Online Appendices to: “Long-Run Saving Dynamics: Evidence from Unexpected Inheritances”

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Abstract

This document contains (C) supplementary details on the identification strategy, (D) additional figures and tables, (E) details on the solution algorithm, (F) information about access to administrative data and the definitions of the wealth variables used in the analysis and (G) additional robustness checks and the full list of γ_n coefficients estimated in the empirical section of the paper.

C Identification: DiDs and event study

This appendix highlights the connection between the identification strategy of Fadlon and Nielsen (2015)—henceforth FN—and that of this paper. FN compare the labor market outcomes of a given group of individuals whose spouse experiences a health shock at time τ_1 (treatment) with those of individuals whose spouse experiences a shock at time $\tau_2 = \tau_1 + \Delta$. The time interval between shocks Δ is a fixed, pre-established number. FN thus explicitly assign a placebo shock at time τ_1 for individuals actually experiencing a shock at time τ_2, which are used as explicit controls, and estimate the effect of the shock for $\Delta - 1$ time periods using a difference-in-differences estimator. The crucial advantage of this strategy is to be able to separately identify and distinguish the dynamic effects of a shock from spurious time and group fixed effects.

Figure C.1 illustrates this identification strategy for a subset of our data, comparing the average wealth holdings of individuals inheriting in 2000 with that of individuals inheriting in 2006 ($\Delta = 6$ in the notation of FN). The average wealth holdings of the two groups overlap until 2000, after which the wealth of the group inheriting first increases, and then starts converging towards the path established before inheritance over time. We can thus identify the effect of inheritance for the group of heirs inheriting in 2000 for a period of six years.

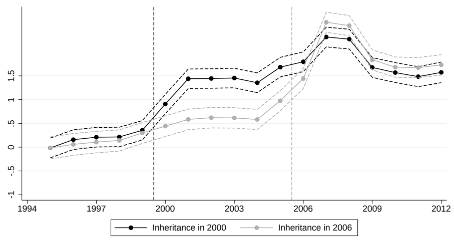
Maintaining the crucial property of separately controlling for time and group fixed effects, we extend this identification strategy in two ways. First, we add a minimal amount of structure to the model, allowing not only a more efficient extraction of information but also, under the same assumptions, the identification of the effect of a shock beyond the time horizon of Δ. Second, as a natural extension, by removing restrictions on Δ we use more data points and groups by year of inheritance in the same estimation.

We show these extensions in three steps. First, we show that the FN DiD estimator and our estimation strategy in a restricted dataset estimate the exact same effects. Second, we show how the additional structure imposed by our strategy allows us to extract information more efficiently from the data, and to identify the effect of inheritance beyond the time range defined by Δ. Third, we generalize the estimation strategy by relaxing the constraints on Δ, thus sacrificing some of the intuition about explicit control groups in favor of maximizing the extraction of information. We show that while the consequence of this approach is to use varying control groups for the estimation of the effects of inheritance as we move further from the time of parental death, selection does not drive our results and, crucially, the convergence patterns we observe.

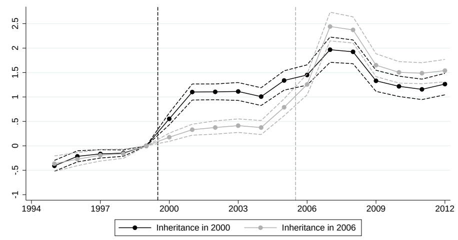
a Comparison with the FN DiD estimator

We begin by rewriting a simplified version of the estimation equation in the paper similar to that used by FN (pp. 14-15), noting the time of parental death

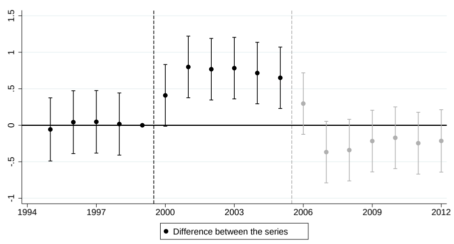
Figure C.1: Improving precision with individual FEs



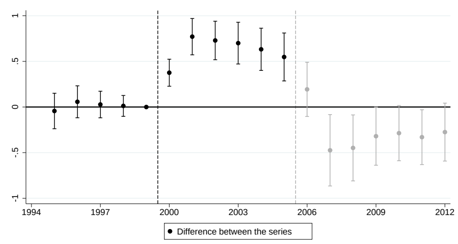
(a) 2000 vs 2006, averages w/o individual FEs



(b) 2000 vs 2006, averages w/ individual FEs



(c) 2000 vs 2006, dynamic DiD w/o FEs



(d) 2000 vs 2006, dynamic DiD w/ FEs

as τ.[1] We describe the wealth holdings at year t of an individual i inheriting at time τ as

$$y_{it} = \Lambda_t + \Psi_\tau + \gamma_n + \varepsilon_{it} \tag{1}$$

where $n = t - \tau$ and $E[\varepsilon_{i,t}] = 0$. This equation, while imposing a minimal amount of structure on the evolution of individual wealth holdings, describes γ_n—the average impact of inheritance on individual wealth holdings over n (years from parental death)—non-parametrically. We impose the standard DiD assumption that, absent the shock, the outcomes of the groups defined by τ would run parallel.

Under the assumption of parallel trends, we can compare the FN DiD estimator for $\gamma_n^{FN} \mid 0 < n < \Delta$ with the quantity γ_n obtained by estimating equation (1) on a sub-sample of our data. More specifically, consistently with

[1] For simplicity, we replace individual and cohort-by-year fixed effects Ψ_i and $\Lambda_{i,t}$ with the aggregated fixed effects by the time of inheritance Ψ_τ and year fixed effects Λ_t. Figure C.1 shows that the inclusion of more granular fixed effects greatly reduces the amount of unexplained variation in the model and improves the precision of our estimates.

FN, we restrict our sample to two groups of individuals inheriting a fixed number Δ of years apart (e.g. comparing people inheriting in 2000 and 2006, with $\Delta = 6$) and explicitly assigning a placebo shock at time τ_1 to people inheriting at time $\tau_2 = \tau_1 + \Delta$.

The FN DiD estimator compares the average wealth outcomes of these two groups at time $t = \tau_1 + n$ as

$$\gamma_n^{FN} \equiv (\bar{y}_t^{\tau_1} - \bar{y}_t^{\tau_1+\Delta}) - (\bar{y}_{\tau_1-1}^{\tau_1} - \bar{y}_{\tau_1-1}^{\tau_1+\Delta}) \tag{2}$$

where $\bar{y}_t^{\tau} = E\left[y_t^{\tau}\right]$. The top two panels of Figure C.2 illustrates this identification strategy for two pairs of τ groups, using individuals inheriting in 2000 as the treatment group and those inheriting in 2006 and 2010 as separate controls. These graphs mirror Figure C.2, and show that, after an initial increase, the average wealth holdings of treatment and control groups converge over time.

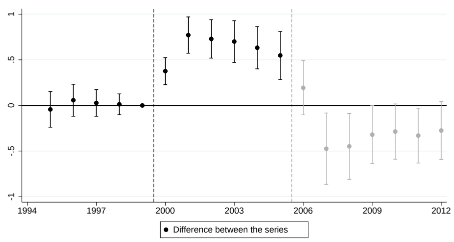
The relationship between γ_n^{FN} and γ_n in our descriptive equation (1) is straightforward. By substituting equation (1) in the FN estimator, we have that

$$\begin{aligned} E\left[\gamma_n^{FN}\right] &= (\Lambda_t + \Psi_{\tau_1} + \gamma_n - \Lambda_t - \Psi_{\tau_2} - \gamma_{n-\Delta}) \\ &\quad -(\Lambda_{\tau_1-1} + \Psi_{\tau_1} + \gamma_{-1} - \Lambda_{\tau_1-1} - \Psi_{\tau_2} - \gamma_{-1-\Delta}) \\ &= \gamma_n - \gamma_{-1} + \gamma_{-1-\Delta} - \gamma_{n-\Delta}. \end{aligned}$$

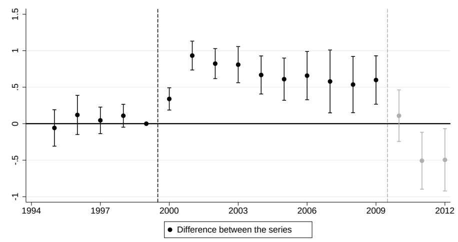
Under the identifying assumption of parallel trends, with respect to γ_{-1} we have that, for $n < \Delta$, $\gamma_{-1-\Delta} = \gamma_{n-\Delta} = \gamma_{-1} = 0$. Thus, γ_n^{FN} identifies γ_n.

This result is a special case of the general principle that any difference-in-differences study can be rewritten as an event study with separately identifiable time and group fixed effects, and dynamic effects of the treatment. In our case, the γ_n coefficients and year fixed-effects are separately identifiable for all n observed in at least two separate years. E.g. with our data the fixed effect relative to year 2010 and $\gamma_{n=14}$—only observed in 2010 for individuals inheriting in 1996— are not separately identifiable: The 2010 fixed effect will identify the

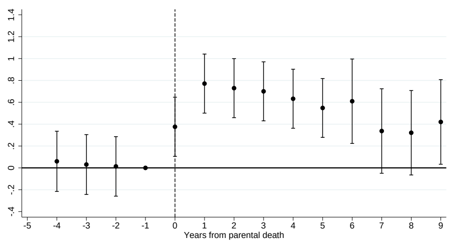
Figure C.2: Estimation of γ_n for net worth using pairs of τ groups



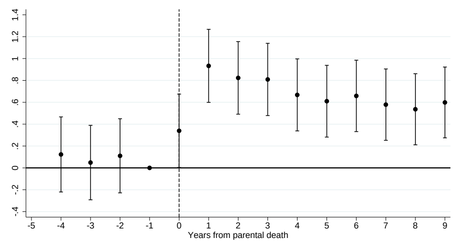
(a) 2000 vs 2006, dynamic DiD



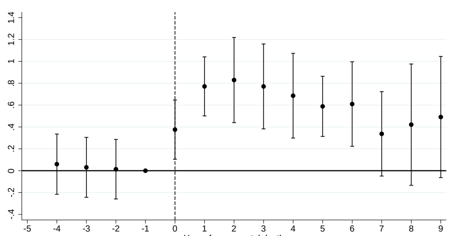
(b) 2000 vs 2010, dynamic DiD



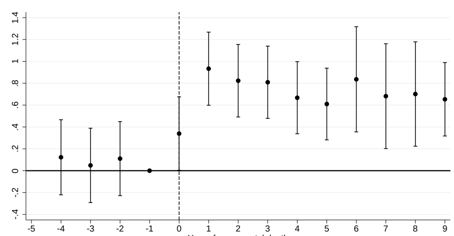
(c) 2000 vs 2006, event study (restr. identification)



(d) 2000 vs 2010, event study (restr. identification)



(e) 2000 vs 2006, event study



(f) 2000 vs 2010, event study

sum of the real year effect plus the unidentified γ_{14}. In our analysis we thus restrict the estimation to $n \in \{-5, -4, \ldots, 9\}$. Notice that in practice we can recover the exact FN estimator in an event study by substituting γ_n with a separate dummy for observations in group τ_2 for all n, thus using group τ_2 exclusively as a control.

b Identifying γ_n for $n \geq \Delta$

The advantage of imposing a minimal structure and estimating equation (1) instead of an explicit difference-in-difference estimator is that, by sacrificing some of the intuition, under the same assumptions we are able to simultaneously estimate all identifiable γ_n. To see this, we can use the FN estimator in (2) to estimate $\gamma_{\Delta+1}$. In the left panes of Figure C.2, this corresponds to estimating the effect of inheritance in 2007, $n = 7$ years after parental death for the treatment group inheriting in 2000. In a simple DiD framework $\gamma_{\Delta+1}$ is not identifiable, as equation (2) shows that the difference between the two time series (Figure C.2, second-to-last panel) is

$$E\left[\gamma_{\Delta+1}^{FN}\right] = \gamma_{\Delta+1} - \gamma_{-1} + \gamma_{-1-\Delta} - \gamma_1$$

and as $\gamma_1 \neq \gamma_{-1}$, $E\left[\gamma_{\Delta+1}^{FN}\right] \neq \gamma_{\Delta+1}$.

