

Druedahl, Jeppe; Martinello, Alessandro

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Long-Run Saving Dynamics: Evidence from Unexpected Inheritances

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Department of Economics
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Jeppe Druedahl
Alessandro Martinello

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Long-Run Saving Dynamics: Evidence from Unexpected Inheritances*

Jeppe Druedahl[†] and Alessandro Martinello[‡]

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Abstract

Long-run saving dynamics are a crucial component of consumption-saving behavior. This paper makes two contributions to the consumption literature. First, we exploit inheritance episodes to provide novel causal evidence on the long-run effects of a large financial windfall on saving behavior. For identification, we combine a longitudinal panel of administrative wealth reports with variation in the timing of sudden, unexpected parental deaths. We show that after inheritance net worth converges towards the path established before parental death, with only a third of the initial windfall remaining after a decade. These dynamics are qualitatively consistent with convergence to a buffer-stock target. Second, we analyze our findings through the lens of a generalized consumption-saving framework, and show that life-cycle consumption models can replicate this behavior, but only if the precautionary saving motive is stronger than usually assumed. This result also holds for two-asset models, which imply a high marginal propensity to consume.

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[†]CEBI, Department of Economics, University of Copenhagen, Øster Farimagsgade 5, Building 26, DK-1353 Copenhagen K, Denmark. E-mail: jeppe.druedahl@econ.ku.dk.

[‡]Department of Economics, School of Economics and Management at Lund University and KWC and VIVE, Tycho Brahe Väg 1, Lund, Sweden. E-mail: alessandro.martinello@nek.lu.se.

Life-cycle consumption behavior has been a central area of economic research for decades (Modigliani and Brumberg, 1954 and Friedman, 1957; later Deaton, 1991 and Carroll, 1997). Recent years have seen critical advances in understanding the short-run dynamics of life-cycle models. These advances, obtained by e.g. incorporating illiquid assets in life-cycle models (Kaplan and Violante, 2014), have focused on matching the empirical estimates of short-run consumption responses out of small transitory shocks (Shapiro and Slemrod, 2003; Johnson, Parker and Souleles, 2006; Parker et al., 2013).

By focusing instead on long-run saving dynamics, this paper contributes to the consumption literature in two ways. First, we provide novel reduced-form evidence on the long-run evolution of savings following a large financial windfall. We find that heirs quickly deplete their inheritance, and that net worth converges towards the path established before parental death: only about a third of the initial increase in net worth remains nine years after parental death. Second, we show that life-cycle consumption models can replicate both the amount of wealth people accumulate over their life-cycle and the high depletion rate we observe after inheritance, but only if the precautionary saving motive is stronger than usual. Because life-cycle models are a commonly used tool for evaluating the design of social security, taxation, and pension systems (Heathcote, Storesletten and Violante, 2009), their long-run properties have direct policy implications. Our results imply that these evaluations should rest on models with a stronger than usual precautionary saving motive, and therefore with higher values assigned to private and social insurance mechanisms.

To produce our first contribution, we exploit unexpected inheritance episodes and a unique panel dataset drawn from seventeen years of third-party reported Danish administrative records on individual wealth holdings to estimate the causal effect of large financial shocks on wealth accumulation in the decade following parental death. To identify the causal effect of inheritances, we exploit the random timing of sudden parental deaths due to car crashes, other accidents, and unexpected heart attacks. We then compare the behavior of individuals receiving an inheritance a few years apart from one another.¹

Heirs respond to this sudden, salient, and sizable increase in available financial resources by decreasing their saving efforts in the ten years after inheriting, caus-

¹Fadlon and Nielsen (2015) exploit a similar identification strategy to estimate the effect of health shocks on household labor supply.

ing their net worth to converge back towards the path established before parental death. Moreover, the convergence patterns of different wealth components differ substantially. While heirs quickly deplete their excess of liquid assets, financing consumption or investments in real estate and financial instruments, accumulated wealth in housing equity, stocks, bonds, and mutual funds persists longer.

These findings are qualitatively consistent with convergence to a buffer-stock target. In order to assess their quantitative implications, we analyze them through a general structural consumption-saving framework, which allows for inheritance expectations and a bequest motive (De Nardi, 2004; De Nardi and Yang, 2014). As special cases, this framework nests the standard buffer-stock model (Deaton, 1991; Carroll, 1997; Gourinchas and Parker, 2002), a buffer-stock model with heterogeneous preferences (Krueger, Mitman and Perri, 2016; Carroll et al., 2017), and a two asset model distinguishing between liquid and illiquid wealth (Kaplan and Violante, 2014).

We show that standard parametrizations of the buffer-stock model—with the degree of impatience and the strength of the bequest motive calibrated to match the life-cycle profile of median wealth—are unable to quantitatively reproduce the long-run saving dynamics we document. Holding constant the ability of the model to replicate the empirical life-cycle wealth profile, we show that the buffer-stock model requires a stronger than usual precautionary saving motive to generate a high enough rate of wealth depletion after inheritance. Specifically, we show that buffer-stock models able to replicate both the life-cycle wealth profile and the long-run saving dynamics imply a 25 to 50 percent increase in precautionary savings compared to a standard parametrization, and that agents start accumulating assets for retirement and bequest purposes only in the last 20 years before retirement.

Our results highlight that the long-run saving dynamics provide orthogonal information relative to the life-cycle profile. We show that an appropriate simultaneous increase in impatience, risk aversion, and the strength of the retirement saving and bequest motives does not change the life-cycle profile of wealth: While impatience reduces overall wealth accumulation, higher risk aversion induces more saving early in life, and stronger retirement saving and bequest motives induce more saving late in life (Cagetti, 2003). However, the implied long-run saving dynamics differ sharply across these different combinations of parameters. By evaluating a model by its

ability to replicate not only the life-cycle wealth profile, but also the long-run saving dynamics, we are able to exclude a large set of potential parametrizations.

More specifically, we find that a buffer stock model needs a coefficient of relative risk aversion equal to 6.17 to replicate both sets of empirical moments. While higher than its standard value of 2 (Carroll, 1997; Aaronson, Agarwal and French, 2012; Berger and Vavra, 2015), this coefficient is reasonable and within the range of usual choices. Moreover, adjusting risk aversion is not necessary for replicating our empirical findings. Amplifying the precautionary saving motive through alternative channels, such as the income risk faced by agents, or their beliefs about income risk, achieves the same result. These findings are consistent with recent evidence by Guvenen et al. (2016), who show that estimating a more general income process than the standard permanent-transitory process we use can triple the welfare cost of idiosyncratic income risk.

We further show that our findings also apply to models with heterogeneous patience and to two-asset models. Our results on the two-asset model highlight the conceptual difference between short- and long-run saving dynamics. If the precautionary saving motive is too weak, despite implying a marginal propensity to consume of 37 percent, a two-asset model is worse at replicating the empirical long-run saving dynamics than a single-asset buffer-stock model implying a marginal propensity to consume of just 6 percent. If the precautionary saving motive is strong enough, the two-asset model replicates not only the life-cycle profile of wealth, but also the long-run dynamics of both total and liquid net worth.

This paper adds to the literature studying consumption responses out of liquidity (Gross and Souleles, 2002; Leth-Petersen, 2010) and wealth changes.² Compared to the shocks exploited in this literature, our use of inheritance has the combined advantage of being a sizable, salient, and sudden windfall. Inheritance not only releases enough financial resources to allow intensive and extensive margin responses in both the financial (Andersen and Nielsen, 2011) and housing markets, but also requires no effort or any degree of financial sophistication for agents to be aware of it. Moreover, by focusing on long-run effects, we provide novel evidence compared to the existing short-run estimates of the elasticity of consumption on wealth (Paiella

²Estimates of wealth effects have been performed with both aggregate (Lettau and Ludvigson, 2001; Lettau, Ludvigson and others, 2004) and household-level data (Juster et al., 2006; Browning, Gørtz and Leth-Petersen, 2013; Paiella and Pistaferri, 2016). Jappelli and Pistaferri (2010) provide a detailed review of the evidence.

and Pistaferri, 2016) and housing equity (Mian, Rao and Sufi, 2013; Kaplan, Mitman and Violante, 2016).

The remainder of the paper is organized as follows. Section 1 describes the data we use in our analysis. Section 2 illustrates our identification strategy. Section 3 presents our estimates of the causal effect of inheritance on wealth accumulation in the long run. Section 4 presents a general structural framework of life-cycle consumption-saving behavior augmented with rational inheritance expectations. Section 5 analyzes our reduced-form results through the lens of our structural framework. Section 6 concludes.

1 Data

This paper exploits Danish administrative register data from 1995 through 2012.³ In a unique dataset we combine birth and mortality registers, individual tax returns, housing and land registers, and yearly third-party reports from financial institutions on individual wealth holdings. For every individual in the sample, yearly reports from financial institutions separately record the December 31 market value of liquid assets held in checking and savings accounts, debts with and without collateral, and the sum of financial investments in stocks, bonds and mutual funds. The combination of data on collateralized debts (chiefly mortgages) and data from the land and housing registers provides us with a measure not only of wealth held in housing equity, but also of the number of housing units (apartments, houses, summer homes) owned by each individual in the sample. Moreover, we construct a measure of permanent income computed as a moving weighted average of disposable income after tax and transfers over the previous five years.

