then solve the first period problem to obtain the optimal C_1 and α_1.

Figure A.1 shows how consumption and the risky asset share chosen in the first period depend on the expected value of the second period payment. We consider values for B from 0 to 50, i.e., $E_1[B]$ ranges from 0 to 40. At the higher end of this range, the payment, if received, substantially raises the liquid assets of the household (compared with $W_0 = 50$), and this increase is largely anticipated since $p_B = 0.8$ – just like it might be the case for the typical inheritance. Panel (a) shows that the risky asset share of a household with habit ($X = 10$) does not significantly increase as we increase B. Despite the fact that the household anticipates a substantial asset inflow in the second period, this does not induce the household to increase the allocation to risky asset. The reason is – as we discuss in the main part of the paper – that the small, but non-negligible risk that B will be zero forces the household to still save enough in riskless assets to be able to self-insure future habit. A likely, but not entirely certain payment in the second period cannot be utilized for insuring future habit, and therefore does not significantly increase the household's willingness to hold the risky asset. In fact, there is actually a small decline in the risky asset share with higher B. This effect has to do with the household's consumption decision. As Panel (b) shows, and as one would expect, the anticipation of a large payment raises consumption in the first period, which in turn implies that less liquid assets are available to insure future habit, and so a higher proportion of those liquid assets must be invested in the riskless asset.

For comparison, Panels (a) and (b) also show the optimal consumption and risky asset

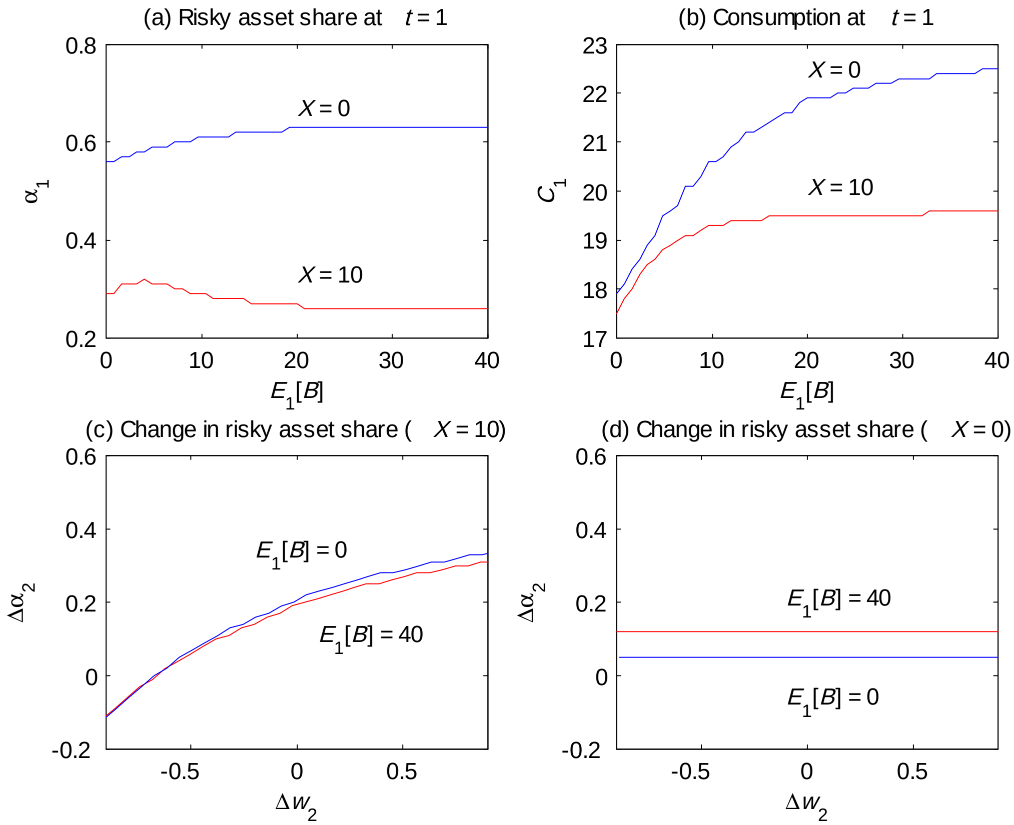

Figure A.1: Numerical Solutions of Three-Period Model

share of a household without habit ($X = 0$). As one would expect, the promise of a large payment raises the willingness of a CRRA household to hold risky assets in the first period, because the risky inflow in the second period provides some diversification of the risk associated with the risky asset, akin to the effect of risky, uncorrelated labor income.