By estimating (1) instead we estimate simultaneously all γ_n coefficients. As Section b shows that γ_1 is identified, $\gamma_{\Delta+1}$ is also identified as $E\left[\gamma_{\Delta+1}^{FN}\right] + \hat{\gamma}_1$. The coefficient $\gamma_{\Delta+1}$ is thus identified separately from year and group fixed effects. The bottom four panels of Figure C.2 show that by estimating all γ_n simultaneously in an event study with identifiable group and time fixed effects we can recover estimates of γ_n for $n > \Delta$ by using two treatment groups (e.g. τ_{2000} and τ_{2006}) and imposing the structure in equation (1) augmented with individual fixed effects.

The second row of panels in Figure C.2 identifies $\gamma_n \forall n < \Delta$ exclusively from the DiD comparison of τ_{2000} and τ_{2006}.[2] The third row of panels in Figure C.2 estimates equation (1), augmented with individual fixed effects, with no data restrictions. In the third row, all identifiable γ_n coefficients are estimated simultaneously.

[2] In practice, we estimate equation (1) augmented with individual fixed effects and substituting γ_n with a separate dummy for observations in group τ_2 for all $n < 0$.

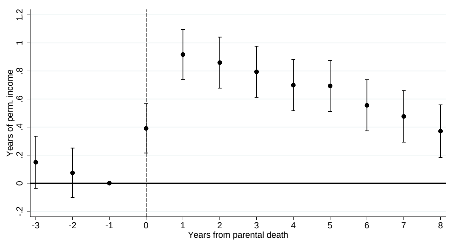
c Allowing for multiple Δ

As Δ does not restrict the estimation of γ_n, a natural generalization of the estimation of equation (1) is relaxing the restriction of a fixed Δ and allowing for multiple implicit control groups in the regression. As in the previous section, as long as time and group fixed effects are separately identifiable, under the assumption of parallel trends equation (1) estimates the same quantities as a DiD design. However, allowing for multiple Δ in the same equation, thus abandoning the assignment of explicit control groups, not only sacrifices part of the intuition but highlights how the composition of the sample changes into that of an unbalanced panel. Namely, the observations on which γ_{n_1} and γ_{n_2} are estimated will be different, as the equation uses different τ-groups for identification. However, under the assumptions stated in this appendix, that the panel is unbalanced does not necessarily affect our results. More specifically, it does not mechanically drive the convergence patterns we document.

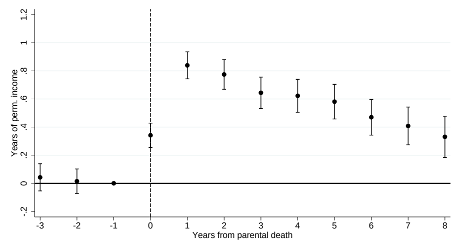
We highlight this point in Figure C.3, which compares estimates obtained by the FN estimator (on a balanced panel) with those obtained estimating equation (1) on the same data. In the left panels of Figure C.3 we thus impose $\Delta = 9$ and estimate the effect of inheriting between 1999 and 2001 explicitly using people inheriting between 2008 and 2010 as a control. As in FN, we explicitly assign a placebo shock in 1999 to individuals inheriting in 2008, a placebo shock in 2000 to individuals inheriting in 2009, and a placebo shock in 2001 to individuals inheriting in 2010. We choose these specific years as they allow not only a high Δ but also the estimation of coefficients for $n < 0$. In the results appearing in the figure we restrict the sample to be balanced over all observed years.

The right panels of Figure C.3 estimate the same quantity through (1), thus using the full information provided by the data and changing the combinations of inheritance-group years providing identification. That is, coefficient γ_1 is not only identified by three combination of inheritance years, but also by the comparison between people inheriting in 1999, 2000 and 2001, and 2008, 2009 and 2010.

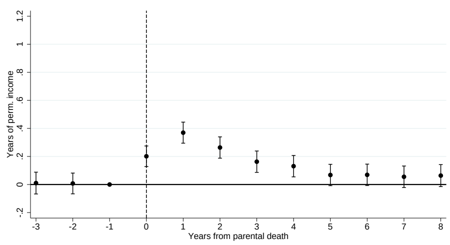
Figure C.3: Comparison of explicit control group (FN, balanced panel) versus event study design (this paper, varying control groups), estimated on individuals inheriting in 1999-2001 and 2008-2010



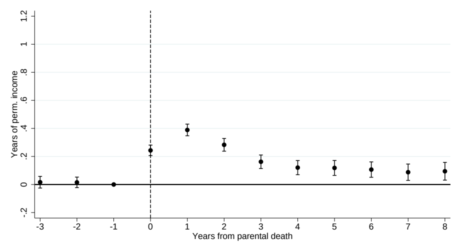
(a) Net worth, explicit control groups



(b) Net worth, event study design



(c) Liquid assets, explicit control groups



(d) Liquid assets, event study design

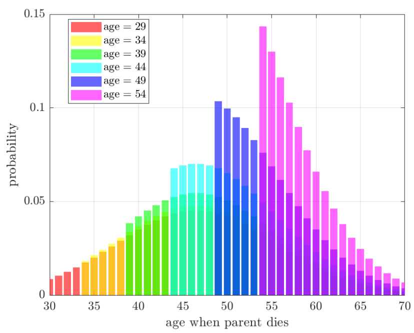
The figure shows not only that the convergence paths estimated by the two approaches are virtually identical, but also that by exploiting the structure of the dynamic response (and thereby using more information), the event study approach improves the precision of the empirical estimates. This improvement in precision occurs primarily for coefficients for which more combination of inheritance year provide identification, i.e. for n close to zero. Figure C.3 also shows that our results are robust to imposing a balanced panel and a balanced (explicit) control group across n. The full list of estimated coefficients and standard errors for all n appear in Table C.1.

Table C.1: Comparison of DiD (balanced and unbalanced) and our identification strategy for individuals inheriting in 1999-2001 and 2008-2010

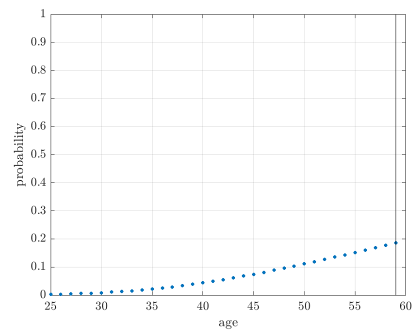
	Net worth			Liquid assets		
n	Event study	DiD	DiD, balanced	Event study	DiD	DiD, balanced
-3	0.042	0.175	0.149	0.016	0.018	0.010
	(0.049)	(0.093)	(0.095)	(0.021)	(0.040)	(0.040)
-2	0.015	0.104	0.074	0.015	0.012	0.007
	(0.044)	(0.088)	(0.090)	(0.019)	(0.038)	(0.038)
0	0.342	0.399	0.391	0.243	0.214	0.201
	(0.044)	(0.086)	(0.090)	(0.019)	(0.037)	(0.037)
1	0.839	0.931	0.917	0.389	0.379	0.370
	(0.049)	(0.088)	(0.091)	(0.021)	(0.038)	(0.038)
2	0.775	0.890	0.860	0.283	0.273	0.264
	(0.054)	(0.089)	(0.093)	(0.023)	(0.038)	(0.039)
3	0.644	0.794	0.794	0.162	0.166	0.163
	(0.057)	(0.089)	(0.093)	(0.025)	(0.038)	(0.039)
4	0.623	0.694	0.699	0.120	0.126	0.131
	(0.060)	(0.089)	(0.093)	(0.026)	(0.038)	(0.039)
5	0.581	0.677	0.693	0.118	0.078	0.068
	(0.063)	(0.089)	(0.093)	(0.027)	(0.038)	(0.039)
6	0.470	0.560	0.555	0.106	0.081	0.069
	(0.065)	(0.088)	(0.093)	(0.028)	(0.038)	(0.039)
7	0.408	0.491	0.476	0.088	0.066	0.055
	(0.069)	(0.089)	(0.094)	(0.030)	(0.038)	(0.039)
8	0.331	0.378	0.371	0.094	0.080	0.064
	(0.075)	(0.092)	(0.096)	(0.032)	(0.040)	(0.040)
# episodes	2508	2483	2125	2508	2483	2125

NOTE. The table compares the saving dynamics estimated on the sample of heirs inheriting between 1999 and 2001, and between 2008-2010. The first and fourth column use the identification strategy of the paper, estimating equation (1) in the paper on the full sample. The second and fifth column use the DiD identification strategy introduced in Appendix A.b, assigning an explicit control group to each inheritance year (e.g., the control group for heirs inheriting in 1999 is heirs inheriting in 2008). The third and sixth column replicate this estimation strategy on a strictly balanced sample.

D Additional Figures and Tables



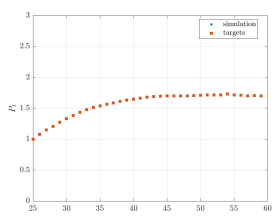
(a) Conditional distribution given age



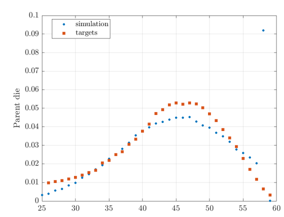
(b) Marginal probability, $\Pr[d_t = 1 | d_t = 0]$

Figure D.1: Inheritance process

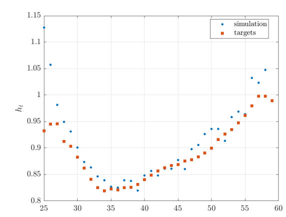
NOTE. This figure shows central properties of the inheritance process common across all model specifications.



(a) Permanent income



(b) Receiving inheritance



(c) Size of inheritance

Figure D.2: Fit of external calibration

NOTE. This figures compares moments in our sample of treated individuals with simulation outcomes common across all model specifications. Panel (a) shows the average level of permanent income, panel (b) shows the probability of receiving inheritance conditional on age, panel (c) shows the average size of the received inheritance relative to permanent income.