In our analysis we focus on individuals likely to inherit amounts large enough to affect savings in the long run. Danish central authorities do not store information on actual inheritance. Therefore, we exploit data on parental wealth at death to identify individuals with large potential inheritance. We follow Andersen and Nielsen (2011, 2012) and calculate a measure of potential inheritance by splitting the wealth holdings of a deceased parent equally among his or her children, and deducting inheritance tax accordingly.⁴ We then use this measure to identify our

³To construct a measure of permanent income we use tax returns from 1991 through 2012 .

⁴Details on this calculation appear in Online Appendix F. This procedure for identifying heirs likely

estimation sample. More specifically, our main sample consists of heirs whose parents die unmarried between 1995 and 2012, and for whom our measure of potential inheritance is larger than their yearly permanent income. To estimate the effect of inheritance on saving dynamics, we use the net worth of these heirs as an outcome and the timing of parental death for identification.

As we observe heirs for up to 10 years after parental death, we focus on individuals inheriting when aged between 25 and 50 years and thus always in working age. We exclude the wealthiest 1 percent of the population because their inheritance structure, saving motives and saving trajectories differ markedly from those of the general population.

In our analysis we focus on unexpected inheritances, defined as those due to a sudden death caused by either violent accidents (e.g. car crashes) or heart attacks for people with no known history of cardiac disease. These deaths, identified according to the WHO's ICD-10 codes, represent about 10 percent of all deaths in the sample.⁵ We thus exploit a total of 6,286 heirs. Table 1 describes the characteristics of heirs one year before parental death according to the type of inheritance received. The first column pools all inheritance episodes in the sample. The second and third columns progressively select inheritance episodes that are unexpected and larger than one year of permanent income.

Table 1 shows that while heirs who receive unexpected inheritances receive similar windfalls and are only slightly poorer than heirs receiving potentially expected inheritances, inheritance size is not random in the population. Heirs who are going to receive larger inheritances are wealthier even before a sudden parental death. This difference, while important for correctly interpreting the results, is consistent with earlier studies (Holtz-Eakin, Joulfaian and Rosen, 1993; Avery and Rendall, 2002; Zagorsky, 2013). As a consequence, we restrict our analysis to heirs receiving sizable inheritances, and use heirs receiving small or no bequests as a placebo rather than as a control.

to receive large inheritances has the advantage of circumventing the potential endogeneity of inheritance if parents allocate bequests strategically among their children (Bernheim, Shleifer and Summers, 1985; Francesconi, Pollak and Tabasso, 2015). This approach is similar to that adopted by Boserup, Kopczuk and Kreiner (2016) in studying the role of inheritance in shaping wealth inequality in Denmark.

⁵The ICD-10 codes defining a death as sudden are I21*-I22*, V*, X*, Y* and R96*.

Table 1: Inheritance and heir characterization, one year before parental death

	All	Unexpected inheritance	
		All	Sizable pot. inheritance
Permanent income, 1000 DKK	207.628	202.391	205.363
Net worth, normalized	0.250	0.195	0.636
– Liquid assets, normalized	0.229	0.216	0.304
– Uncollateralized debts, normalized	0.596	0.585	0.515
– Financial investments, normalized	0.061	0.056	0.095
– Housing equity, normalized	0.556	0.508	0.752
– Housing value, normalized	1.895	1.776	2.166
– Mortgage, normalized	1.339	1.268	1.414
– Home owner	0.507	0.501	0.571
– Owner of 2+ units	0.051	0.046	0.058
Disposable income, 1000 DKK	212.878	207.583	210.379
Married	0.467	0.462	0.518
Year of inheritance	2003.669	2002.641	2002.609
Age at inheritance	39.890	39.307	40.615
Parental age at death	70.994	70.639	74.022
# individuals	223355	21750	6286

NOTE. Unexpected inheritances are those due to sudden parental death. Sizable potential inheritances are those larger than one year of the permanent income of the heir. Permanent and disposable income are in thousands DKK. In 2012 (December 31), one USD was equal to 5.64 DKK. All wealth measures are normalized by permanent income.

2 Identification

Estimating the causal effect of inheritance on wealth accumulation is challenging for three reasons. First, unlike extraordinary transitory income shocks such as lottery winnings (Cesarini et al., 2017; Imbens, Rubin and Sacerdote, 2001), individuals may expect to receive an inheritance at some point in their life. Second, heirs could predict the time of parental death, for example in cases of terminal illness, and react to it in advance. Third, inheriting from a parent requires parental death, an event that may affect individual wealth accumulation independently from the wealth transfer.

The first challenge stresses the danger of comparing the behavior of heirs with that of other individuals in the population, some of whom might already have inherited and thus do not expect another such windfall in their lifetime. While Andersen and Nielsen (2011, 2012) use a matching algorithm to find a suitable control group of non-heirs for their sample of heirs, this strategy relies heavily on the conditional

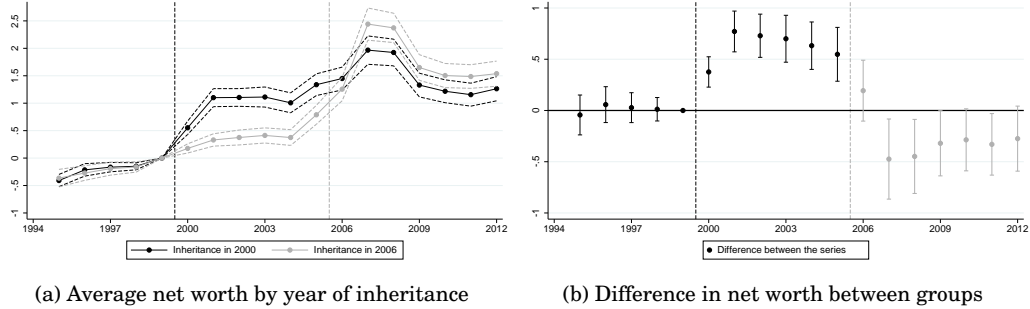


Figure 1: Identification strategy: An example

NOTE. The figure shows the average change with respect to 1999 in individual net worth of heirs inheriting more than one year of their permanent income in 2000 and 2006 due to a sudden parental death. The units of the vertical axes are years of permanent income.

independence assumption. To ensure the internal validity of our results, we focus instead on a homogeneous sample that by construction has similar expectations. All heirs in our sample inherit a comparable inheritance between 1996 and 2012, and all know that they will inherit at some point in the future. Thus they differ only in the timing of parental death. This identification strategy exploits the randomness in the timing of parental death and is similar to that used by Fadlon and Nielsen (2015) to estimate the effect of health shocks on household labor market supply and by Johnson, Parker and Souleles (2006), Agarwal, Liu and Souleles (2007), and Parker et al. (2013) to estimate the effect of tax rebates on short-term consumption.

To tackle the second concern and to ensure that heirs do not anticipate—and thus react in advance to—the timing of parental death, we perform our analysis on a sample of heirs inheriting because of sudden deaths, as defined in Section 1. Moreover, the long panel of yearly wealth observations allows us to check for anticipatory behavior by analyzing wealth accumulation trends in the years preceding parental death.

To deal with the third challenge and show that parental death alone does not affect the wealth accumulation strategies of heirs, we replicate our analysis on a sample of heirs whose parents died with little or no wealth to leave as a bequest. This placebo analysis reinforces the validity of our identification strategy: If our strategy cleanly identifies the effect of inheritances, then the placebo should have zero effect on wealth accumulation patterns in the medium and long run.

Figure 1 illustrates our identification strategy. In the left panel of the figure we compare the evolution of average net worth (normalized by permanent income) of individuals inheriting more than one year of permanent income in 2000 and 2006, respectively. In this example, individuals inheriting in 2000 represent the treated group. Individuals inheriting in 2006 act as a natural control group through 2005. Both groups inherit because of a sudden parental death. The right panel of Figure 1 shows the difference between the two groups, effectively identifying the effect of receiving an inheritance in 2000 on wealth accumulation between 2000 and 2005.

The difference-in-differences (DiD) approach of Figure 1 works by eliminating confounding year and group (or individual) fixed effects. However, this approach exploits a limited subset of the information available in the data. Observations after 2005 are not used, and the data contains more combinations across years of inheritance than that in Figure 1. To fully exploit the available information while maintaining the identification of Figure 1, we describe the wealth holdings y at year t of an individual i inheriting at time τ_i as

$$y_{i,t} = \gamma_{<-5} \mathbf{1}[t - \tau_i < -5] + \sum_{n=-5}^{-2} \gamma_n^{pre} \mathbf{1}[t - \tau_i = n] + \sum_{n=0}^9 \gamma_n^{post} \mathbf{1}[t - \tau_i = n] + \Lambda_{i,t} + \Psi_i + \varepsilon_{i,t}, \quad (1)$$

where Ψ_i and $\Lambda_{i,t}$ are respectively individual and year-by-cohort fixed effects. The reference category for the set of coefficients γ_n^{pre} and γ_n^{post} , which estimate the effect of inheritance n years before and after parental death respectively, is one year before parental death, or $n = -1$. In all estimations we allow for arbitrary autocorrelation of errors $\varepsilon_{i,t}$ within individuals.