Panels (c) and (d) plot $\Delta\alpha_2 \equiv \alpha_2 - \alpha_1$ against the change in the log of liquid assets $\Delta w_2 = w_2 - w_1$, comparable to the variables that we measure in the empirical data, for several values of B. It is apparent that the risky asset share of a household with habit utility strongly responds to changes in the level of liquid assets (Panel (c)), while the risky asset share of a household with CRRA utility does not (Panel (d)). Most importantly, with habit utility the relationship is almost identical, irrespective of whether changes in the level of liquid assets are unexpected ($E_1[B] = 0$) or a large increase is anticipated ($B = 50$, $E_1[B] = 40$).

Overall, the results from this model support our intuitive argument in Section I.B of the paper that the effects of unexpected and anticipated changes in liquid asset holdings on the risky asset share should be similar.

A.3. Estimation in the Presence of Aggregate Shocks

Gary Chamberlain (1984) points out that when households are subject to common aggregate shocks, the fact that a model implies that the time-series average of shocks converges to zero as $T \rightarrow \infty$ (a typical implication of rational expectations models), does not imply that the cross-sectional average must go to zero as the number of cross-sectional units $N \rightarrow \infty$. If the shock is identical across the population, then including time dummies absorbs the common shock. But if different groups of households have different sensitivity to the common shock, there is again no guarantee that the time dummies eliminate the common shock. Hence, estimation with cross-sectional moments may lead to biased coefficients. In our setting, however, this issue does not arise. To show this, we closely follow Angus Deaton (1992), p. 148. Assume that household i's log wealth is subject to an aggregate shock ξ_t with household-specific sensitivity $(1 + \eta_i)$ and an idiosyncratic shock (uncorrelated across households) ν_{it}, so that

$$\Delta w_{it} = \xi_t + \eta_i \xi_t + \nu_{it}, \tag{A.14}$$

where the cross-sectional average of η_i is zero. Our model implies that the change in the risky asset share follows

$$\Delta \alpha_t = \rho \left(\eta_i \xi_t + \nu_{it} \right) + \lambda \rho \xi_t, \quad 0 < \lambda < 1, \tag{A.15}$$

where the coefficient on the aggregate shock is lower by the factor λ, because ξ_t implies a change in the aggregate demand for stocks which leads to a change in prices and expected returns, not to a change in the quantity of stocks held (holding the supply of stocks fixed). Now suppose we run a single cross-sectional regression, with intercept (i.e., a time dummy), of $\Delta\alpha_t$ on Δw_{it}. It is easy to show that the OLS estimator for the slope coefficient has the probability limit

$$\underset{N\to\infty}{\text{plim}}\widehat{\beta} = \frac{\rho Var\left[\eta_i\xi_t + \nu_{it}\right]}{Var\left[\eta_i\xi_t + \nu_{it}\right]} = \rho, \tag{A.16}$$

where $Var\left(.\right)$ denotes the cross-sectional variance. Thus, we can consistently estimate ρ by including time-dummies in our panel regressions.

The reason that the Chamberlain (1984) problem does not arise in our setting is that dependent and explanatory variable are contemporaneous. As a consequence, the effects of $\eta_i\xi_t$ in the dependent and explanatory variable cancel out in numerator and denominator of plim $\widehat{\beta}$. In contrast, the examples discussed by Deaton (1992), p. 146-148, are ones where consumption growth is regressed on *lagged* income growth.