Table D.1: Robustness: Various σ

Parameters				Fits		
β	ρ	σ	ζ	LCP	LRD	MPC
$0.969^{\dagger}$	1.50	0.50	$1.14^{\dagger}$	$0.007^{\ddagger}$	0.369	0.06
$0.965^{\dagger}$	2.00	0.50	$1.20^{\dagger}$	$0.006^{\ddagger}$	0.281	0.06
$0.951^{\dagger}$	4.00	0.50	$1.38^{\dagger}$	$0.006^{\ddagger}$	0.070	0.09
$0.940^{\dagger}$	6.00	0.50	$1.49^{\dagger}$	$0.009^{\ddagger}$	0.032	0.12
$0.932^{\dagger}$	8.00	0.50	$1.54^{\dagger}$	$0.014^{\ddagger}$	0.045	0.14
$0.927^{\dagger}$	10.00	0.50	$1.57^{\dagger}$	$0.021^{\ddagger}$	0.060	0.16
$0.968^{\dagger}$	1.50	0.80	$1.15^{\dagger}$	$0.006^{\ddagger}$	0.440	0.05
$0.963^{\dagger}$	2.00	0.80	$1.23^{\dagger}$	$0.006^{\ddagger}$	0.361	0.06
$0.946^{\dagger}$	4.00	0.80	$1.49^{\dagger}$	$0.006^{\ddagger}$	0.128	0.08
$0.932^{\dagger}$	6.00	0.80	$1.66^{\dagger}$	$0.007^{\ddagger}$	0.048	0.10
$0.923^{\dagger}$	8.00	0.80	$1.76^{\dagger}$	$0.010^{\ddagger}$	0.031	0.12
$0.914^{\dagger}$	10.00	0.80	$1.85^{\dagger}$	$0.016^{\ddagger}$	0.032	0.14
$0.965^{\dagger}$	1.50	1.50	$1.19^{\dagger}$	$0.006^{\ddagger}$	0.519	0.05
$0.958^{\dagger}$	2.00	1.50	$1.29^{\dagger}$	$0.006^{\ddagger}$	0.453	0.05
$0.933^{\dagger}$	4.00	1.50	$1.75^{\dagger}$	$0.005^{\ddagger}$	0.209	0.07
$0.914^{\dagger}$	6.00	1.50	$2.11^{\dagger}$	$0.006^{\ddagger}$	0.104	0.09
$0.898^{\dagger}$	8.00	1.50	$2.41^{\dagger}$	$0.008^{\ddagger}$	0.056	0.10
$0.885^{\dagger}$	10.00	1.50	$2.68^{\dagger}$	$0.011^{\ddagger}$	0.033	0.12

NOTE. † internally calibrated parameter. ‡ targeted moment.

Table D.2: Robustness: CRRA

	Parameters						Fits		
	β	ρ	σ	ζ	$\tilde{\alpha}$	α	LCP	LRD	MPC
	Panel A: Targeting Life-Cycle Profile (LCP) only								
Fixed risk aversion (ρ)	$0.965^{\dagger}$	1.50	1.50	$1.19^{\dagger}$	1.00	1.00	$0.006^{\ddagger}$	0.519	0.05
	$0.955^{\dagger}$	2.00	2.00	$1.34^{\dagger}$	1.00	1.00	$0.005^{\ddagger}$	0.491	0.05
	$0.893^{\dagger}$	4.00	4.00	$2.83^{\dagger}$	1.00	1.00	$0.005^{\ddagger}$	0.361	0.06
	$0.805^{\dagger}$	6.00	6.00	$8.41^{\dagger}$	1.00	1.00	$0.004^{\ddagger}$	0.242	0.07
	Panel B: Targeting both life-cycle profile (LCP) and Long-Run Dynamics (LRD)								
Free perceived risk ($\tilde{\alpha}$)	$0.766^{\dagger}$	4.00	4.00	$15.11^{\dagger}$	$1.68^{\dagger}$	1.00	$0.017^{\ddagger}$	$0.025^{\ddagger}$	0.14
Free risk (α)	$0.833^{\dagger}$	4.00	4.00	$5.31^{\dagger}$	1.00	$1.38^{\dagger}$	$0.009^{\ddagger}$	$0.031^{\ddagger}$	0.10

NOTE. † internally calibrated parameter. ‡ targeted moment.

Table D.3: Robustness: $\tilde{\alpha}$ and α vs. ρ

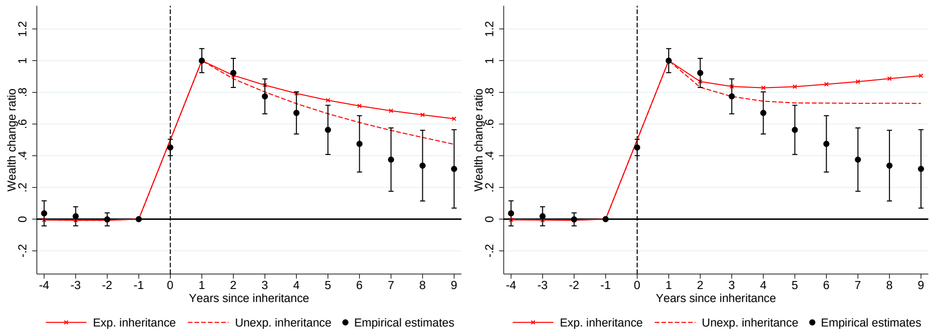
Parameters						Fits		
β	ρ	σ	ζ	$\tilde{\alpha}$	α	LCP	LRD	MPC
Panel A: Perceived income risk ($\tilde{\alpha}$)								
$0.941^{\dagger}$	1.50	0.67	$1.54^{\dagger}$	$1.94^{\dagger}$	$1.00^{\dagger}$	$0.013^{\ddagger}$	$0.028^{\ddagger}$	0.12
$0.938^{\dagger}$	2.00	0.67	$1.57^{\dagger}$	$1.73^{\dagger}$	$1.00^{\dagger}$	$0.011^{\ddagger}$	$0.028^{\ddagger}$	0.12
$0.936^{\dagger}$	3.00	0.67	$1.60^{\dagger}$	$1.44^{\dagger}$	$1.00^{\dagger}$	$0.010^{\ddagger}$	$0.029^{\ddagger}$	0.12
$0.935^{\dagger}$	4.00	0.67	$1.61^{\dagger}$	$1.25^{\dagger}$	1.00	$0.009^{\ddagger}$	$0.030^{\ddagger}$	0.11
Panel B: Actual income risk (α)								
$0.957^{\dagger}$	1.50	0.67	$1.33^{\dagger}$	1.00	$1.42^{\dagger}$	$0.007^{\ddagger}$	$0.029^{\ddagger}$	0.08
$0.951^{\dagger}$	2.00	0.67	$1.43^{\dagger}$	1.00	$1.33^{\dagger}$	$0.010^{\ddagger}$	$0.027^{\ddagger}$	0.08
$0.944^{\dagger}$	3.00	0.67	$1.50^{\dagger}$	1.00	$1.25^{\dagger}$	$0.007^{\ddagger}$	$0.029^{\ddagger}$	0.10
$0.939^{\dagger}$	4.00	0.67	$1.53^{\dagger}$	1.00	$1.21^{\dagger}$	$0.008^{\ddagger}$	$0.031^{\ddagger}$	0.11

NOTE. † internally calibrated parameter. ‡ targeted moment.

Table D.4: Robustness: External calibration

	Parameters				Fits		
	β	ρ	σ	ζ	LCP	LRD	MPC
$\kappa = 0.80$	$0.933^{\dagger}$	$6.31^{\dagger}$	0.67	$1.54^{\dagger}$	$0.008^{\ddagger}$	$0.032^{\ddagger}$	0.11
$\kappa = 1.00$	$0.935^{\dagger}$	$5.92^{\dagger}$	0.67	$1.72^{\dagger}$	$0.009^{\ddagger}$	$0.031^{\ddagger}$	0.11
$\sigma_{\psi} = 0.08$	$0.919^{\dagger}$	$19.58^{\dagger}$	0.67	$1.81^{\dagger}$	$0.018^{\ddagger}$	$0.030^{\ddagger}$	0.13
$\sigma_{\psi} = 0.10$	$0.924^{\dagger}$	$11.31^{\dagger}$	0.67	$1.74^{\dagger}$	$0.014^{\ddagger}$	$0.030^{\ddagger}$	0.13
$\sigma_{\xi} = 0.05$	$0.934^{\dagger}$	$6.13^{\dagger}$	0.67	$1.63^{\dagger}$	$0.010^{\ddagger}$	$0.032^{\ddagger}$	0.11
$\sigma_{\xi} = 0.07$	$0.934^{\dagger}$	$6.11^{\dagger}$	0.67	$1.63^{\dagger}$	$0.009^{\ddagger}$	$0.031^{\ddagger}$	0.11
$\omega = 0.15$	$0.933^{\dagger}$	$6.36^{\dagger}$	0.67	$1.63^{\dagger}$	$0.009^{\ddagger}$	$0.030^{\ddagger}$	0.11
$\omega = 0.35$	$0.933^{\dagger}$	$6.30^{\dagger}$	0.67	$1.64^{\dagger}$	$0.009^{\ddagger}$	$0.030^{\ddagger}$	0.11
$R = 1.01$	$0.945^{\dagger}$	$5.86^{\dagger}$	0.67	$1.64^{\dagger}$	$0.009^{\ddagger}$	$0.027^{\ddagger}$	0.10
$R = 1.03$	$0.921^{\dagger}$	$7.21^{\dagger}$	0.67	$1.64^{\dagger}$	$0.009^{\ddagger}$	$0.034^{\ddagger}$	0.13
$R_{-} = 1.06$	$0.933^{\dagger}$	$6.38^{\dagger}$	0.67	$1.63^{\dagger}$	$0.009^{\ddagger}$	$0.030^{\ddagger}$	0.11
$R_{-} = 1.10$	$0.933^{\dagger}$	$6.38^{\dagger}$	0.67	$1.63^{\dagger}$	$0.009^{\ddagger}$	$0.030^{\ddagger}$	0.11
$\mu_H = 70$	$0.933^{\dagger}$	$6.14^{\dagger}$	0.67	$1.67^{\dagger}$	$0.006^{\ddagger}$	$0.033^{\ddagger}$	0.11
$\mu_H = 85$	$0.935^{\dagger}$	$6.55^{\dagger}$	0.67	$1.58^{\dagger}$	$0.010^{\ddagger}$	$0.033^{\ddagger}$	0.11
$\sigma_H = 6$	$0.933^{\dagger}$	$6.54^{\dagger}$	0.67	$1.63^{\dagger}$	$0.011^{\ddagger}$	$0.032^{\ddagger}$	0.11
$\sigma_H = 12$	$0.932^{\dagger}$	$6.83^{\dagger}$	0.67	$1.63^{\dagger}$	$0.008^{\ddagger}$	$0.029^{\ddagger}$	0.12
$h_{45} = 0.70$	$0.934^{\dagger}$	$6.35^{\dagger}$	0.67	$1.62^{\dagger}$	$0.008^{\ddagger}$	$0.037^{\ddagger}$	0.11
$h_{45} = 1.10$	$0.931^{\dagger}$	$6.99^{\dagger}$	0.67	$1.64^{\dagger}$	$0.010^{\ddagger}$	$0.027^{\ddagger}$	0.12
$\eta = 0.99$	$0.933^{\dagger}$	$6.29^{\dagger}$	0.67	$1.65^{\dagger}$	$0.009^{\ddagger}$	$0.031^{\ddagger}$	0.11
$\eta = 1.01$	$0.934^{\dagger}$	$6.40^{\dagger}$	0.67	$1.62^{\dagger}$	$0.009^{\ddagger}$	$0.031^{\ddagger}$	0.11

Note. † internally calibrated parameter. ‡ targeted moment.