Our approach can be viewed as an event study with separately identifiable year(-by-cohort) fixed effects. However, while this approach maintains the identification argument and the assumptions (crucially, that of common trends) of a standard DiD, it has two advantages over the DiD approach. First, for a given comparison of inheritance-year groups, we exploit the ordered structure of dynamic effects to identify the effect of inheritance beyond the point in time at which the control group receives its inheritance.⁶ Second, we can include all available data in the same esti-

⁶Intuitively, in Figure 1, this approach means decomposing the difference between groups in, e.g., 2008 as the sum of γ_8^{post} for the treated group and γ_2^{post} for the control group. If the sequence of γ_n^{post} is the same for heirs inheriting in different years and if γ_2^{post} is identified by the group comparison in 2002, then γ_8^{post} can also be identified.

mation, thereby exploiting more combinations across time of inheritance τ_i .⁷

Our approach has two related consequences. First, effects for small n are identified by more combinations over τ_i than effects for high n . Our estimates are thus more precise as n approaches zero. Therefore, we focus on the first 10 years after parental death and exclude all observations for which $n > 9$, as after this period the estimation is too imprecise for a meaningful interpretation of the results. Second, the control group varies at each n . We show that the varying control group over n does not drive our result both by performing a placebo estimation for individuals inheriting small or zero wealth, and by replicating our results while enforcing a (balanced) fixed control group over n (thus replicating the identification of Fadlon and Nielsen, 2015). While more imprecisely estimated, the results obtained following this second approach are virtually identical to those resulting from estimating equation (1) on the same sample. This second robustness check appears in Table 8 in Appendix A.

3 The causal effect of inheritance

This section reports the causal effect of inheritance on long-run saving dynamics, and demonstrate the robustness of our results to alternative explanations. We proceed in three steps. First, we present our main empirical results, obtained on the sample of heirs for whom our measure of potential inheritance is larger than a year of their permanent income. Second, we test the validity of our identification strategy and exclude that parental death alone drives our results by performing a placebo test. Third, we exclude that confounding factors such as endogenous labor supply responses or committed expenditures drive our results.

Figure 2 presents the main empirical results of the paper. The scales of all vertical axes refer to years of permanent income.⁸ The top left panel of Figure 2 shows the effect of inheritance on net worth up to ten years after parental death. Heirs deplete most of the initial burst of wealth obtained through inheritance within six years of parental death, and continue a gradual convergence towards the path established before parental death throughout our estimation period.

⁷A step-by-step dissection of our identification strategy, and on how it nests the approach of Fadlon and Nielsen (2015), appears in Online Appendix C.

⁸We show in Table 2 that the normalization with permanent income is not important for our results but simplifies the interpretation.

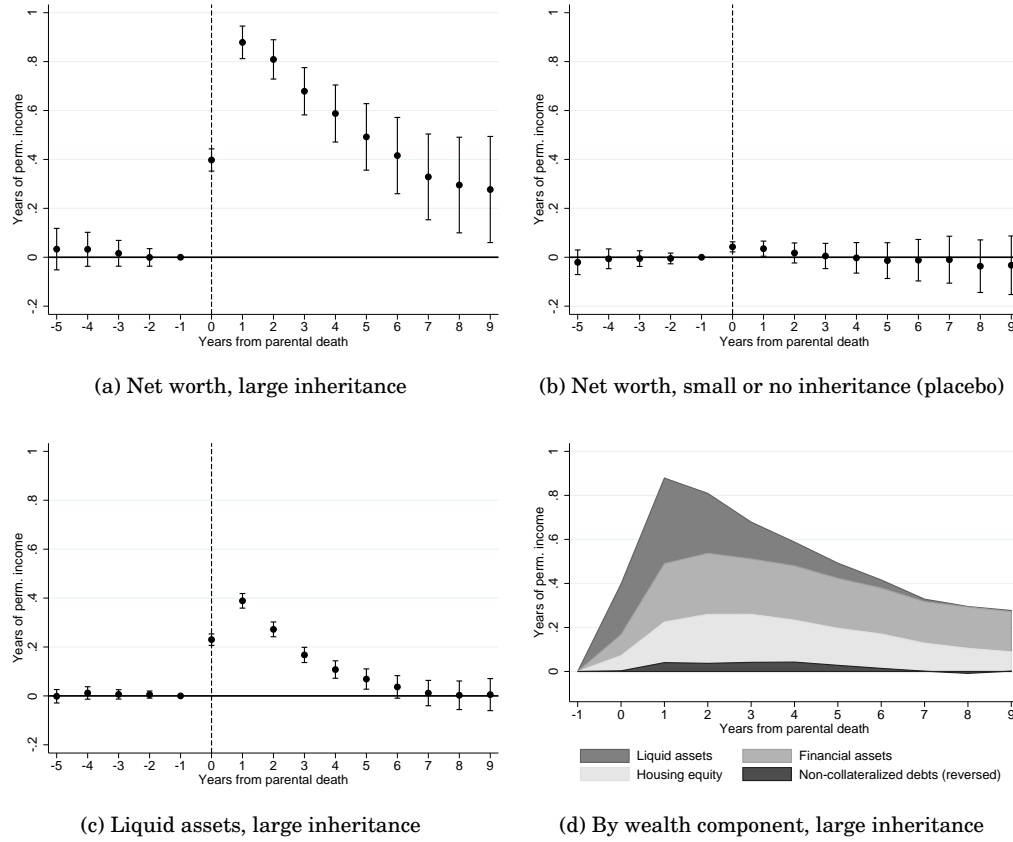


Figure 2: The effect of inheritance on wealth accumulation

NOTE. The left panels of the figure show the estimated effects and 95 percent confidence intervals of large unexpected inheritances on the accumulation of net worth and liquid assets respectively. The top right panel shows the estimated effects and 95 percent confidence intervals of a small inheritance on wealth accumulation. These effects are estimated according to equation (1) both before and after parental death. Standard errors are clustered at the individual level. The bottom right panel of the figure decomposes the effects shown in the top left panel in the period after parental death into its main components. The scale of all vertical axes refer to years of permanent income.

Table 2: The effect of inheritance on wealth accumulation

Years from shock	Absolute values (thousands of Danish Kroner)				Normalized values (years of permanent income)			
	-2	1	5	9	-2	1	5	9
<i>Panel A: Potential inheritance larger than a year of perm. income</i>								
Net worth	1.181 (4.305)	188.284 (8.065)	126.459 (18.418)	70.358 (29.577)	-0.001 (0.018)	0.879 (0.034)	0.492 (0.069)	0.277 (0.111)
– Liq. assets	0.960 (1.614)	80.823 (3.118)	21.212 (4.962)	6.012 (7.828)	0.005 (0.007)	0.389 (0.015)	0.069 (0.021)	0.005 (0.033)
– Housing equity	1.896 (3.886)	40.775 (6.508)	44.694 (15.290)	22.554 (24.628)	-0.002 (0.017)	0.184 (0.027)	0.168 (0.061)	0.088 (0.096)
– Fin. investments	-1.071 (1.294)	59.363 (3.270)	57.147 (5.866)	49.784 (9.809)	-0.004 (0.005)	0.265 (0.014)	0.227 (0.021)	0.182 (0.033)
– Unc. debts	0.603 (1.681)	-7.322 (2.587)	-3.405 (5.670)	7.991 (9.738)	0.000 (0.008)	-0.040 (0.014)	-0.028 (0.030)	-0.002 (0.047)
<i>Panel B: Potential inheritance smaller than a month of perm. income (placebo)</i>								
Net worth	-1.204 (2.557)	6.577 (3.682)	-4.812 (9.280)	-10.757 (14.990)	-0.005 (0.011)	0.035 (0.016)	-0.014 (0.037)	-0.033 (0.061)
– Liq. assets	1.096 (0.892)	4.361 (1.323)	-0.346 (3.204)	-3.263 (4.973)	0.007 (0.004)	0.022 (0.006)	-0.004 (0.011)	-0.007 (0.018)
– Housing equity	-0.132 (2.432)	-2.360 (3.457)	-11.742 (8.186)	-19.560 (13.279)	-0.004 (0.010)	0.001 (0.014)	-0.019 (0.032)	-0.037 (0.052)
– Fin. investments	-0.493 (0.435)	1.831 (0.652)	0.952 (1.391)	0.620 (2.208)	-0.000 (0.002)	0.010 (0.003)	0.009 (0.006)	0.007 (0.009)
– Unc. debts	1.675 (1.466)	-2.744 (2.060)	-6.324 (5.530)	-11.446 (8.989)	0.008 (0.006)	-0.001 (0.009)	-0.001 (0.021)	-0.004 (0.034)

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 full set of coefficients appears in Online Appendix G. The coefficients are estimated according to equation (1). The coefficients in the top panel are estimated on a sample of heirs receiving unexpected inheritances larger than one year of the heir's permanent income; those in the bottom panel, on a sample of heirs receiving unexpected inheritances smaller than a month of permanent income. The specification includes individual and year-by-cohort fixed effects. Standard errors, clustered at the individual level, are shown in parentheses.

We separately analyze the convergence pattern of liquid assets held in checking and saving accounts. The bottom left panel of Figure 2 shows that the effect of inheritance on liquid assets disappears within seven years of parental death. These assets are either consumed or invested in other types of assets, and explain the majority of the convergence of total net worth. The bottom right panel of the figure, which decomposes the effect of inheritance on total net worth, shows that changes in housing equity and financial investments (stocks, bonds, and mutual funds) due to inheritance instead persist over time, suggesting that these vehicles are the preferred ones for channeling and investing long-term life-cycle savings.