One issue that may complicate things is if λ is also heterogeneous in the population and is correlated with η_i. Then it no longer drops out completely through the time dummy. With $\Delta\alpha_t$ as the LHS variable, λ should have some heterogeneity, because a given percentage change in stock prices due to the aggregate shock should have a bigger effect for households with high α_t than for those with low α_t. However, we can also linearize Eq. (8) differently so that $\Delta\log\alpha_t$ is on the LHS. In that case, the effect of a given percentage change in prices on $\Delta\log\alpha_t$ would be the same for all households (assuming the composition of their risky asset portfolios is similar). We report regressions with $\Delta\log\alpha_t$ in Table A.2 in this Appendix. They yield similar results compared with those that have $\Delta\alpha_t$ as the dependent variable, which suggests that heterogeneity in λ does not have a significant effect on our results.

A.4. Data: Panel Study of Income Dynamics

We now provide additional details about our data from the PSID and variable construction. Whenever possible, we use the Wealth Supplement Files and the Income Plus Files to construct our variables, and the Core Family Files otherwise. Annual sample sizes in the PSID range from 5,000 to 7,000, but they are significantly reduced by the data availability requirements we impose.

In terms of timing, wealth data is reported as of the time the interview takes place (e.g., some time during 2003 in the 2003 wave), while income data refer to the calendar year preceding the date of the interview. Hence, the income and wealth data are not perfectly aligned, but for our tests this does not constitute a problem, because we focus on the relationship of different wealth variables which are all measured at the same date for a given household.

Riskless assets comprise the PSID categories cash (checking and savings accounts, money market funds, certificates of deposits, savings bonds, and treasury bills) plus bonds and life insurance (bonds, bond funds, cash value in a life insurance, valuable collection for investment purposes, and rights in a trust or estate). Risky liquid assets are defined as the amount reported in the PSID survey question asking for the combined value of shares of stock in publicly held corporations, mutual funds, and investment trusts. In the PSID, subjects are asked to report securities holdings net of amounts owed on the position. Other debts comprise items such as credit card debt, student loans, medical or legal bills, and loans from relatives. Home equity is the value of the home minus remaining mortgage principal.

Before 1999, subjects were asked explicitly to include assets held in individual retirement accounts (IRA) when reporting their financial asset holdings. Since 1999, they are asked to exclude assets in employer-based pensions and IRAs. Instead, there is a separate question on the value of IRA assets and their allocation to different asset classes. Based on the answer to the latter question, we allocate the IRA assets to stocks and bonds. If subjects state "mostly stocks" we allocate 100% of the IRA value to stocks, if the answer is "split" we allocate 50% to stocks and 50% to bonds, if it says "mostly interest bearing" we put 100% to bonds.

When we use data on purchases and sales of risky assets to back out capital gains and losses, we need to make an assumption regarding the timing of investment. The reported investment could either have occurred early or late in the measurement period. We assume that half of it has been made at the beginning of the period, and half of it at the end. For IRA assets in 1999, 2001, and 2003 we only have a combined active investment figure for all IRA assets. As an approximation, we assume that new IRA funds are allocated pro rata among the prior holdings.

A.5. Robustness Checks

Correction for weak instruments—In our TSLS regressions, our instruments are highly significant in the first-stage regression, but comparing the first stage F-statistic for the test that the coefficients on the instruments are jointly zero with the results of Stock and Yogo (2005) nevertheless suggests that we cannot reject with high confidence that the TSLS estimator could have some bias and the test statistics could have size distortions. For this reason, we re-run our tests with a limited information maximum likelihood (LIML) estimator and compute coverage-corrected confidence intervals along the lines proposed by (Moreira 2003). Table A.1 presents the results. The point estimate shown is the LIML estimate and the coverage-corrected 95% confidence interval is shown in brackets. In Specification (1) the dependent variable is the change in the proportion of risky assets in liquid wealth, and in Specification (2) the dependent variable is the change in the proportion of risky assets in financial wealth. Comparing the results with Tables II.3 and II.4, it is apparent that the LIML estimator produces results that are almost identical to those with the TSLS estimator. The only difference is that the coverage-corrected confidence intervals are slightly wider than the TSLS confidence intervals based on the usual normal approximation. Overall, our TSLS results do not seem to be much affected by a weak-instruments problem.