(a) Buffer-stock model

(b) Two-asset model

Figure D.3: Long-run saving dynamics without inheritance expectations

NOTE: The figure shows the long-run saving dynamics of net worth assuming agents do not expect to receive any inheritance. We use a ρ of 2 and the β and ζ calibrated to match the life-cycle profile of wealth in the main text.

E Solution algorithm

The appendix contains detailed information on the solution algorithm, its implementation and some validation tests.

a Choice-specific value functions

Let $z_t \in \{0,1\}$ denote the choice of whether to adjust or not. The model can then alternatively be written as a maximum over z_t-specific value functions conditioning on the discrete choice of whether to adjust or not, i.e.

$$V_t(M_t, P_t, N_t, d_t) = \max_{z_t \in \{0,1\}} v_t(M_t, P_t, N_t, d_t, z_t), \tag{3}$$

where $z_t = 0$ denote no adjustment of the illiquid assets, and $z_t = 1$ denote some adjustment triggering the fixed adjustment cost.

We have that the value function for no-adjustment is

$$\begin{aligned} v_t(M_t, P_t, N_t, d_t, 0) &= \max_{C_t} \begin{cases} C_t^{1-\rho}/(1-\rho) + \beta_i W_t & \text{if } \rho = \sigma \\ [(1-\beta_i)C_t^{1-\sigma} + \beta_i W_t^{1-\sigma}]^{\frac{1}{1-\sigma}} & \text{else} \end{cases} \\ &\text{s.t.} \\ A_t &= M_t - C_t \\ B_t &= N_t, \end{aligned} \tag{4}$$

and the value function for adjustment is

$$\begin{aligned} v_t(M_t, P_t, N_t, d_t, 1) &= \max_{C_t, B_t} \begin{cases} C_t^{1-\rho}/(1-\rho) + \beta_i W_t & \text{if } \rho = \sigma \\ [(1-\beta_i)C_t^{1-\sigma} + \beta_i W_t^{1-\sigma}]^{\frac{1}{1-\sigma}} & \text{else} \end{cases} \\ &\text{s.t.} \\ A_t &= M_t - C_t + (N_t - B_t) - \lambda \\ B_t &\geq 0, \end{aligned} \tag{5}$$

where the remaining constraints in both cases are as in the main text.

We denote the optimal choice functions by $C_t^\star(\bullet, 0)$, $C_t^\star(\bullet, 1)$ and $B_t^\star(\bullet, 1)$. The optimal discrete choice is denoted $z_t^\star(\bullet)$.

b EGM for non-adjusters

Using a standard variational argument it can be proven that the optimal consumption choice for non-adjusters must satisfy one of the following four conditions

$$
\begin{aligned}
C_t^{-\sigma} &= \beta R \mathbb{E}_t \left[C_{t+1}^{-\sigma} V_{t+1}^{\sigma-\rho} \right] W_t^{\rho-\sigma}, \;\; C_t < M_t && (6) \\
C_t^{-\sigma} &= \beta R \mathbb{E}_t \left[C_{t+1}^{-\sigma} V_{t+1}^{\sigma-\rho} \right] W_t^{\rho-\sigma}, \;\; C_t \in (M_t, M_t + \omega P_t) && (7) \\
C_t &= M_t + \omega_t P_t && (8) \\
C_t &= M_t. && (9)
\end{aligned}
$$

The first two equations are Euler-equations for the saving and borrowing regions, and the latter two amount to being at the borrowing constraint or at the kink between saving and borrowing. Notice that under CRRA preferences, $\rho = \sigma$, the value function terms disappears and we are back to standard Euler-equations.

In the buffer-stock model the Euler-equations (6) and (7) are both necessary and sufficient, and the endogenous grid method (EGM) originally developed by Carroll (2006) can be used to solve the model. In the two-asset model they are, however, only necessary. They are not sufficient because the value function, due to the fixed adjustment cost, might not be globally concave. As first showed by Fella (2014) and Iskhakov et al. (2017) the EGM can, however, still be used if a so-called upper envelope algorithm is applied to discard solutions to the Euler-equations which are not globally optimal. Specifically, we use the approach proposed in Druedahl (2018) building on the upper envelope algorithm in Druedahl and Jørgensen (2017) developed for multi-dimensional EGM in models with non-convexities and multiple constraints (but for a model class not including the present model).

c Reducing the state space for adjusters

To reduce the state space for the adjusters it is useful to define the following problem

$$
\begin{aligned}
\tilde{v}_t(X_t, P_t, d_t) &= \max_{C_t, B_t} \begin{cases} C_t^{1-\rho}/(1-\rho) + \beta_i W_t & \text{if } \rho = \sigma \\ [(1-\beta_i)C_t^{1-\sigma} + \beta_i W_t^{1-\sigma}]^{\frac{1}{1-\sigma}} & \text{else} \end{cases} \qquad (10) \\
&\text{s.t.} \\
A_t &= X_t - C_t - B_t - \omega P_t \\
B_t &\geq 0.
\end{aligned}
$$

By using the result that the distinction between beginning-of-period liquid assets, M_t, and illiquid assets, N_t, does not matter for adjusters, we now have that

$$
\begin{aligned}
v_t(M_t, P_t, N_t, d_t, 1) &= \tilde{v}_t(X_t, P_t, d_t) \qquad (11) \\
&\text{s.t.} \\
X_t &= M_t + N_t - \lambda + \omega P_t.
\end{aligned}
$$

We can further also see that the consumption choice for the adjusters can be profiled out by using the optimal consumption choice for the non-adjusters as follows

$$\begin{aligned}
\tilde{v}_t(X_t, P_t, d_t) &= \max_{s_t \in [0,1]} \begin{cases} C_t^{1-\rho}/(1-\rho) + \beta_i W_t{}^{1-\sigma}) & \text{if } \rho = \sigma \\ [(1-\beta_i) C_t^{1-\sigma} + \beta_i W_t]^{\frac{1}{1-\sigma}} & \text{else} \end{cases} \qquad (12) \\
& \text{s.t.} \\
M_t &= (1 - s_t) X_t - \omega P_t \\
N_t &= s_t X_t \\
C_t &= C_t^\star(M_t, N_t, P_t, d_t, 0) \\
A_t &= M_t - C_t^\star \\
B_t &= N_t.
\end{aligned}$$

This reduces the choice problem for the adjusters to a one-dimensional problem. Given that finding the global maximum for each point in the state space can be challenging, and requires a multi-start algorithm, this is computationally very beneficial.

d Some implementation details

Interpolation. We never need to construct the over-arching value function, $V_t(M_t, P_t, N_t, d_t)$. With Epstein-Zin preferences we can instead e.g. use that

$$W_t(\bullet) = \beta \mathbb{E}_t \left[\begin{cases} v_{t+1}(\bullet, 0)^{1-\rho} & \text{if } z_{t+1}^\star(\bullet) = 0 \\ \tilde{v}_{t+1}(\bullet)^{1-\rho} & \text{if } z_{t+1}^\star(\bullet) = 1 \end{cases} \right]^{\frac{1}{1-\rho}} \qquad (13)$$

where

$$X_{t+1} = M_{t+1} + N_{t+1} - \lambda + \omega P_{t+1}$$

We also interpolate $\mathbb{E}_t \left[C_{t+1}^{-\sigma} V_{t+1}^{\sigma-\rho} \right]$ from equations (6)-(7) in a similar way.

Grids. We have separate grids for P_t, M_t, N_t, A_t and X_t while the grid for B_t is the same as that for N_t. All grids vary by t, and the assets grids vary by the current element in P_t, but are otherwise tensor product grids.

1. The grid for A_t is chosen to explicitly include $\{-\omega P_t, -\omega P_t + \epsilon, -\epsilon, \epsilon\}$, where ϵ is a small number, such that the borrowing constraint and the kink at $A_t = 0$ is well-approximated. A dense grid for A_t is costly as we for each element need to do numerical integration of the next-period value function and apply EGM.
2. A dense grid for N_t (and thus B_t) is costly for the same reason as A_t.
3. The grid for M_t is only used in the upper envelope algorithm, and it is therefore feasible for this grid to be very dense.
4. The grid for X_t is only used for the adjusters. Consequently it is feasible to has a rather dense grid.
5. A dense grid for P_t is costly both for the same reason as A_t and because it implies that the adjuster problem has to be solved more times.

In general all grids are specified such that they are relatively more dense for smaller values, and this even more so for small P_t. The largest node in each grid is proportional to P_t. In the two-asset model we chose grid sizes $\#_M = 300$, $\#_X = 200$ and $\#_A = \#_N = 100$ and $\#_P = 150$. For the buffer-stock model we instead use $\#_M = 600$ and $\#_A = 150$.

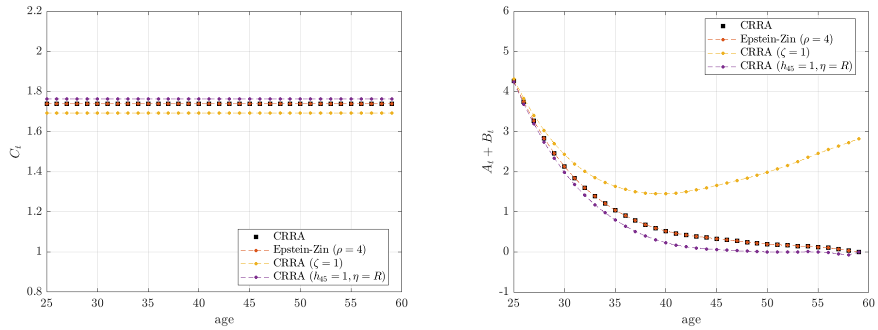
Numerical integration. For evaluating expectations we use Gauss-Hermit quadrature with 6 points for each shock, $\#_\psi = \#_\xi = 6$.

Multi-start. For solving the problem in (12) we use $\#_k = 5$ multi-start values for s_t.

Code. The code is written in `C++` (`OpenMP` is used for parallelization) with an interface to `MATLAB` for setting up grids and printing figures. The optimization problems are solved by the Method of Moving Asymptotes from Svanberg (2002), implemented in `NLopt` by Johnson (2014).

e Code validation

In this section we show that the code package developed for this paper delivers robust simulation results, which also aligns with theoretical results when



(a) Consumption

(b) Net worth

Figure E.1: Buffer-stock: Constant consumption

Note. This figure shows life-cycle profiles of average consumption and average net worth from a buffer-stock model with $\beta = 0.97$, $,\sigma = \rho = 2$, $\zeta = 0$, $\sigma_\psi = \sigma_\varepsilon = 0$, $R = \beta^{-1}$, $\omega = 2$, $h_{45} = 0$ and the remaining parameters as in the main text. In the simulation all agents are born wealthy with $A_0 = 5$.

available.