The top panel of Table 2 expands the results in Figure 2 for all wealth compo-

Table 3: Dynamics of housing equity components

Years from shock	-2	1	5	9
Housing equity	-0.002 (0.017)	0.184 (0.027)	0.168 (0.061)	0.088 (0.096)
– Housing value	-0.018 (0.022)	0.318 (0.039)	0.347 (0.090)	0.387 (0.144)
– Home owner	0.004 (0.004)	0.052 (0.006)	0.050 (0.015)	0.050 (0.024)
– Owner of 2+ units	0.002 (0.002)	0.042 (0.004)	0.038 (0.008)	0.028 (0.013)
– Mortgage	-0.016 (0.016)	0.133 (0.028)	0.179 (0.066)	0.300 (0.106)

NOTE. The table shows the effect of inheritance on several outcomes measured two years before and one, five and nine years after parental death. The full set of coefficients appears in Online Appendix G. The coefficients are estimated according to equation (1) on a sample of unexpected inheritances larger than one year of the heir's permanent income. The specification includes individual and year-by-cohort fixed effects. Standard errors, clustered at the individual level, are shown in parentheses.

nents. The table shows four $\hat{\gamma}_n \equiv (\gamma_n^{pre}, \gamma_n^{post})$ coefficients (from equation 1) describing, respectively, eventual anticipatory behavior one year before parental death, the burst of wealth due to inheritance one year after parental death, and the evolution of wealth components in the medium run (five years after parental death) and the long run (nine years after parental death).⁹ Because inheritance is not always received in the same year of parental death, the effect of inheritance on accumulated wealth one year after parental death provides a reference for interpreting the start of the convergence process.

The left part of the table shows the effect of inheritance on nominal wealth in thousands DKK. The right part of the table shows the effect of inheritance on wealth normalized by permanent income. The convergence pattern is the same in both sets of results, demonstrating that these results do not depend on the permanent income normalization.

The effect of inheritance on the accumulation of housing equity is not as straightforwardly interpretable. By separately analyzing the components of housing equity, Table 3 provides the necessary details to describe this convergence process. The table shows that although total housing value increases over time following parental death, mortgages increase more than proportionally. The response at the extensive margins provides the key mechanism: While the proportion of individuals owning

⁹The full list of coefficients for all regressions appears in Online Appendix G.

any real estate increases by 5 percent after inheritance and remains stable in the following years, the number of people owning more than one real estate unit decreases over time after the initial jump due to inheritance. These patterns suggest that heirs sell excess housing units not only to finance consumption but also to upgrade their main estate and climb the property ladder, maxing out their mortgage debt in the process.

We demonstrate that invalid identification or parental death alone do not affect wealth holdings in the bottom panel of Table 2. Here we replicate the analysis on a sample of individuals receiving little or no inheritance. We show that a parental death associated with an inheritance worth less than a month of permanent income does not affect trends of wealth accumulation, and has only a negligible impact on assets held one year after parental death. We estimate that heirs receiving such small inheritances accumulate an excess worth of 3.5 percent of yearly permanent income one year after parental death, depleting it within a year.

Similarly, Table 4 shows that other changes in inflows and outflows of individual resources as a response to inheritance are unable to explain our results. Holtz-Eakin, Joulfaian and Rosen (1993) show that large inheritances can lead to lower labor market participation, and Cesarini et al. (2017) and Imbens, Rubin and Sacerdote (2001) show that lottery winnings decrease labor supply, reducing the inflow of resources to the household. We find no evidence of inheritance reducing yearly disposable income after tax and transfers, and only a small short-term effect of inheritance on gross yearly salary (gross earnings minus income from self-employment, bonuses and professional fees). This short-run effect is comparable in magnitude with that estimated by Cesarini et al. (2017) on a sample of Swedish lottery winners, but disappears after two years from parental death.

Finally, Table 4 shows that endogenous household formation or sudden increased contributions to pension funds do not explain the convergence patterns shown in Table 2. Marriage rates and fertility remain stable around parental death and net worth is not transferred to spouses. Moreover, while we cannot directly observe wealth held in pension funds, Panel 3 of Table 2 show that contribution flows to individually managed pension funds increase on average of only 0.8 percent of permanent income one year after parental death and fade out quickly thereafter, for a cumulative impact of 2.5 percent of permanent income in five years.

Table 4: Other budget incomings and outgoings

Years from shock	-2	1	5	9
<i>Panel A: Income and labor supply (1000DKK)</i>				
Net disposable income	0.060 (0.751)	2.115 (1.114)	8.522 (4.097)	8.096 (4.147)
Gross earnings	2.265 (1.521)	-2.974 (2.038)	1.297 (5.370)	7.086 (8.860)
Gross salary	2.399 (1.438)	-3.878 (1.946)	-1.291 (5.221)	0.930 (8.521)
<i>Panel B: Pension contributions (fraction of perm. income)</i>				
Employment scheme	0.000 (0.001)	-0.002 (0.001)	-0.003 (0.003)	-0.004 (0.005)
Personal funds	-0.001 (0.001)	0.008 (0.002)	0.001 (0.002)	-0.000 (0.003)
<i>Panel C: Household composition</i>				
Married	-0.000 (0.004)	0.009 (0.006)	0.003 (0.015)	0.002 (0.025)
# children	0.035 (0.035)	0.012 (0.027)	-0.003 (0.052)	0.036 (0.094)
Spouse net worth ^a	-0.028 (0.074)	0.092 (0.065)	-0.061 (0.148)	-0.097 (0.263)
Household net worth ^b	-0.029 (0.043)	0.756 (0.045)	0.472 (0.106)	0.341 (0.185)

NOTE. The table shows the effect of inheritance on several outcomes measured two years before and one, five and nine years after parental death. The full set of coefficients appears in Online Appendix G. The coefficients are estimated according to equation (1) on a sample of unexpected inheritances larger than one year of the heir's permanent income. The specification includes individual and year-by-cohort fixed effects. Standard errors, clustered at the individual level, are shown in parentheses.

^aThese results are estimated on a sample restricted to individuals that are either married or in a registered partnership.

^bThese results are estimated on the unrestricted sample (i.e., singles are included), but only for the years for which the household composition is identical with that observed the year before parental death. Household net worth is normalized by household permanent income.

Overall, labor supply and committed expenditures do not explain the long-run convergence dynamics of wealth after large financial shocks. These causally estimated patterns represent a novel empirical moment that life-cycle consumption models should be able to replicate. Qualitatively, the observed patterns of wealth convergence are consistent with convergence to a buffer-stock target. In the remainder of the paper we show that, quantitatively, standard parametrizations of life-cycle models imply too little convergence with respect to what we observe empirically.

4 A general consumption-saving framework

This section describes the modeling framework we use to draw insights from the long-run dynamics of saving estimated in the previous section. Our starting point is the single-asset buffer-stock consumption model of Deaton (1991, 1992) and Carroll (1992, 1997, 2012), with a flexible retirement value function similar to Gourinchas and Parker (2002). To account for inheritance expectations, we augment the standard model with an exogenous process for receiving inheritance. We assume that the agents are fully aware of this process and thus have rational expectations. We further generalize this model by considering both heterogeneity in the discount factor¹⁰ and a two-asset version of the model distinguishing between liquid and illiquid assets as in Kaplan and Violante (2014) and Kaplan, Moll and Violante (2018). These two extensions strengthen the baseline model's ability to match short-run saving dynamics (i.e., the marginal propensity to consume). They further allow us to fit the distribution of wealth over the life-cycle, and to investigate heterogeneous saving dynamics across asset types.

4.1 The model

The economy is populated by a continuum of individuals indexed by i and working for T_R periods, $t \in \{1, 2, \dots, T_R\}$. All individuals have Epstein-Zin preferences with $1/\sigma$ as the elasticity of intertemporal substitution and ρ as the relative risk aversion coefficient. The discount factor is denoted β_i . We assume that the discount factor is uniformly distributed with $[\beta - \Delta, \beta + \Delta]$, where $\Delta = 0$ is the baseline case of homogeneous preferences.

Individuals can always save in and borrow from a liquid asset, A_t . Saving in the liquid asset provides a risk-free gross return of R , and borrowing from it costs a gross interest rate of $R_- > R$. The individual can borrow up to a fraction ω of his permanent income P_t , but cannot retire with debt, such that

$$A_t \geq -\omega P_t. \tag{2}$$

$$A_{T_R} \geq 0$$

¹⁰In practice, we discretize the heterogeneity into five types. Similar approaches are used by Carroll et al. (2017) and Krueger, Mitman and Perri (2016).

In the two-asset versions of the model, the individual can additionally save in, but not borrow from, an illiquid asset B_t providing a risk-free gross return of $R_B > R$. To transact in the illiquid asset, the individual must pay a fixed adjustment cost of $\lambda \geq 0$.