Transformations of the risky asset share—In Section I.B, we linearized the relationship between the risky asset share and liquid wealth. Our linearization is not the only way in which one could linearize the relationship. For example, one could linearize in such a way that the dependent variable on the left-hand size of Equation (9) is the k-period difference of some transformation of the risky asset share. Here we consider the log and logit transformations and we check whether we obtain similar results if we use the k-period difference in the log risky asset share (Specification (1) in Table A.2) or logit risky asset share (Specification (2) in Table A.2) as the dependent variable in our regressions. As the table shows, we still obtain a slighly negative coefficient, as in Table II.3, between two and three standard errors from zero. In addition, Specification (3) uses as the dependent variable a risky asset share that accounts for leverage. Instead of scaling stock holdings by the amount of liquid assets, we scale by liquid wealth (liquid assets minus non-mortgage debt, such as credit card debt, for example). As a result, the risky asset share can be bigger than one. Because there are some households with liquid wealth close to zero or negative at time t, we have to discard observations with negative liquid wealth and we winsorize values of the risky asset share above 2. In the main part of the paper, we scale by liquid assets to avoid such truncation and winsorizing, but as Table A.2 shows the OLS results are very similar when we scale by liquid wealth instead of liquid assets. The coefficient on Δ_k log liquid wealth is significantly negative in the 1984-1999 sample period. Only for Specification (2) in the in the 1999-2003 subsample, the coefficient is higher than in our basic Specification in Table II.3. For all three Specifications in Table A.2 we also re-ran our TSLS regressions with the risky asset share transformations and obtained similar results. Overall, the results are not systematically different if we choose a different linearization or take into account leverage.

One might suspect that the log transformation could have a stronger effect on the regressions that use changes in the proportion of financial wealth invested in risky asset, because the financial wealth risky asset share has some negative skewness, with observations being somewhat concentrated close to one (see Table I.1). However, as Table A.3 shows, the transformations make little difference. The point estimates using the log transformation (Specification 1) and the logit transformation (Specification 2) are again negative, as in Table II.4.

Note that the logit transformation yields a lower number of observations here, because it excludes households with more than 100% invested in risky assets. Recall that the denominator of the risky asset share in this case is financial wealth (unlike the liquid assets risky asset share, which has liquid assets, not liquid wealth, as the denominator), which can be smaller than the amount of risky financial assets. In summary, these tests confirm that our results are robust to choosing a different linearization of our estimating equation.

Sampling weights—Our tests in the main part of the paper weight all observations equally (except for the summary statistics in Table I.1), despite the fact that households with different characteristics have different sampling probabilities in the PSID. The reason is that our model should apply to all households. Hence, for estimating habit effects it would be inefficient to use sample weights (see, e.g., the discussion in Angus Deaton (1997), p. 70). If some household characteristics need to be controlled for, we do so by including them in the regression. But it turns out that we also obtain similar results if we weight households by the PSID sample weights, as shown in Table A.4.

The results are almost identical to those in Table II.3. The same is true for the regressions with the proportion of financial wealth invested in risky assets (not tabulated).

LAD regressions—To check whether our results might be driven by outliers, we run least-absolute deviation (LAD) regressions (median regressions). The results are shown in Table A.5, with bootstrap standard errors in parentheses. It is apparent that the estimates are virtually identical to our OLS estimates. Therefore, we conclude that our results are not driven by outliers.