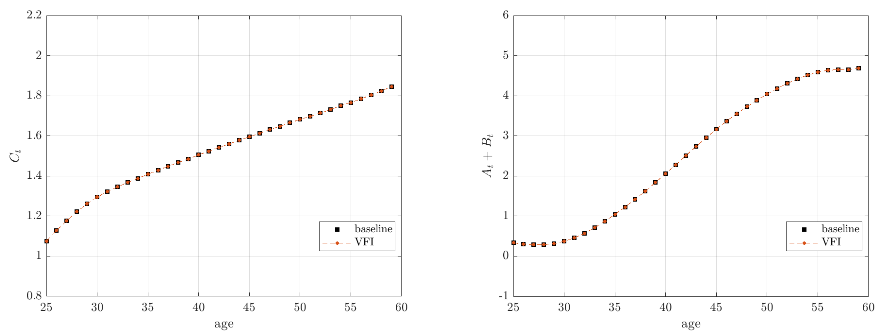
Figure E.1 firstly illustrates that consumption is constant in a buffer-stock model with:

1. No risk ($\sigma_\psi = \sigma_\varepsilon = 0$ and $h_{45} = 0$),
2. CRRA preferences ($\sigma = \rho = 2$) where $R = \beta^{-1} = \frac{1}{0.97}$,
3. No post-retirement saving motive ($\zeta = 0$),
4. Loose borrowing constraint ($\omega = 2$).

This aligns well with theory as the model then basically becomes a Permanent Income Hypothesis (PIH) model where the Euler-equation directly imply that consumption should be constant.

Next, it illustrates that consumption is also constant in the following three alternative cases

1. Epstein-Zin preferences with $\rho \neq \sigma$.
2. Active post-retirement saving motive, $\zeta > 0$.
3. Some inheritance, $h_{45} > 0$, if and only if $\eta = R$.



(a) Consumption

(b) Net worth

Figure E.2: Buffer-stock model: VFI

Note. This figure shows life-cycle profiles of average consumption and average net worth from a buffer-stock model with the calibration from the main text and $\sigma = 2/3$, $\beta = 0.97$, $\rho = 2$ and $\zeta = 1$.

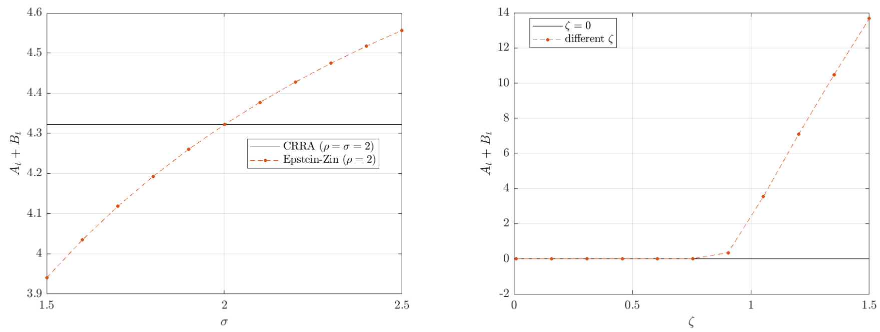
This also aligns well with theory. (1) With no risk the choice of risk aversion (ρ) does not affect the optimal consumption choice. (2) A motive to save for retirement does not affect the Euler-equation, and thus not the growth rate of consumption, but only the level of consumption. (3) When there is no risk and $\eta = R$ then inheritance is a perfect liquidity shock and only the level of consumption should be affected, not its growth rate.

Figure E.2 shows that we obtain very similar life-cycle profiles of average consumption and average net worth when using a simpler, but much slower, Value Function Iteration (VFI) algorithm.

Figure E.3 shows average net worth at retirement when varying σ and ζ. First, we see that when $\rho = \sigma$ then model is the same with CRRA and Epstein-Zin preferences. Second, we see that when $\zeta \to 0$ agents save less and less for retirement, specifically $\lim_{\zeta \to 0} A_{T_R} = 0$.

Figure E.4 shows average net worth at age 45 and at retirement when varying the grid size scaled by j. We see that choosing too sparse grids can result in biased results. Denser grids than in the baseline ($j = 0$) does not affect the results.

Now we turn to the two-asset models. Figure E.5 shows that when $\lambda \to 0$

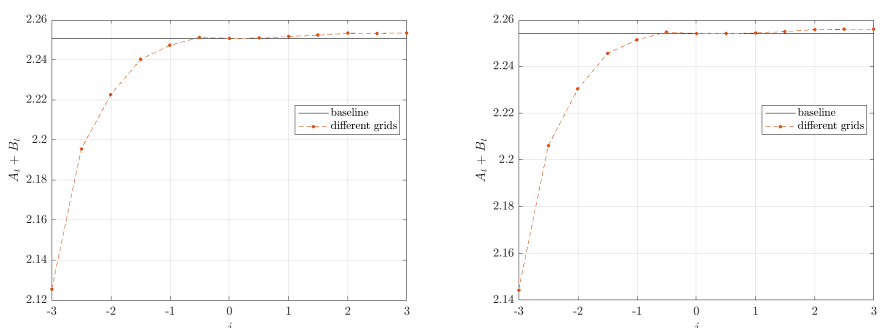


(a) Net worth at retirement

(b) Net worth at retirement

Figure E.3: Buffer-stock model: Varying σ and ζ

Note. This figure shows average net worth at retirement across various σ and ζ starting from a buffer-stock model with the calibration from the main text and $\sigma = 2/3$, $\beta = 0.97$, $\rho = 2$ and $\zeta = 1$.

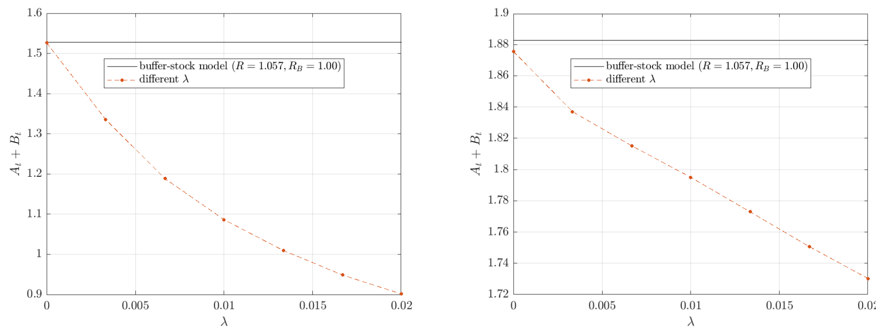


(a) Net worth at age 45

(b) Net worth at retirement

Figure E.4: Buffer-stock model: Grids

Note. This figure shows average net worth at age 45 and retirement across various grid sizes from a buffer-stock model with the calibration from the main text and $\sigma = 2/3$, $\beta = 0.97$, $\rho = 2$ and $\zeta = 1$. Grids are specified as $\#_M = 600 + j \cdot 100$, $\#_P = 150 + j \cdot 40$ and $\#_A = 150 + j \cdot 40$.



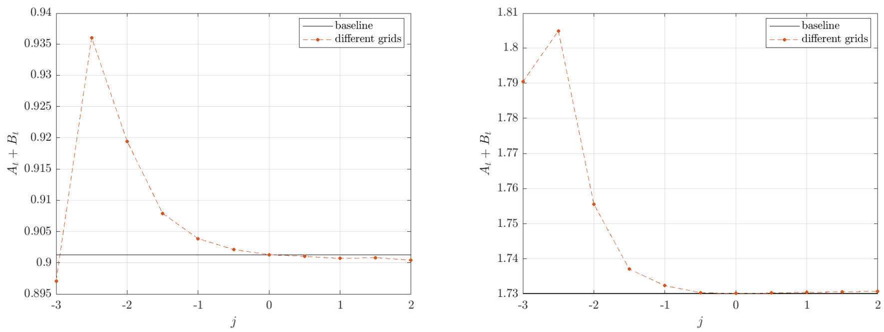
(a) Net worth at age 45 (b) Net worth at retirement

Figure E.5: Two-asset model: $\lambda \to 0$

Note. This figure shows average net worth at age 45 and retirement when $\lambda \to 0$ starting from a two-asset model with the calibration from the main text and $\sigma = 2/3$, $\beta = 0.935$, $\rho = 2$ and $\zeta = 1$.

then average net worth at age 45 and at retirement converge to the levels implied by a buffer-stock model with the same return opportunities. When λ is negligible in a two-asset model there should be no saving in the liquid asset, so this aligns well with theory.

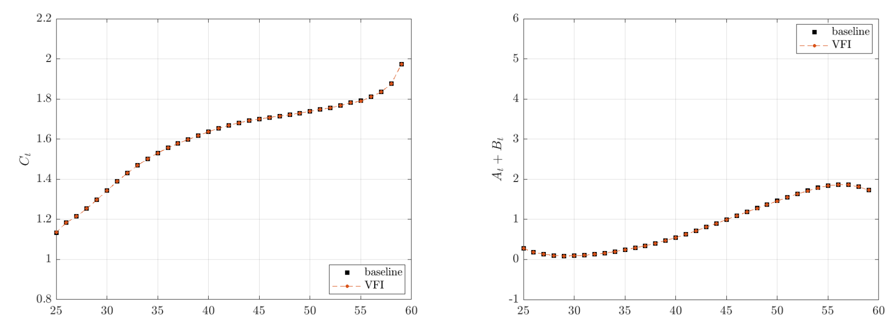
Figure E.5 shows that grids denser than in the baseline does not affect the implied average net worth at age 45 or at retirement. Figure E.7 shows that we obtain very similar life-cycle profiles of average consumption and average net worth when using a simpler, but much slower, Value Function Iteration (VFI) algorithm. Finally, Figure E.8 shows that varying β, ρ, σ, ζ, κ, and σ_ψ imply results in line with economic intuition.