Labor earnings are given by a standard permanent-transitory income process

$$Y_t = P_t \xi_t \quad (3)$$

$$P_t = G_{t-1} P_{t-1} \psi_t \quad (4)$$

where

$$\log \psi_t \sim \mathcal{N}(-0.5\alpha^2\sigma_\psi^2, \alpha^2\sigma_\psi^2)$$

$$\log \xi_t \sim \mathcal{N}(-0.5\alpha^2\sigma_\xi^2, \alpha^2\sigma_\xi^2),$$

and G_{t-1} is the common deterministic age-specific growth factor of income. The parameter α scales the volatility of the permanent and transitory income shocks, and thus allow us to parsimoniously vary the strength of the precautionary saving motive by amplifying income risk. Similarly, we introduce the parameter $\tilde{\alpha}$, which scales the agent's belief regarding the volatility of the permanent and transitory income shocks.

To account for inheritance expectations, consistently with the assumptions of our empirical analysis we assume that the agents know the size of the inheritance they will receive but are uncertain about its timing. Let $d_t \in \{0, 1\}$ denote whether or not the individual's parent has died: If $d_t = 0$, the last parent is still alive in the beginning of period t . We denote the age-dependent chance of receiving the age-dependent inheritance H_t at the end of the period t by π_t , and model the parental age at death as a normal distribution with mean μ_H and standard deviation σ_H . Given the age difference between child and the parent δ_H , this distribution determines the life-cycle profile of the probability of receiving inheritance. The beginning-of-period levels of cash-on-hand and illiquid wealth are thus given by

$$M_{t+1} = R(A_t)A_t + Y_{t+1} + H_t \mathbf{1}_{d_t=0} \mathbf{1}_{d_{t+1}=1} \quad (5)$$

$$N_{t+1} = R_B B_t. \quad (6)$$

To model the motive to save for retirement and bequests flexibly we use the analytical solution to a frictionless perfect foresight problem to compute the consumption and value functions in the terminal period T_R . Specifically, we assume that agents live in retirement from period T_R to T with pension benefits as a fraction, κ , of their permanent income at retirement, P_{T_R} , and that their utility function in retirement is scaled by the taste shifter $\zeta \geq 0$. The parameter ζ controls the strength of the retirement saving motive. For $\zeta = 0$, there is thus no retirement saving or bequest motive, while for $\zeta = 1$, the only motive is consumption smoothing in retirement. Values of $\zeta > 1$ represents additional saving motives due to, e.g., bequest or non-modeled uncertainty. Details on the consumption and value functions in the terminal period appear in Appendix B.

4.2 Recursive formulation

Defining the post-decision value function

$$W_t \equiv \begin{cases} \mathbb{E}_t[V_{t+1}(\bullet)] & \text{if } \rho = \sigma \\ \mathbb{E}_t[V_{t+1}(\bullet)^{1-\rho}]^{\frac{1}{1-\rho}} & \text{else} \end{cases}. \quad (7)$$

the recursive formulation of the model is

$$\begin{aligned}
V_t(M_t, N_t, P_t, d_t) &= \max_{C_t, B_t} \begin{cases} C_t^{1-\rho}/(1-\rho) + \beta_i W_t & \text{if } \rho = \sigma \\ [(1-\beta_i)C_t^{1-\sigma} + \beta_i W_t^{1-\sigma}]^{\frac{1}{1-\sigma}} & \text{else} \end{cases} \quad (8) \\
\text{s.t.} & \\
A_t &= M_t - C_t + (N_t - B_t) - \mathbf{1}_{B_t \neq N_t} \lambda \\
M_{t+1} &= R(A_t)A_t + Y_{t+1} + H_t \mathbf{1}_{d_t=0} \mathbf{1}_{d_{t+1}=1} \\
Y_t &= \xi_{t+1} P_t, \quad \log \xi_{t+1} \sim \mathcal{N}(-0.5 \tilde{\alpha}^2 \alpha^2 \sigma_\xi^2, \tilde{\alpha}^2 \alpha^2 \sigma_\xi^2) \\
P_t &= G_{t-1} P_{t-1} \psi_t, \quad \log \psi_{t+1} \sim \mathcal{N}(-0.5 \tilde{\alpha}^2 \alpha^2 \sigma_\psi^2, \tilde{\alpha}^2 \alpha^2 \sigma_\psi^2) \\
N_{t+1} &= R_B B_t \\
\Pr[d_{t+1} = 1] &= \begin{cases} 1 & \text{if } d_t = 1 \\ \pi_t & \text{else} \end{cases} \\
B_t &\geq 0 \\
A_t &\geq -\omega P_t \\
A_{T_R} &\geq 0.
\end{aligned}$$

We solve the single-asset buffer-stock model by using the endogenous grid method originally presented in Carroll (2006). We solve the two-asset buffer-stock model by using an extended endogenous grid method proposed in Druedahl (2018), which builds on extensions of the endogenous grid method to non-convex (Fella, 2014; Iskhakov et al., 2017) and multi-dimensional (Druedahl and Jørgensen, 2017) models. Online Appendix E provides details on these methods.

4.3 Calibration

We calibrate the model in two steps. In the first step we externally fix all parameters except for the preference parameters $(\beta, \rho, \sigma, \zeta, \Delta)$ and the scaling parameters α and $\tilde{\alpha}$, which we internally calibrate in a second step (see Section 5). The fixed and externally calibrated parameters appear in Table 5. The fits of the exogenous income and inheritance processes appear in Online Appendix D.

Individuals enter the model at age 25, work until age 60 ($T_R = 35$), and die at age 85 ($T = 60$). The average earnings profile during working life (regulated by G_t) is

Table 5: Fixed and externally calibrated parameters

Parameter	Description	Value	Target / source
T	Life span after age 25	60	
T_R	Working years	35	
G_t	Growth factor of income	see text	Externally calibrated
σ_ψ	Std. of permanent shock	0.120	Externally calibrated
σ_ξ	Std. of transitory shock	0.087	Externally calibrated
κ	Retirement replacement rate	0.90	Jørgensen (2017)
ω	Borrowing constraint, working	0.25	Standard choice
δ_H	Age difference	30	Externally calibrated
μ_H	Mean death age of parent.	77	Externally calibrated
σ_H	Std. of death age of parent.	9	Externally calibrated
h_{45}	Inheritance size	0.93	Externally calibrated
η	Growth factor of inheritance	1.00	Externally calibrated
<i>Single-asset buffer-stock model</i>			
R	Return of <i>liquid</i> assets, <i>saving</i>	1.020	Kaplan, Moll and Violante (2018)
R_-	Return of <i>liquid</i> assets, <i>borrowing</i>	1.078	Kaplan, Moll and Violante (2018)
<i>Two-asset model</i>			
R	Return of <i>liquid</i> assets, <i>saving</i>	1.020	Kaplan, Moll and Violante (2018)
R_-	Return of <i>liquid</i> assets, <i>borrowing</i>	1.078	Kaplan, Moll and Violante (2018)
R_B	Return of <i>illiquid</i> assets	1.057	Kaplan, Moll and Violante (2018)
λ	Fixed adjustment cost	$0.02 \cdot \mathbb{E}[P_t]$	Kaplan and Violante (2014)

NOTE. The table shows the externally calibrated parameters that we fix for all our model iterations. In the fourth column we report the source of these parameters.

chosen to match the profile in our data. Using the method in Meghir and Pistaferri (2004), we estimate the standard deviation of the permanent shocks to be $\sigma_\psi = 0.120$, and the standard deviations of the transitory shocks to be $\sigma_\xi = 0.087$. Following Jørgensen (2017), we set the retirement replacement rate equal to $\kappa = 0.90$.

We use the same interest rates and borrowing constraints as in Kaplan, Moll and Violante (2018). The individuals can borrow up to a fraction $\omega = 0.25$ of their annual permanent income, and the fixed cost for illiquid asset adjustment λ is 2 percent of average yearly income.

We choose the parameters regulating the timing of inheritance by matching the life-cycle profile of inheritance receipts. This calibration gives us $\delta_H = 30$ as the age difference between child and parent, and $\mu_H = 71$ and $\sigma_H = 8$ as the mean and

standard deviation of death age of the parent. For the size of the inheritance we assume that $H_t = \eta^{(25+t)-45} \cdot h_{45}$, where we choose $h_{45} = 0.93$ to match the average inheritance at age 45 relative to permanent income, and $\eta = 1.00$ to match the life-cycle profile of inheritances.

To calibrate the initial states, we model the initial distribution of permanent income as a log-normal distribution, whose variance matches that observed in the data. The correlation between income and wealth is very weak at early ages. We thus match the initial wealth holdings we observe in the data at age 25 by assigning zero wealth to 70 percent of all agents, and some (illiquid) assets to the remaining 30 percent independently of income. We model the initial distribution of assets for these 30 percent as a log-normal distribution, whose variance matches that in the data.

5 Implications for consumption-saving behavior

In this section we interpret our causal evidence on long-run saving dynamics after inheritance through the lens of the consumption-saving framework presented in Section 4. We investigate under which conditions consumption-saving models can replicate the patterns observed in the data, and quantify the implications of matching the long-run saving dynamics for the amount of precautionary savings held through the life-cycle.

We proceed in three steps. We begin by showing that, in line with the previous literature (Cagetti, 2003), a range of different parametrizations can equally replicate the observed life-cycle profile of wealth. Specifically, a calibrated simultaneous increase in impatience, risk aversion, and the strength of the retirement saving and bequest motives leaves the life-cycle profile of wealth unchanged. Although stronger impatience reduces overall wealth accumulation, higher risk aversion induces more saving early in life, and stronger retirement saving and bequest motives induce more saving late in life.