Table I.1: Summary Statistics

Variable	Mean	10^{th} pct.	Median	90^{th} pct.	N
All Households, 1984 - 1999 ($k = 5$ *years*)					
Liquid wealth	156,391	480	52,532	349,116	3,313
Financial wealth	430,238	26,728	184,756	830,154	3,313
Income	92,515	24,367	72,760	160,369	3,319
Stock mkt. particip.	0.45	0	0	1	3,319
Stock mkt. entry	0.35	0	0	1	1,408
Stock mkt. exit	0.24	0	0	1	1,909
All Households, 1999 - 2003 ($k = 2$ years)					
Liquid wealth	201,783	1,003	62,936	399,129	3,035
Financial wealth	479,317	24,989	202,029	890,536	3,035
Income	99,665	26,884	76,397	172,540	3,033
Stock mkt. particip.	0.58	0	1	1	3,035
Stock mkt. entry	0.34	0	0	1	888
Stock mkt. exit	0.19	0	0	1	2,147
Stock Market Participants, 1984 - 1999 ($k = 5$ years)					
Liquid wealth	269,609	19,137	101,827	576,663	1,439
Financial wealth	630,488	71,442	286,508	1,155,371	1,439
Income	118,502	37,917	90,570	196,475	1,439
Δ_k log liq. wealth	0.36	-0.98	0.47	1.62	1,399
Δ_k log fin. wealth	0.30	-0.53	0.29	1.16	1,429
Δ_k log income	0.05	-0.52	0.09	0.60	1,439
%liq. assets risky	0.56	0.13	0.57	0.95	1,439
%fin. wealth risky	0.74	0.36	0.78	0.99	1,438
Δ_k %liq. assets risky	0.09	-0.37	0.06	0.59	1,439
Δ_k %fin. wealth risky	0.05	-0.30	0.03	0.41	1,438
Stock Market Participants, 1999 - 2003 ($k = 2$ years)					
Liquid wealth	294,622	16,904	110,980	550,204	1,710
Financial wealth	640,382	63,540	296,664	556,920	1,710
Income	116,432	34,000	90,126	198,552	1,710
Δ_k log liq. wealth	-0.04	-1.29	-0.02	1.24	1,654
Δ_k log fin. wealth	0.09	-0.74	0.10	0.88	1,694
Δ_k log income	-0.09	-0.62	0.00	0.39	1,710
%liq. assets risky	0.58	0.17	0.59	0.96	1,710
%fin. wealth risky	0.75	0.39	0.81	0.99	1,710
Δ_k %liq. assets risky	-0.02	-0.46	-0.01	0.40	1,710
Δ_k %fin. wealth risky	0.00	-0.32	0.00	0.33	1,710

Table II.1: Changes in Liquid Wealth and Stock Market Entry and Exit: Probit Regressions

	Entry		Exit	
	$k = 5$	$k = 2$	$k = 5$	$k = 2$
	(1984-1999)	(1999-2003)	(1984-1999)	(1999-2003)
Δ_k log liq. wealth$_t$	0.124	0.108	-0.058	-0.072
	(0.014)	(0.016)	(0.006)	(0.007)
Δ_2 log income$_{t-k}$	0.048	0.019	-0.051	-0.034
	(0.032)	(0.035)	(0.021)	(0.015)
Δ_2 log income$_{t-k-2}$	0.009	0.004	-0.024	-0.020
	(0.024)	(0.026)	(0.018)	(0.011)
Log income$_{t-k-4}$	0.203	0.122	-0.097	-0.044
	(0.039)	(0.040)	(0.023)	(0.014)
Preference shifters	Y	Y	Y	Y
Life-cycle controls	Y	Y	Y	Y
Year-region FE	Y	Y	Y	Y
Pseudo R^2	0.22	0.18	0.15	0.19
N	971	607	1,556	1,724

Notes: Estimates are marginal effects evaluated at sample averages of the explanatory variables. Standard errors are reported in parentheses.

Table II.2: First Stage Regressions

	Δ_k log liq. wealth$_t$		Δ_k log fin. wealth$_t$	
	$k = 5$ (1984-1999)	$k = 2$ (1999-2003)	$k = 5$ (1984-1999)	$k = 2$ (1999-2003)
Instruments:				
$I_{(\Delta_k \text{ log income}_t < 10^{th} \text{ pct.})}$	-0.211	-0.110	-0.217	-0.116
	(0.131)	(0.093)	(0.093)	(0.073)
$I_{(\Delta_k \text{ log income}_t > 90^{th} \text{ pct.})}$	0.480	0.098	0.257	0.062
	(0.121)	(0.082)	(0.082)	(0.067)
Inheritance$_t$	0.290	0.559	0.111	0.417
	(0.160)	(0.174)	(0.082)	(0.104)
Controls:				
Δ_2 log income$_{t-k}$	0.165	0.087	0.077	0.033
	(0.101)	(0.057)	(0.048)	(0.046)
Δ_2 log income$_{t-k-2}$	0.141	0.092	0.085	0.033
	(0.120)	(0.043)	(0.043)	(0.029)
Log income$_{t-k-4}$	0.133	0.068	0.040	0.014
	(0.102)	(0.042)	(0.045)	(0.031)
Preference shifters	Y	Y	Y	Y
Life-cycle controls	Y	Y	Y	Y
Year-region FE	Y	Y	Y	Y
Partial R^2 of instruments	0.01	0.01	0.02	0.01
F-test of instruments	8.39	5.09	6.19	7.41
[p-value]	[0.00]	[0.00]	[0.00]	[0.00]
N	1,234	1,455	1,258	1,489

Notes: Heteroskedasticity- and autocorrelation-robust standard errors are reported in parentheses.