(a) Net worth at age 45 (b) Net worth at retirement

Figure E.6: Two-asset model: Grids

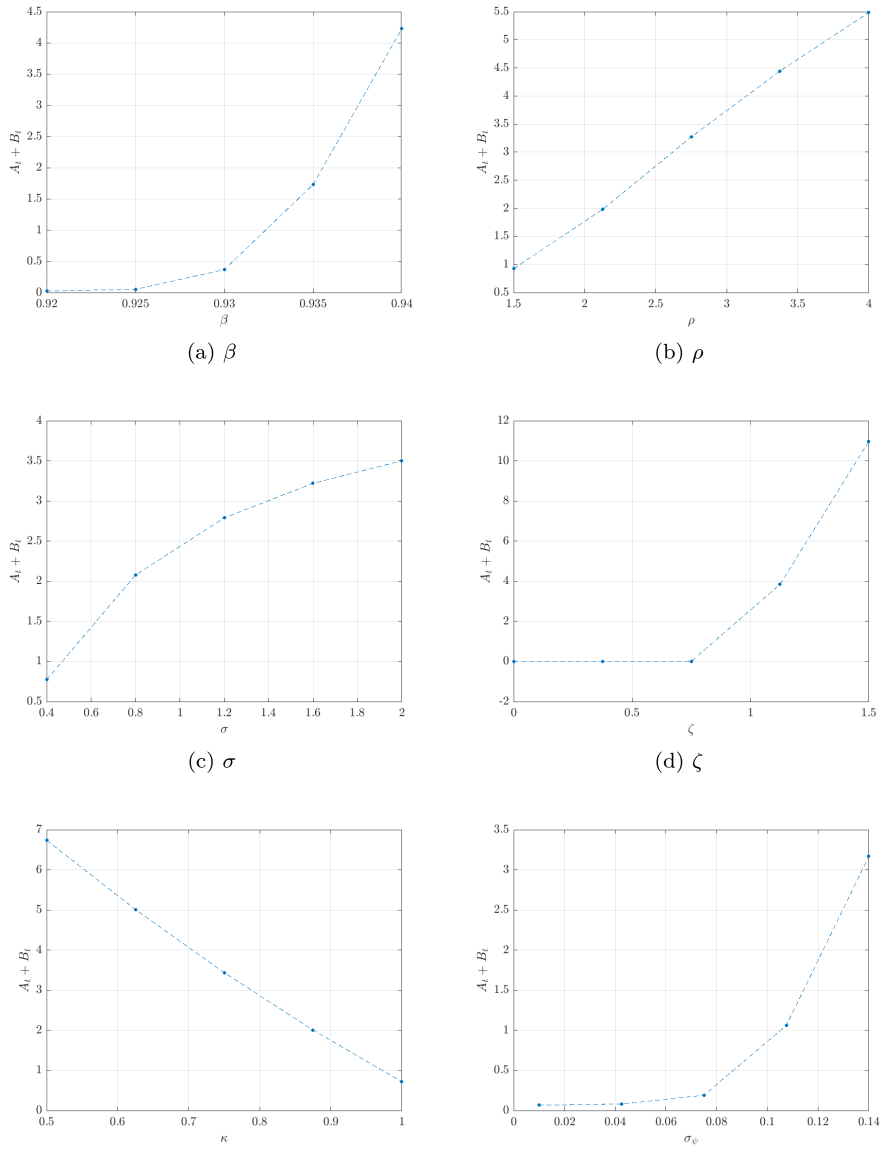
Note. This figure shows average net worth at age 45 and retirement across various grid sizes from a two-asset model with the calibration from the main text and $\sigma = 2/3$, $\beta = 0.935$, $\rho = 2$ and $\zeta = 1$. Grids are specified as $\#_M = 300 + j \cdot 80$, $\#_X = 200 + j \cdot 60$, $\#_P = 150 + j \cdot 40$, $\#_N = 100 + j \cdot 30$, and $\#_A = 100 + j \cdot 30$.



(a) Consumption (b) Net worth

Figure E.7: Two-asset model: VFI

Note. This figure shows life-cycle profiles of average consumption and average net worth from a two-asset model with the calibration from the main text and $\sigma = 2/3$, $\beta = 0.935$, $\rho = 2$ and $\zeta = 1$.



(a) β (b) ρ

(c) σ (d) ζ

(e) κ (f) σ_ψ

Figure E.8: Two-asset model: Varying β, ρ, σ, ζ, κ, and σ_ψ

Note. This figure shows average net worth at retirement starting from a two-asset model with the calibration from the main text and $\sigma = 2/3$, $\beta = 0.935$, $\rho = 2$ and $\zeta = 1$.

F Data Appendix

This appendix contains details with respect to the data and the specific variables used in the analysis of the paper.

The paper exploits confidential administrative register data from Denmark. Researchers can gain similar access by following a procedure described at the Statistics Denmark website. Researchers need to submit a written application to Statistics Denmark. The application should include a detailed research proposal describing the goals and methods of the project, a detailed list of variables, and the selection criteria to be used. Once received, applications must be approved by the Danish Data Protection Agency in order to ensure that data are processed in a manner that protects the confidentiality of registered individuals. Conditional on these approvals, Statistics Denmark will then determine which data one may obtain in accordance with the research plan. All processing of individual data takes place on servers located at Statistics Denmark via secure remote terminal access. Statistics Denmark is able to link individual data from different administrative registers thanks to a unique individual social security code (CPR). While Statistics Denmark provides access to this anonymized data for research purposes, the data is confidential.

We now provide a short description of the variables used in the paper, their construction, and the list of the names of their basic components as defined by Denmark Statistics with a link to its official description (this information is only available in Danish).

Tables F.1 and F.2 reports sources and construction of the variables used in the analysis—with the exception of potential inheritance and permanent income, whose construction we describe next.

In order to identify individuals likely to receive larger inheritances, we follow Andersen and Nielsen (2011, 2012) and calculate a measure of potential inheritance by splitting the wealth holdings of a deceased individual equally among his or her children. For each heir we then calculate the net inheritance after taxes, applying the marginal rate of 15 percent to the portion of inheritance exceeding a tax-free threshold, which varies yearly. The applied tax-free thresholds are reported in Table F.3.[3]

Given parental net worth $networth_p$ at and the number of heirs n_heirs at the time of parental death, we compute potential inheritance as

$$inheritance = \begin{cases} \frac{(0.85\cdot(networth_p - bundfr)+bundfr)}{n\_heirs} & \text{if} \quad networth_p > bundfr \\ \frac{networth_p}{n\_heirs} & \text{if} \quad networth_p \leq bundfr \end{cases}$$

where $bundfr$ is the deduction applicable at the time of parental death. Table F.3 reports the yearly deductions.

We compute permanent income at time t, $perminc_t$, as the weighted average

$$perminc_t = 0.45dispinc_t + 0.25dispinc_{t-1} + 0.15dispinc_{t-2} + 0.10dispinc_{t-3} + 0.05dispinc_{t-4}.$$

We define sudden deaths according to WHO's ICD-10 codes. More specifically, We define a death as sudden if the primary cause of death is coded as I21*-I22*, V*, X*, Y* or R96*.

[3]This calculation is appropriate in Denmark both because a minority of Danes draft a will (Andersen and Nielsen, 2011) and because under Danish law the surviving children are always entitled to a part of the inheritance even in presence of a will (Danish Inheritance Act No. 515 of 06 June 2007 Section 5). Using reported inheritance data in a similar legal and cultural context, Erixson and Ohlsson (2014) show that only few estates in Sweden are not equally divided among surviving children.

Table F.1: Wealth variables definitions

Housing equity	hequity	KOEJD - OBLGAELD-PANTGAELD	The value of real estate owned by the individual minus the amount of collateralized debts (calculated via the market value of the associated bonds at the end of the year)
Liquid assets	liq_assets	BANKAKT	The sum of all cash and savings account held by an individual in Denmark
Uncollateralized debts	debts	BANKGAELD	The sum of all debts not associated to a bond granted by banks in Denmark
Financial wealth	finw	KURSANP + KURSAKT + OBLAKT	The sum of the market value of stocks, bonds and mutual funds directly owned by an individual via an investment account
Net worth	networth	hequity + liq_assets + debts + finw	The sum of housing equity, liquid assets, uncollateralized debts and financial investments. Includes all wealth directly held by an individual. Pension funds and large durable goods as cars and boats are not included

Table F.2: Other outcome variables definitions

Disposable income	BRUTTO + SKAT-FRIYD + AKTIEINDK - SKATMVIALT_NY	Income available for consumption after taxes and transfers
Labor income	ERHVERVSINDK	Labor market income, including bonuses, compensations and income from self-employment
Salary	LOENMV	Part of ERHVERVSINDK, only salary (excludes bonuses and other compensations)
Pension contr - personal	QPRIPEN	Pension contributions to pension funds, personal (voluntary) contributions
Pension contr - employment	QARBPEN	Pension contributions to pension funds from employment scheme (mandatory by employment contract)
Number of children	ANTBOERNH	Number of children aged 17 or less living at home
Spouse	EFALLE | CIVST	Indicator for married status. Includes civil unions

Table F.3: Inheritance deductions and CPI

Year	Deduction (DKK)	CPI
1996	184900	74.43
1997	186000	76.06
1998	191100	77.45
1999	196600	79.41
2000	203500	81.70
2001	210600	83.66
2002	216900	85.62
2003	224600	87.42
2005	231800	88.48
2004	236900	90.03
2006	242400	91.75
2007	248900	93.30
2008	255400	96.49
2009	264100	97.79
2010	264100	100.00
2011	264100	102.78
2012	264100	105.23

NOTE. Deductions for inheritance taxation vary according to the proximity the heir to the deceased. This table reports deductions valid for the direct offspring of the deceased. Deductions are stable between 2009 and 2013, and start increasing again in 2014.

Table G.1: The role of liquidity constraints

Years from shock	-2	1	5	9
Net worth	-0.032	0.826	0.560	0.539
	(0.024)	(0.046)	(0.095)	(0.152)
– Liq. assets	0.044	0.416	0.222	0.251
	(0.006)	(0.019)	(0.021)	(0.033)
– Housing equity	-0.060	0.143	0.141	0.115
	(0.022)	(0.038)	(0.084)	(0.134)
– Fin. investments	-0.001	0.190	0.124	0.105
	(0.005)	(0.016)	(0.019)	(0.030)
– Unc. debts	0.015	-0.077	-0.072	-0.068
	(0.011)	(0.018)	(0.040)	(0.064)

NOTE. The table shows the effect of inheritance on different wealth components two years before and one, five and nine years after parental death. The liquidity constraint sample refers to heirs holding less than one month of permanent income in liquid assets one year before inheriting.

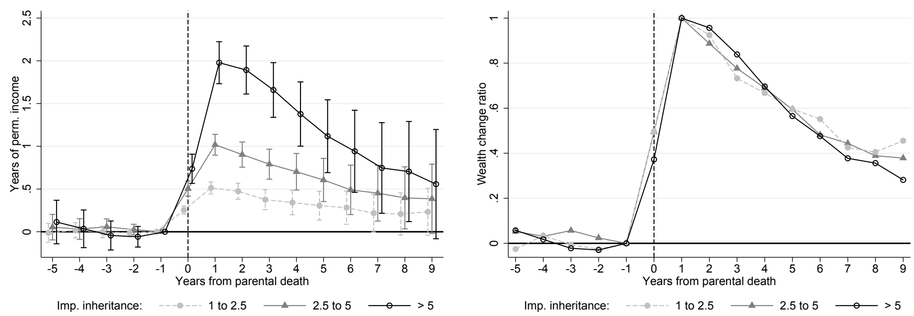
G Extended empirical results

a Further empirical robustness checks

Table G.1 shows that shows that heirs who hold less than a month of permanent income in liquid assets before parental death do not dissipate the excess of wealth accumulated with inheritance quicker that those who are not constrained. If anything, heirs holding relatively little liquid assets before parental death exploit their inheritance to accumulate a buffer stock of liquid assets in the long run and escape their liquidity-constrained state.