However, the implied long-run saving dynamics differ sharply across these different parametrizations. In our second step, we show that specifications with high impatience, a strong precautionary saving motive, and strong retirement saving and bequest motives imply much faster convergence of wealth to the path established

Table 6: Replicating long-run saving dynamics

	Parameters						Fits		
	β	ρ	σ	ζ	$\bar{\alpha}$	α	LCP	LRD	MPC
<i>Panel A: Targeting Life-Cycle Profile (LCP) only</i>									
Fixed risk aversion (ρ)	0.969 [†]	1.50	0.67	1.15 [†]	1.00	1.00	0.006 [‡]	0.424	0.05
	0.964 [†]	2.00	0.67	1.22 [†]	1.00	1.00	0.006 [‡]	0.322	0.06
	0.948 [†]	4.00	0.67	1.44 [†]	1.00	1.00	0.006 [‡]	0.104	0.08
	0.936 [†]	6.00	0.67	1.58 [†]	1.00	1.00	0.008 [‡]	0.038	0.11
<i>Panel B: Targeting both Life-Cycle Profile (LCP) and Long-Run Dynamics (LRD)</i>									
Free risk aversion (ρ)	0.935 [†]	6.17 [†]	0.67	1.59 [†]	1.00	1.00	0.008 [‡]	0.034 [‡]	0.11
Free perceived risk ($\bar{\alpha}$)	0.935 [†]	4.00	0.67	1.61 [†]	1.25 [†]	1.00 [†]	0.009 [‡]	0.030 [‡]	0.11
Free risk (α)	0.939 [†]	4.00	0.67	1.53 [†]	1.00	1.21 [†]	0.008 [‡]	0.031 [‡]	0.11

NOTE. The table shows preference and scaling parameters, fit measures and the implied marginal propensity to consume for alternative parametrizations of the buffer-stock model from Section 4. The remaining model parameters are shown in Table 5. β is the discount factor. ρ is the relative risk aversion coefficient. $1/\sigma$ is the intertemporal elasticity of substitution. ζ controls the strength of the retirement saving and bequest motives. $\bar{\alpha}$ scales perceived income risk. α scales actual income risk. The marginal propensity to consume (MPC) is the median for agents between age 30 and 59. The fit of the Life-Cycle Profile of median wealth (LCP) is the mean squared difference between the profile implied by the model and that in the data from age 30 to age 59. The fit of the Long-Run Dynamics (LRD) is the weighed mean squared difference between our empirical estimates from Section 3 and estimates on simulated data from the model with the same sample selection on age.

[†] internally calibrated parameter. [‡] targeted moment.

before the shock. Whether the strength of the precautionary saving motive is due to risk aversion, income risk, or perceived income risk does not affect our results.

Finally, we quantify through a structural decomposition the share of wealth held for precautionary motives over the life-cycle. This wealth represents the buffer to which households wish to have access in order to smooth income shocks over their life-cycle. We show that this buffer is much larger in specifications matching not only the life-cycle profile of wealth, but also the observed long-run saving dynamics. We argue that this result has direct implications for counter-factual policy evaluations.

Table 6 collects our main results. The top panel of the table shows that different combinations of preference parameters deliver very similar life-cycle profiles of wealth. In each row, we set an intertemporal elasticity ($1/\sigma$) of 1.5 and a relative risk aversion coefficient (ρ) of either 1.5, 2, 4 or 6. For each of these choices, we in-

ternally calibrate the discount factor (β) and the strength of the retirement saving and bequest motives (through the utility shifter ζ) to replicate the life-cycle profile of median wealth.¹¹

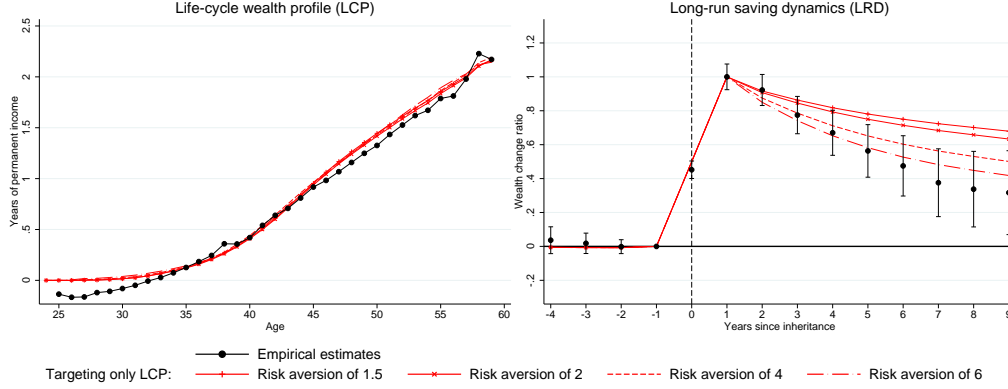
The seventh column (LCP) of the table—which reports the mean squared difference between the life-cycle profile of wealth implied by the model and that in the data—shows that each of these models can equally well replicate the life-cycle profile of wealth. The top-left plot of Figure 3 shows this result graphically.

However, these alternative parametrizations imply sharply different long-run saving dynamics. These differences are evident both graphically in the top-right panel of Figure 3, and in the eighth column (LRD) of Table 6—which reports the weighed mean squared difference between our empirical estimates and estimates on simulated data from the model. For the standard choice of a relative risk aversion coefficient of 2 (Carroll, 1997; Aaronson, Agarwal and French, 2012; Berger and Vavra, 2015), the model implies that the amount of the initial shock left after under a decade is twice as large as what we estimate empirically. However, the gap between the empirical and the simulated dynamics decreases in the high risk aversion specifications, for which the calibrated discount factor is lower and the motive to save for retirement and bequests is stronger.¹²

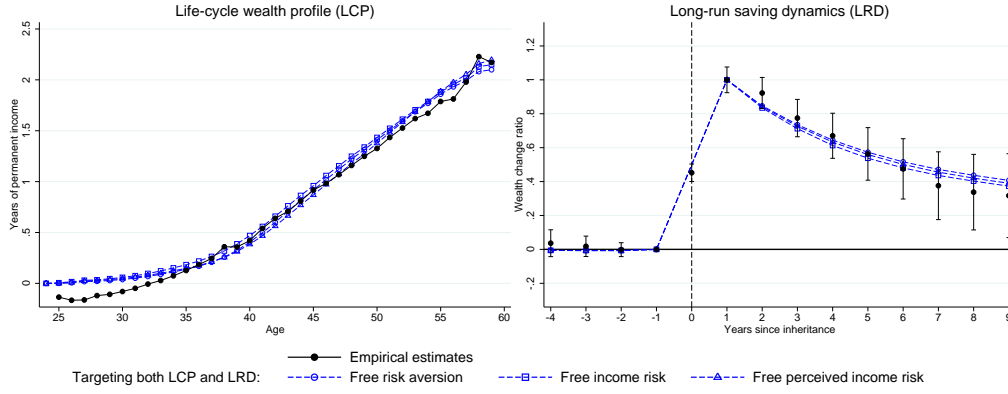
These results show that the long-run saving dynamics provide orthogonal information relative to the life-cycle profile. In other words, by evaluating a model by its ability to replicate not only the life-cycle wealth profile, but also the empirical long-run saving dynamics, we are able to exclude a large set of potential parametrizations. In the first row of Panel B of Table 6 we explicitly exploit this additional information, and also calibrate the relative risk aversion coefficient by simultaneously targeting the life-cycle profile of wealth and the long-run saving dynamics. The resulting risk aversion coefficient of 6.17 is higher than the standard value of 2, but within the range of usual choices (e.g., Favilukis, Ludvigson and Van Nieuwerburgh, 2017, use a risk aversion coefficient equal to 8). Similarly, the discount factor β decreases with

¹¹In Online Appendix Table D.1, we show that our results are not sensitive to our choice of the intertemporal elasticity of substitution ($1/\sigma$).

¹²All specifications appearing in Table 6 have Epstein-Zin preferences. Under the more restrictive assumption of CRRA preferences, where the intertemporal elasticity of substitution is equal to the inverse of the relative risk aversion coefficient ($\sigma = \rho$), increasing aversion still improves the model fit of the long-run saving dynamics for a constant fit of the life-cycle profile of wealth. However, the improvement in the fit of the long-run saving dynamics is smaller, and the required decrease in the discount factor is larger. These results appear in Online Appendix Table D.2.



(a) Targeting Life-Cycle Profile (LCP) only



(b) Targeting both the Life-Cycle Profile (LCP) and the Long-Run Dynamics (LRD)

Figure 3: Replicating long-run saving dynamics

NOTE. The figure compares the empirical and simulated life-cycle profiles of median net worth (left) and long-run saving dynamics after inheritance (right) for the parametrizations of the buffer-stock model in Table 6.

respect to the standard case, but its value (0.94) is within the range of reasonable parameter values.