Table II.3: Changes in the Proportion of Liquid Assets Invested in Risky Assets

	$k = 5$ (1984-1999)			$k = 2$ (1999-2003)		
	OLS	OLS	TSLS	OLS	OLS	TSLS
Δ_k log liquid wealth$_t$	-0.013	-0.009	-0.012	0.023	0.017	-0.136
	(0.007)	(0.009)	(0.058)	(0.011)	(0.015)	(0.076)
Asset composition controls		Y			Y	
Preference shifters	Y	Y	Y	Y	Y	Y
Life-cycle controls	Y	Y	Y	Y	Y	Y
Year-region FE	Y	Y	Y	Y	Y	Y
Adj. R^2	0.01	0.01	–	0.01	0.02	–
Overidentification test	–	–	[0.41]	–	–	[0.64]
N	1,234	1,234	1,234	1,455	1,455	1,455

Notes: Heteroskedasticity- and autocorrelation-robust standard errors are reported in parentheses, p-values in brackets.

Table II.4: Changes in the Proportion of Financial Wealth Invested in Risky Assets

	$k=5$ (1984-1999)			$k=2$ (1999-2003)		
	OLS	OLS	TSLS	OLS	OLS	TSLS
Δ_k log financial wealth$_t$	-0.160	-0.172	-0.198	-0.108	-0.103	-0.355
	(0.059)	(0.091)	(0.090)	(0.031)	(0.036)	(0.130)
Asset composition controls		Y			Y	
Preference shifters	Y	Y	Y	Y	Y	Y
Life-cycle controls	Y	Y	Y	Y	Y	Y
Year-region FE	Y	Y	Y	Y	Y	Y
Adj. R^2	0.11	0.11	–	0.06	0.06	–
Overidentification test	–	–	[0.56]	–	–	[0.57]
N	1,258	1,258	1,258	1,489	1,489	1,489

Notes: Heteroskedasticity- and autocorrelation-robust standard errors are reported in parentheses, p-values in brackets.

Table II.5: Effects of Inertia on Changes in the Proportion of Liquid Assets Invested in Risky Assets, OLS

	$k=5$ (1984-1999)			$k=2$ (1999-2003)		
Δ_k log liq. wealth$_t$	-0.061	0.000	-0.003	-0.167	0.005	-0.001
	(0.025)	(0.005)	(0.003)	(0.014)	(0.006)	(0.002)
Δ_k log liq. wealth$_t$ $\times$ Trade$_t$			0.001			0.003
			(0.002)			(0.010)
Risky asset return$_t$	0.151			0.227		
	(0.012)			(0.013)		
Δ_kInert$_t$		0.743	1.002		0.754	1.004
		(0.027)	(0.010)		(0.054)	(0.006)
Δ_kInert$_t$ $\times$ Trade$_t$			-0.347			-0.369
			(0.037)			(0.068)
Trade$_t$			0.128			0.021
			(0.011)			(0.010)
Preference shifters	Y	Y	Y	Y	Y	Y
Life-cycle controls	Y	Y	Y	Y	Y	Y
Year-region FE	Y	Y	Y	Y	Y	Y
Adj. R^2	0.34	0.64	0.70	0.57	0.72	0.76
N	1,042	1,080	1,080	1,308	1,325	1,325

Notes: Heteroskedasticity- and autocorrelation-robust standard errors are reported in parentheses.