Figure G.1 replicates our estimates of the effect of inheritance in the main sample in three subsamples selected according to the imputed potential inheritance. The distribution of potential inheritance appears in Figure G.2. Figure G.1 shows that while the initial shock is naturally increasing with the amount of potential inheritance, once we normalize our estimates by the estimated initial shock $\hat{\gamma}_1^{post}$ the convergence patterns are the same in all subsamples. This figure shows that our results are not solely due to a small fraction of our sample.

Figure G.1: Effect of inheritance on net worth by increasing amounts of potential inheritance

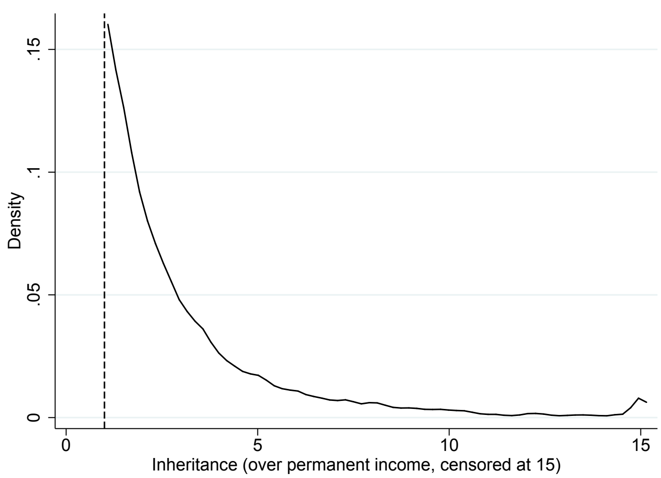


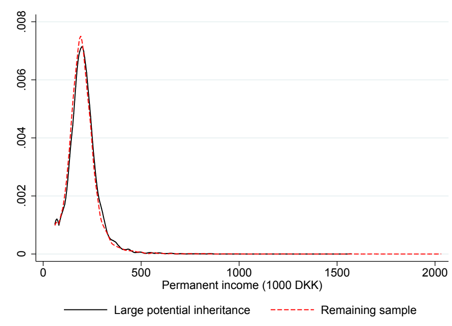
(a) Effect in proportions of permanent income

(b) Effect normalized by $\hat{\gamma}_1^{post}$

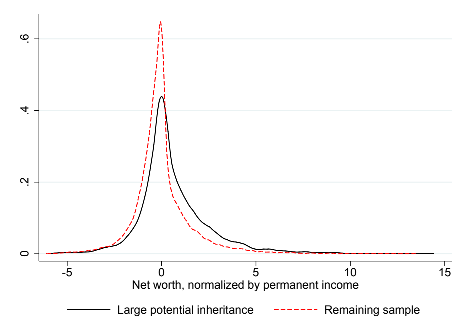
Note. The left panel of the figure show the estimated effects and 95 percent confidence intervals of large unexpected inheritances on the accumulation of net worth for different samples selected according to the amount of potential inheritance. We estimate equation (1) for each sample. In the right panel, we standardize the effects in each sample by the respective estimated initial shock $\hat{\gamma}_1^{post}$.

Figure G.2: Distribution of potential inheritance





(a) Two-asset model



(b) Buffer-stock model

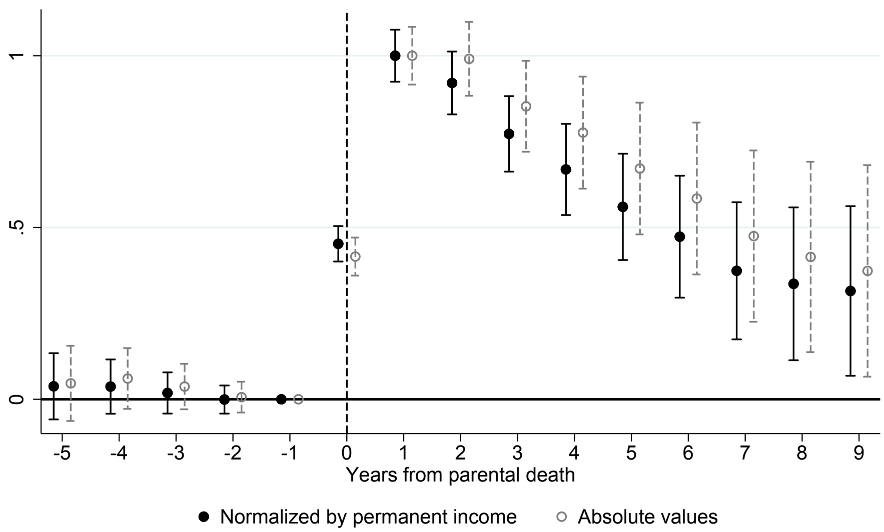
Figure G.3: Distributions of permanent income and normalized wealth before inheritance

NOTE: The figure compares the distributions of permanent income and net worth over permanent income for sudden, unexpected inheritances. The black lines represent these distributions in the sample likely to receive large inheritances, used for the main analysis of the paper. The red dashed lines represent the distribution of the remaining households.

b Extended main results

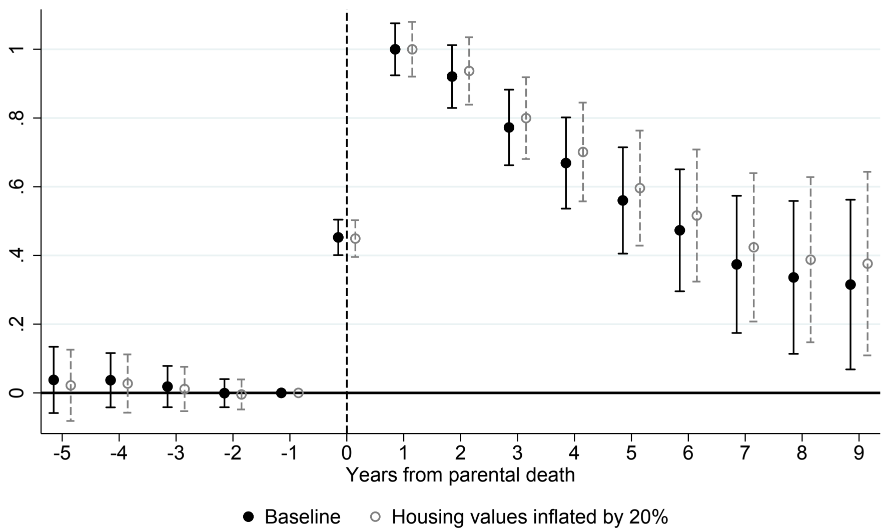
This section displays the set of estimated coefficients γ_n for $n \in \{-5, \ldots, 9\}$ estimated in the empirical section of the paper.

Figure G.4: Convergence of normalized and absolute wealth



NOTE: The figure compares the implied convergence of our estimates on normalized and absolute measures of wealth. The coefficients and confidence intervals shown in the figure are normalized by the effect at $n = 1$, consistently with how we interpret those estimates in the structural models. The coefficients shown in the figure appears in Table 2 in the main text and appendix table G.2.

Figure G.5: Convergence of normalized and absolute wealth



NOTE: The figure compares the implied convergence of our baseline estimates with those obtained on an artificial measure of wealth where we inflate all observed housing values by 20%, to assess the sensitivity of our results to mispricing of housing values by tax authorities. The coefficients and confidence intervals shown in the figure are normalized by the effect at $n = 1$, consistently with how we interpret those estimates in the structural models.

Table G.2: Extended results: Table 2, normalized values

n	Net worth	Liq. assets	Housing equity	Fin. invest.	Unc. Debts
-5	0.033	-0.001	0.020	-0.001	-0.016
	(0.043)	(0.014)	(0.038)	(0.012)	(0.020)
-4	0.032	0.012	0.014	-0.001	-0.007
	(0.035)	(0.013)	(0.031)	(0.010)	(0.016)
-3	0.016	0.006	-0.002	-0.003	-0.015
	(0.027)	(0.010)	(0.024)	(0.007)	(0.012)
-2	-0.001	0.005	-0.002	-0.004	0.000
	(0.018)	(0.007)	(0.017)	(0.005)	(0.008)
0	0.398 **	0.230 **	0.069 **	0.096 **	-0.003
	(0.023)	(0.012)	(0.018)	(0.008)	(0.008)
1	0.879 **	0.389 **	0.184 **	0.265 **	-0.040 **
	(0.034)	(0.015)	(0.027)	(0.014)	(0.014)
2	0.809 **	0.272 **	0.222 **	0.278 **	-0.037 *
	(0.041)	(0.015)	(0.035)	(0.015)	(0.017)
3	0.679 **	0.168 **	0.218 **	0.251 **	-0.042 +
	(0.049)	(0.016)	(0.044)	(0.016)	(0.022)
4	0.588 **	0.108 **	0.191 **	0.247 **	-0.043 +
	(0.059)	(0.018)	(0.052)	(0.018)	(0.025)
5	0.492 **	0.069 **	0.168 **	0.227 **	-0.028
	(0.069)	(0.021)	(0.061)	(0.021)	(0.030)
6	0.416 **	0.037	0.156 *	0.209 **	-0.014
	(0.080)	(0.024)	(0.070)	(0.024)	(0.034)
7	0.329 **	0.012	0.127	0.188 **	-0.001
	(0.089)	(0.026)	(0.078)	(0.026)	(0.038)
8	0.295 **	0.003	0.114	0.187 **	0.009
	(0.100)	(0.030)	(0.087)	(0.030)	(0.043)
9	0.277 *	0.005	0.088	0.182 **	-0.002
	(0.111)	(0.033)	(0.096)	(0.033)	(0.047)

NOTE. Standard errors in parentheses; $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$

Table G.3: Extended results: Table 2, absolute values

n	Net worth	Liq. assets	Housing equity	Fin. invest.	Unc. Debts
-5	8.711	-0.244	8.742	2.570	2.358
	(10.506)	(3.100)	(8.671)	(4.159)	(4.157)
-4	11.386	3.503	9.168	0.241	1.526
	(8.504)	(2.998)	(7.156)	(2.529)	(3.237)
-3	6.974	1.396	4.203	-1.142	-2.517
	(6.352)	(2.054)	(5.478)	(1.819)	(2.318)
-2	1.181	0.960	1.896	-1.071	0.603
	(4.305)	(1.614)	(3.886)	(1.294)	(1.681)
0	78.209 **	44.604 **	12.270 **	20.807 **	-0.528
	(5.314)	(2.359)	(4.221)	(1.863)	(1.631)
1	188.284 **	80.823 **	40.775 **	59.363 **	-7.322 **
	(8.065)	(3.118)	(6.508)	(3.270)	(2.587)
2	186.560 **	62.046 **	52.279 **	67.027 **	-5.208
	(10.328)	(3.380)	(8.577)	(3.991)	(3.269)
3	160.557 **	41.127 **	55.515 **	61.062 **	-2.853
	(12.707)	(3.722)	(11.038)	(4.344)	(4.888)
4	146.127 **	30.115 **	49.737 **	61.659 **	-4.616
	(15.665)	(4.247)	(13.095)	(5.160)	(4.880)
5	126.459 **	21.212 **	44.694 **	57.147 **	-3.405
	(18.418)	(4.962)	(15.290)	(5.866)	(5.670)
6	110.028 **	15.414 **	41.578 *	54.762 **	1.726
	(21.231)	(5.687)	(17.782)	(6.895)	(6.768)
7	89.426 **	10.212	33.924 $^{+}$	51.030 **	5.740
	(23.952)	(6.243)	(20.020)	(7.642)	(7.677)
8	78.007 **	8.250	29.610	51.859 **	11.711
	(26.613)	(7.157)	(22.269)	(8.778)	(9.133)
9	70.358 *	6.012	22.554	49.784 **	7.991
	(29.577)	(7.828)	(24.628)	(9.809)	(9.738)