Adjusting risk aversion is however not necessary for replicating the empirical long-run saving dynamics. Amplifying the precautionary saving motive through alternative channels equivalently allows the model to simultaneously replicate the life-cycle profile of wealth and the long-run saving dynamics. We prove this result by fixing the degree of risk aversion, and instead calibrate the standard deviations of shocks in the income process (via the scaling parameter α) or the agent's beliefs about these standard deviations (via the scaling parameter $\tilde{\alpha}$). For ρ equal to 4, we

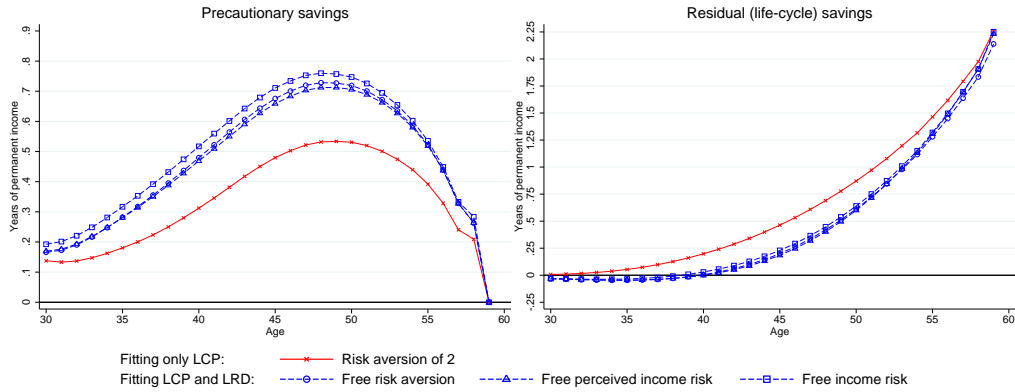


Figure 4: Structural decomposition of wealth held for precautionary (left) and life-cycle motives (right)

NOTE. Using the models calibrated in Table 6, we calculate savings accumulated exclusively for precautionary motives by simulating a counterfactual wealth profile under the assumption of no motive to save for retirement or bequests ($\zeta = 0$). This counterfactual simulation isolates wealth held solely for precautionary purposes. We label the residual accumulated wealth as life-cycle savings.

show that a 25 percent increase in the standard deviation of income shocks, or a 21 percent perceived increase in these standard deviations, is sufficient to replicate the convergence we observe in the data holding the fit of the life-cycle profile of wealth constant.¹³

Although increasing risk aversion, income risk, or beliefs about income risk all represent amplifications of the precautionary saving motive, translating these different structural parameters into a quantifiable and clearly interpretable statistic is less immediate. We therefore follow Gourinchas and Parker (2002) and calculate the average amount of wealth held solely for precautionary purposes for the parametrizations presented in Table 6. Using the calibrated model parameters, we simulate counterfactual life-cycle wealth profiles assuming households have no motive to save for retirement or bequests ($\zeta = 0$). These households save solely to smooth income fluctuations throughout their life-cycle, and therefore the wealth they accumulate over the life-cycle represent their precautionary savings. We label the residual wealth as life-cycle savings.

Figure 4 shows that, with respect to the standard case, models able to fit both

¹³While in the interest of space we only report in Table 6 calibrations for $\rho = 4$, we replicate these results for different choices of risk aversion. Naturally, the required scaling parameters are decreasing in the choice of risk aversion. These results appear in Online Appendix Table D.3.

the life-cycle profile of wealth and the long-run saving dynamics imply substantially higher precautionary savings (between 50 percent and 25 percent higher in the ages between 35 and 55). The amount of precautionary savings implied by the model does not depend on the choice of internally calibrated parameters, but only on whether the model is capable of replicating the empirically observed long-run saving dynamics.

Moreover, because wealth levels are constant across models, agents matching our empirical sets of moments do not begin accumulating wealth for retirement purposes until after age 40. This behavior is consistent with recent evidence that households approaching retirement age make more active decisions when managing their holdings (Agarwal et al., 2009), and that tax incentives aimed at increasing retirement savings have small or no effects on young savers (Chetty et al., 2014).

Overall, our results make the general point that, in order to replicate empirical regularities, consumption-saving models need to incorporate a stronger than usual precautionary saving motive. This finding is consistent with the recent evidence that generalizations of the permanent-transitory income process, e.g. with non-linear dynamics and non-Gaussian income shocks, can triple the welfare costs of income risk (Guvenen et al., 2016). In our framework, scaling perceived income risk approximates the implications of introducing an income process with higher order income risk. Incorporating financial or expense risk into the model represent alternative channels to affect the strength of the precautionary saving motive.

The relative strength of various saving motives has direct implications for counterfactual policy evaluations. On one hand, a strong precautionary saving motive indicates high welfare costs of imperfections in asset markets, which limit the ability of the agents to smooth income shocks. On the other hand, a strong precautionary saving motive also implies large welfare benefits from social insurance programs.

5.1 Extensions to the buffer-stock model

We have shown that the long-run saving dynamics we estimate in our data identify buffer-stock models with a strong precautionary saving motive. In this subsection, we show that the same conclusion generalizes to common extensions of the standard buffer-stock model, such as a two-asset model and a model with preference heterogeneity. These extensions allow us to capture more complex empirical features, such as the increase in the interquartile range of wealth over the life-cycle, and

the high marginal propensity to consume documented, among others, by (Shapiro and Slemrod, 2003), Johnson, Parker and Souleles (2006) and Parker et al. (2013). Nonetheless, we find that for both extensions a stronger than usual precautionary saving motive is necessary to simultaneously replicate the observed life-cycle profile of wealth and long-run saving dynamics.

Table 7 replicates the results of Table 6 for a buffer-stock model with heterogeneity in the discount factor (Krueger, Mitman and Perri, 2016; Carroll et al., 2017) and a two-asset model à la Kaplan and Violante (2014). With respect to Table 6, we additionally evaluate the performance of these models in replicating the increase in the interquartile range of wealth over the life-cycle and, in the two-asset model, the empirical long-run saving dynamics of net liquid worth. For completeness, in the top panel of the table we report the same measures for the buffer-stock model specifications presented in Table 6.

Panel B shows that introducing heterogeneous impatience slightly improves the ability of the model to replicate the empirical long-run dynamics of savings. However, consistently with the results of Table 6, the model with heterogeneous patience fails to replicate the empirical long-run saving dynamics with a standard risk aversion parameter of 2. Moreover, the fit of the long-run dynamics improves as the degree of risk aversion increases, holding constant the fit of the life-cycle wealth profile. By simultaneously targeting the life-cycle profile of wealth, the increase in the interquartile range of wealth, and the long-run saving dynamics, we calibrate a relative risk aversion coefficient of 6.82, in line with our results for the buffer-stock model with homogeneous preferences.

In the third panel of the table, we extend the model with an illiquid asset (Kaplan and Violante, 2014). This extension enables the model to produce a high marginal propensity to consume (MPC), and thus replicate the short-run dynamics documented in the empirical literature. However, for the same degree of risk aversion, the two-asset model is less capable of replicating the observed long-run saving dynamics compared to the single-asset model, which implies a much smaller MPC. This difference stresses the qualitative difference between short- and long-run dynamics in consumption-saving models. Moreover, our main results apply also to the two-asset model: As the precautionary saving motive increases, the fit of long-run saving dynamics improves. Simultaneously targeting the life-cycle profile of wealth and the

Table 7: Extensions: Preference heterogeneity and two-asset model

Targeting	Parameters				LCP		LRD		MPC
	β	ρ	σ	ζ	Median	IQR	Net worth	Liquid worth	
Panel A: Buffer-stock model									
LCP only	0.969 [†]	1.50	0.67	1.15 [†]	0.006 [‡]	0.194	0.424	-	0.05
LCP only	0.964 [†]	2.00	0.67	1.22 [†]	0.006 [‡]	0.198	0.322	-	0.06
LCP only	0.948 [†]	4.00	0.67	1.44 [†]	0.006 [‡]	0.184	0.104	-	0.08
LCP only	0.936 [†]	6.00	0.67	1.58 [†]	0.008 [‡]	0.159	0.038	-	0.11
LCP & LRD	0.935 [†]	6.17 [†]	0.67	1.59 [†]	0.008 [‡]	0.160	0.034 [‡]	-	0.11
Panel B: Buffer-stock model with preference heterogeneity									
LCP only	[0.960;0.977]	1.50	0.67	1.16 [†]	0.007 [‡]	0.009 [‡]	0.302	-	0.05
LCP only	[0.955;0.973]	2.00	0.67	1.22 [†]	0.006 [‡]	0.009 [‡]	0.251	-	0.06
LCP only	[0.937;0.963]	4.00	0.67	1.40 [†]	0.008 [‡]	0.011 [‡]	0.134	-	0.08
LCP only	[0.923;0.953]	6.00	0.67	1.54 [†]	0.008 [‡]	0.010 [‡]	0.068	-	0.10
LCP & LRD	[0.915;0.952]	6.82 [†]	0.67	1.63 [†]	0.010 [‡]	0.015 [‡]	0.049 [‡]	-	0.11
Panel C: Two-asset model									
LCP only	0.941 [†]	1.50	0.67	1.00 [†]	0.005 [‡]	0.146	1.056	0.128	0.36
LCP only	0.937 [†]	2.00	0.67	1.05 [†]	0.005 [‡]	0.155	0.862	0.109	0.37
LCP only	0.922 [†]	4.00	0.67	1.23 [†]	0.005 [‡]	0.164	0.315	0.043	0.37
LCP only	0.911 [†]	6.00	0.67	1.35 [†]	0.005 [‡]	0.149	0.136	0.015	0.37
LCP & LRD	0.901 [†]	8.57 [†]	0.67	1.47 [†]	0.007 [‡]	0.125	0.093 [‡]	0.007	0.36

NOTE. The table shows preference and scaling parameters, fit measures and the implied marginal propensity to consume for alternative parametrizations of the buffer-stock model from Section 4. The remaining model parameters are shown in Table 5. β is the discount factor. ρ is the relative risk aversion coefficient. $1/\sigma$ is the intertemporal elasticity of substitution. ζ controls the strength of the retirement saving and bequest motives. $\bar{\alpha}$ scales perceived income risk. α scales actual income risk. The marginal propensity to consume (MPC) is the median for agents between age 30 and 59. The fit of the Life-Cycle Profile of median wealth (LCP, median) is the mean squared difference between the profile implied by the model and that in the data, from age 30 to age 59. The fit of the life-cycle profile of the increase in the interquartile range of wealth (LCP, IQR) is also computed from age 30 to 59. The fit of the Long-Run Dynamics (LRD) of net worth and liquid assets is the weighed mean squared difference between our empirical estimates from Section 3 and estimates on simulated data from the model with the same sample selection on age.