Table II.6: Future Changes in the Proportion of Liquid Assets Invested in Risky Assets: $\Delta_k \alpha_{t+k}$ as Dependent Variable, OLS

	$k = 5$ (1984-1999)		$k = 2$ (1999-2003)	
Δ_k log liquid wealth$_t$	0.040	0.037	0.006	0.013
	(0.015)	(0.015)	(0.015)	(0.014)
Asset composition controls		Y		Y
Preference shifters	Y	Y	Y	Y
Life-cycle controls	Y	Y	Y	Y
Year-region FE	Y	Y	Y	Y
Adj. R^2	0.00	0.00	0.00	0.02
N	561	561	597	597

Notes: Heteroskedasticity- and autocorrelation-robust standard errors are reported in parentheses.

Table A.1: LIML estimates and coverage-corrected Moreira (2003) confidence intervals

	$k = 5$ (1984-1999)		$k = 2$ (1999-2003)	
	(1)	(2)	(1)	(2)
Δ_k log liquid wealth$_t$	-0.012		-0.143	
	[-0.178, 0.154]		[-0.433, 0.020]	
Δ_k log financial wealth$_t$		-0.199		-0.382
		[-0.460, 0.040]		[-0.770, -0.149]
Preference shifters	Y	Y	Y	Y
Life-cycle controls	Y	Y	Y	Y
Year-region FE	Y	Y	Y	Y
N	1,234	1,258	1,455	1,489

Table A.2: Changes in the Proportion of Liquid Assets Invested in Risky Assets: Transformations of the risky asset share

	$k = 5$ (1984-1999)			$k = 2$ (1984-1999)		
	(1)	(2)	(3)	(1)	(2)	(3)
Δ_k log liquid wealth$_t$	-0.061	-0.077	-0.063	0.017	0.144	-0.089
	(0.023)	(0.038)	(0.010)	(0.036)	(0.069)	(0.034)
Preference shifters	Y	Y	Y	Y	Y	Y
Life-cycle controls	Y	Y	Y	Y	Y	Y
Year-region FE	Y	Y	Y	Y	Y	Y
Adj. R^2	0.00	0.05	0.05	0.01	0.00	0.02
N	1,234	1,234	1,234	1,455	1,455	1,455

Table A.3: Changes in the Proportion of Financial Assets Invested in Risky Assets: Transformations of the risky asset share

	$k=5$ (1984-1999)		$k=2$ (1999-2003)	
	(1)	(2)	(1)	(2)
Δ_k log financial wealth$_t$	-0.225	-0.362	-0.165	-0.140
	(0.036)	(0.097)	(0.037)	(0.099)
Preference shifters	Y	Y	Y	Y
Life-cycle controls	Y	Y	Y	Y
Year-region FE	Y	Y	Y	Y
Adj. R^2	0.18	0.10	0.10	0.04
N	1,254	1,142	1,487	1,303

Table A.4: Changes in the Proportion of Liquid Assets Invested in Risky Assets: Weighted with Sampling Weights

	$k=5$ (1984-1999)			$k=2$ (1999-2003)		
	OLS	OLS	TSLS	OLS	OLS	TSLS
Δ_k log liquid wealth$_t$	-0.015	-0.010	0.024	0.027	0.021	-0.108
	(0.007)	(0.008)	(0.065)	(0.011)	(0.015)	(0.066)
Asset composition controls		Y			Y	
Preference shifters	Y	Y	Y	Y	Y	Y
Life-cycle controls	Y	Y	Y	Y	Y	Y
Year-region FE	Y	Y	Y	Y	Y	Y
Adj. R^2	0.01	0.01	–	0.01	0.02	–
N	1,234	1,234	1,234	1,455	1,455	1,455

Table A.5: Changes in the Proportion of Liquid Assets Invested in Risky Assets: Median regressions

	$k=5$ (1984-1999)		$k=2$ (1999-2003)	
Δ_k log liquid wealth$_t$	-0.010	-0.009	0.022	0.016
	(0.015)	(0.028)	(0.011)	(0.013)
Asset composition controls		Y		Y
Preference shifters	Y	Y	Y	Y
Life-cycle controls	Y	Y	Y	Y
Year-region FE	Y	Y	Y	Y
Pseudo R^2	0.03	0.03	0.02	0.02
N	1,234	1,234	1,455	1,455