Note.. Standard errors in parentheses; $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$

Table G.4: Extended results: Table 2, placebo, normalized values

n	Net worth	Liq. assets	Housing equity	Fin. invest.	Unc. Debts
-5	-0.021	0.007	-0.014	0.001	0.015
	(0.026)	(0.007)	(0.022)	(0.004)	(0.015)
-4	-0.006	0.008	-0.004	0.000	0.011
	(0.021)	(0.006)	(0.018)	(0.004)	(0.012)
-3	-0.006	0.006	0.001	0.000	0.012
	(0.016)	(0.005)	(0.015)	(0.003)	(0.010)
-2	-0.005	0.007	-0.004	-0.000	0.008
	(0.011)	(0.004)	(0.010)	(0.002)	(0.006)
0	0.043 **	0.031 **	-0.002	0.004 *	-0.010 $^{+}$
	(0.011)	(0.005)	(0.010)	(0.002)	(0.006)
1	0.035 *	0.022 **	0.001	0.010 **	-0.001
	(0.016)	(0.006)	(0.014)	(0.003)	(0.009)
2	0.018	0.008	-0.003	0.007 $^{+}$	-0.005
	(0.021)	(0.006)	(0.018)	(0.003)	(0.012)
3	0.005	0.001	-0.014	0.008 $^{+}$	-0.010
	(0.026)	(0.008)	(0.023)	(0.004)	(0.015)
4	-0.002	-0.007	-0.010	0.008	-0.007
	(0.032)	(0.009)	(0.028)	(0.005)	(0.018)
5	-0.014	-0.004	-0.019	0.009	-0.001
	(0.037)	(0.011)	(0.032)	(0.006)	(0.021)
6	-0.012	-0.002	-0.025	0.007	-0.008
	(0.043)	(0.012)	(0.037)	(0.006)	(0.024)
7	-0.010	-0.010	-0.020	0.006	-0.014
	(0.049)	(0.014)	(0.042)	(0.007)	(0.028)
8	-0.037	-0.016	-0.038	0.008	-0.010
	(0.055)	(0.015)	(0.047)	(0.008)	(0.031)
9	-0.033	-0.007	-0.037	0.007	-0.004
	(0.061)	(0.018)	(0.052)	(0.009)	(0.034)

NOTE. Standard errors in parentheses; $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$

Table G.5: Extended results: Table 2, placebo, absolute values

n	Net worth	Liq. assets	Housing equity	Fin. invest.	Unc. Debts
-5	-3.514	1.293	-1.938	-0.472	2.397
	(5.883)	(1.616)	(5.064)	(1.043)	(3.321)
-4	-0.462	0.939	0.779	-0.846	1.334
	(4.713)	(1.268)	(4.088)	(0.847)	(2.723)
-3	-0.609	1.410	1.217	-0.628	2.608
	(3.694)	(1.095)	(3.409)	(0.637)	(2.211)
-2	-1.204	1.096	-0.132	-0.493	1.675
	(2.557)	(0.892)	(2.432)	(0.435)	(1.466)
0	7.136 **	5.507 **	-1.543	0.668 +	-2.504 +
	(2.436)	(0.982)	(2.401)	(0.404)	(1.370)
1	6.577 +	4.361 **	-2.360	1.831 **	-2.744
	(3.682)	(1.323)	(3.457)	(0.652)	(2.060)
2	4.997	2.272	-3.012	1.371 +	-4.366
	(4.892)	(1.569)	(4.490)	(0.823)	(2.809)
3	0.876	-0.446	-6.958	1.604	-6.676 +
	(6.553)	(2.274)	(5.932)	(1.039)	(3.863)
4	-1.229	-2.040	-7.355	1.596	-6.570
	(7.906)	(2.647)	(7.113)	(1.245)	(4.719)
5	-4.812	-0.346	-11.742	0.952	-6.324
	(9.280)	(3.204)	(8.186)	(1.391)	(5.530)
6	-5.145	-0.555	-13.151	0.608	-7.953
	(10.699)	(3.544)	(9.451)	(1.564)	(6.386)
7	-3.804	-1.959	-12.429	0.369	-10.215
	(12.177)	(4.019)	(10.743)	(1.741)	(7.166)
8	-10.433	-3.777	-17.311	0.489	-10.165
	(13.634)	(4.527)	(11.958)	(1.985)	(8.041)
9	-10.757	-3.263	-19.560	0.620	-11.446
	(14.990)	(4.973)	(13.279)	(2.208)	(8.989)

Note. Standard errors in parentheses; $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$

Table G.6: Extended results: Table 3

n	Housing equity	Housing value	Home owner	Owner of 2+ units	Mortgage
-5	0.020	-0.062	0.001	0.002	-0.082 $^{+}$
	(0.038)	(0.056)	(0.010)	(0.005)	(0.043)
-4	0.014	-0.034	0.005	0.005	-0.049
	(0.031)	(0.046)	(0.008)	(0.004)	(0.036)
-3	-0.002	-0.027	0.005	0.003	-0.025
	(0.024)	(0.035)	(0.006)	(0.003)	(0.026)
-2	-0.002	-0.018	0.004	0.002	-0.016
	(0.017)	(0.022)	(0.004)	(0.002)	(0.016)
0	0.069 **	0.128 **	0.023 **	0.025 **	0.059 **
	(0.018)	(0.024)	(0.004)	(0.003)	(0.018)
1	0.184 **	0.318 **	0.052 **	0.042 **	0.133 **
	(0.027)	(0.039)	(0.006)	(0.004)	(0.028)
2	0.222 **	0.369 **	0.059 **	0.044 **	0.147 **
	(0.035)	(0.051)	(0.008)	(0.005)	(0.037)
3	0.218 **	0.373 **	0.061 **	0.042 **	0.155 **
	(0.044)	(0.064)	(0.010)	(0.006)	(0.046)
4	0.191 **	0.364 **	0.053 **	0.040 **	0.174 **
	(0.052)	(0.078)	(0.012)	(0.007)	(0.056)
5	0.168 **	0.347 **	0.050 **	0.038 **	0.179 **
	(0.061)	(0.090)	(0.015)	(0.008)	(0.066)
6	0.156 *	0.353 **	0.048 **	0.033 **	0.197 **
	(0.070)	(0.104)	(0.017)	(0.009)	(0.075)
7	0.127	0.353 **	0.052 **	0.030 **	0.226 **
	(0.078)	(0.117)	(0.019)	(0.010)	(0.085)
8	0.114	0.350 **	0.053 *	0.028 *	0.236 *
	(0.087)	(0.130)	(0.021)	(0.011)	(0.096)
9	0.088	0.387 **	0.050 *	0.028 *	0.300 **
	(0.096)	(0.144)	(0.024)	(0.013)	(0.106)

Note. Standard errors in parentheses; $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$

Table G.7: Extended results: Table 4, income and pension contributions

n	Disp. Income	Labor income	Salary	Pension from empl. scheme	Personal pension
-5	4.797 *	6.996 $^{+}$	8.259 *	0.001	0.000
	(2.443)	(4.030)	(3.908)	(0.002)	(0.002)
-4	1.283	4.733	5.068	0.000	0.000
	(1.490)	(3.207)	(3.151)	(0.002)	(0.001)
-3	1.130	3.609	3.399	-0.001	0.001
	(1.160)	(2.525)	(2.443)	(0.002)	(0.001)
-2	0.060	2.265	2.399 $^{+}$	0.000	-0.001
	(0.751)	(1.521)	(1.438)	(0.001)	(0.001)
0	0.667	-0.920	-1.534	0.000	0.003 **
	(0.742)	(1.421)	(1.347)	(0.001)	(0.001)
1	2.115 $^{+}$	-2.974	-3.878 *	-0.002	0.008 **
	(1.114)	(2.038)	(1.946)	(0.001)	(0.002)
2	5.137 **	-0.274	-2.925	-0.003	0.005 **
	(1.773)	(2.797)	(2.709)	(0.002)	(0.002)
3	5.863 **	1.791	-0.455	-0.003	0.003 *
	(1.863)	(3.735)	(3.601)	(0.002)	(0.002)
4	7.259 **	0.933	-0.795	-0.004	0.001
	(2.596)	(4.589)	(4.463)	(0.003)	(0.002)
5	8.522 *	1.297	-1.291	-0.003	0.001
	(4.097)	(5.370)	(5.221)	(0.003)	(0.002)
6	10.783 *	3.894	0.887	-0.002	0.001
	(4.605)	(6.323)	(6.105)	(0.004)	(0.002)
7	7.019 *	3.912	0.380	-0.001	0.001
	(3.407)	(7.007)	(6.794)	(0.004)	(0.002)
8	7.630 *	5.203	1.239	-0.002	0.002
	(3.702)	(7.992)	(7.757)	(0.005)	(0.003)
9	8.096 $^{+}$	7.086	0.930	-0.004	-0.000
	(4.147)	(8.860)	(8.521)	(0.005)	(0.003)

NOTE. Standard errors in parentheses; $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$

Table G.8: Extended results: Table 4, household outcomes

n	Married	# children	Spouse net worth	Household net worth
-5	0.035 (0.060)	0.001 (0.011)	-0.023 (0.103)	-0.036 (0.073)
-4	-0.025 (0.033)	0.000 (0.009)	-0.000 (0.077)	-0.014 (0.055)
-3	0.010 (0.030)	0.003 (0.006)	-0.008 (0.059)	-0.025 (0.041)
-2	0.035 (0.035)	-0.000 (0.004)	-0.028 (0.074)	-0.029 (0.043)
0	0.006 (0.011)	0.003 (0.003)	0.039 (0.047)	0.340 ** (0.032)
1	0.012 (0.027)	0.009 (0.006)	0.092 (0.065)	0.756 ** (0.045)
2	0.005 (0.038)	0.009 (0.008)	0.023 (0.115)	0.685 ** (0.074)
3	-0.023 (0.035)	0.009 (0.011)	0.076 (0.094)	0.624 ** (0.068)
4	-0.002 (0.046)	0.006 (0.013)	0.027 (0.121)	0.560 ** (0.086)
5	-0.003 (0.052)	0.003 (0.015)	-0.061 (0.148)	0.472 ** (0.106)
6	0.037 (0.069)	0.006 (0.018)	-0.042 (0.172)	0.458 ** (0.123)
7	0.014 (0.069)	0.004 (0.020)	-0.113 (0.207)	0.343 * (0.145)
8	0.019 (0.081)	0.005 (0.023)	-0.097 (0.240)	0.346 * (0.168)
9	0.036 (0.094)	0.002 (0.025)	-0.097 (0.263)	0.341 $^{+}$ (0.185)

NOTE. Standard errors in parentheses; $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$

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