[†] internally calibrated parameter. [‡] targeted moment.

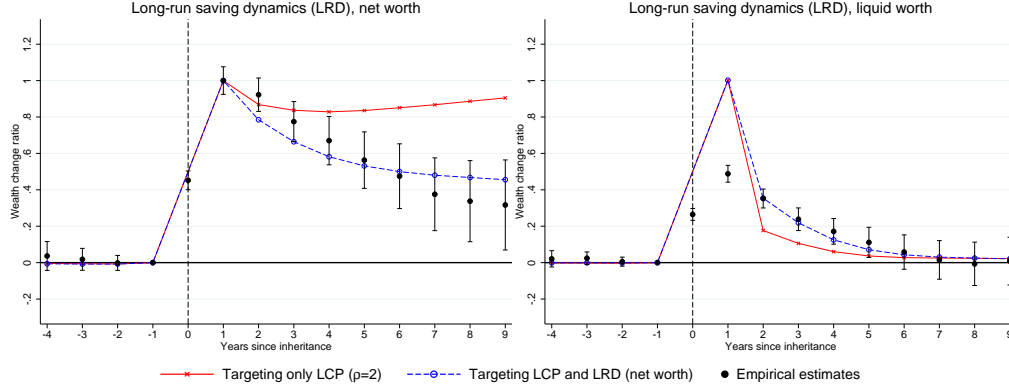


Figure 5: Two-asset model: Long-run saving dynamics of net worth (left) and net liquid worth (right)

NOTE. The figure compares the empirical and simulated and long-run saving dynamics after inheritance of total net worth (left) and liquid net worth (right) for the calibrated two-asset model in Table 7.

long-run saving dynamics, we obtain a calibrated risk aversion coefficient of 8.57. Remarkably, such a model is also able to closely replicate the (non-targeted) empirical dynamics of net liquid worth. The empirical and simulated long-run saving dynamics for the two-asset model appear in Figure 5.

5.2 Additional robustness checks

We conduct a series of additional robustness checks by investigating the implications of changing each of the externally calibrated parameters in Table 5. These robustness checks appear in Online Appendix Table D.4. We find that changing the parameters affecting the borrowing constraint (R_-, ω), or the inheritance process ($\mu_H, \sigma_H, h_{45}, \eta$),¹⁴ only marginally affect the combination of impatience (β), risk aversion (ρ), and retirement saving and bequest motive (ζ) necessary to simultaneously match both the life-cycle wealth profile and the long-run saving dynamics observed empirically. Changing the replacement rate in retirement (κ) affects the scaling of the utility shifter for the strength of the retirement saving and bequest motives (ζ), and changing the interest rate (R) implies an change in the opposite direction of the discount factor (β). However, the calibrated degree of risk aversion does not change substantially.

¹⁴Online Appendix Figure D.1 shows that assuming that inheritance is completely unexpected slightly improves the model's fit of the long-run saving dynamics.

Finally, reducing the standard deviation of the permanent shocks (σ_ψ) implies that a higher degree of risk aversion (ρ), lower discount factor (β) and a stronger retirement saving and bequest motive (ζ) is needed. This result is the flip-side of the effect of increasing the standard deviation of income shocks through α , which appears in the bottom panel of Table 6. Our results are almost not affected by changing the standard deviation of the transitory income shocks (σ_ϵ). Overall, our results are thus very robust to changing our baseline calibration choices.

6 Conclusions

Long-run saving dynamics are a crucial component of life-cycle consumption and saving models. This paper introduces a novel strategy—exploiting large financial windfalls to characterize long-run dynamics of saving—for the calibration of structural consumption models, and is the first to provide quasi-experimental evidence on these dynamics.

We combine a unique panel dataset drawn from seventeen consecutive years of Danish administrative records with large inheritances due to sudden parental deaths, and estimate their effect on wealth accumulation strategies in the following years. We show that after parental death average net worth converges towards the path established before parental death. However, these patterns differ markedly across wealth components, with excess liquid assets being consumed or converted in other saving vehicles within six years. Endogenous labor supply and committed expenditures (e.g., pension savings or family growth) do not drive these results.

We analyze these results through the lens of a structural model of life-cycle consumption and savings, augmented with inheritance expectations and nesting the standard buffer-stock and two-asset models as special cases. We show that long-run saving dynamics provide orthogonal information relative to the life-cycle profile for the calibration of consumption-saving models: Only by allowing for impatient agents with a stronger than usual precautionary saving motive can these models fit both the empirical long-run dynamics of saving and life-cycle wealth levels. The two-asset model can fit the different shock dynamics of both net worth and liquid worth.

These novel model parametrizations carry important policy implications. First,

in these models agents do not save exclusively for retirement until the last twenty years of their working life. Second, as wealth held for precautionary purposes is substantially larger than the standard case, these models imply that liquidity constraints and frictions in financial markets carry higher welfare costs, and that agents place a higher value on insurance able to reduce the risk of income fluctuations.

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A Robustness of the empirical results: DiD and balanced samples

Table 8: Comparison of DiD (balanced and unbalanced) and our identification strategy for individuals inheriting in 1999-2001 and 2008-2010

n	Net worth			Liquid assets		
	Event study	DiD	DiD, balanced	Event study	DiD	DiD, balanced
-3	0.042 (0.049)	0.175 (0.093)	0.149 (0.095)	0.016 (0.021)	0.018 (0.040)	0.010 (0.040)
-2	0.015 (0.044)	0.104 (0.088)	0.074 (0.090)	0.015 (0.019)	0.012 (0.038)	0.007 (0.038)
0	0.342 (0.044)	0.399 (0.086)	0.391 (0.090)	0.243 (0.019)	0.214 (0.037)	0.201 (0.037)
1	0.839 (0.049)	0.931 (0.088)	0.917 (0.091)	0.389 (0.021)	0.379 (0.038)	0.370 (0.038)
2	0.775 (0.054)	0.890 (0.089)	0.860 (0.093)	0.283 (0.023)	0.273 (0.038)	0.264 (0.039)
3	0.644 (0.057)	0.794 (0.089)	0.794 (0.093)	0.162 (0.025)	0.166 (0.038)	0.163 (0.039)
4	0.623 (0.060)	0.694 (0.089)	0.699 (0.093)	0.120 (0.026)	0.126 (0.038)	0.131 (0.039)
5	0.581 (0.063)	0.677 (0.089)	0.693 (0.093)	0.118 (0.027)	0.078 (0.038)	0.068 (0.039)
6	0.470 (0.065)	0.560 (0.088)	0.555 (0.093)	0.106 (0.028)	0.081 (0.038)	0.069 (0.039)
7	0.408 (0.069)	0.491 (0.089)	0.476 (0.094)	0.088 (0.030)	0.066 (0.038)	0.055 (0.039)
8	0.331 (0.075)	0.378 (0.092)	0.371 (0.096)	0.094 (0.032)	0.080 (0.040)	0.064 (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 of Fadlon and Nielsen (2015), 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.

B Terminal consumption and value functions

From period T_R onward the recursive problem is

$$\begin{aligned}
\bar{V}_t(\bar{M}_t, P_{T_R}) &= \max_{C_t} \begin{cases} \zeta_t C_t^{1-\sigma} / (1-\sigma) + \beta_i \bar{V}_{t+1}(\bar{M}_{t+1}, P_{T_R}) & \text{if } \rho = \sigma \\ ((1-\beta_i)\zeta_t C_t^{1-\sigma} + \beta_i \bar{V}_{t+1}(\bar{M}_{t+1}, P_{T_R})^{1-\sigma})^{\frac{1}{1-\sigma}} & \text{else} \end{cases} \\
\text{s.t.} & \\
A_t &= \bar{M}_t - C_t \\
\bar{M}_{t+1} &= \bar{R}A_t + \kappa P_{T_R} \\
\zeta_t &= \mathbf{1}_{t=T_R} + \mathbf{1}_{t>T_R}\zeta \\
A_{T_R} &\geq 0 \\
A_T &\geq 0,
\end{aligned}$$

where $\bar{R} = R$ in the buffer-stock model and $\bar{R} = R_b$ in the two-asset model, and $\bar{M}_{T_R} = M_{T_R} + N_{T_R} + H_{T_R}\mathbf{1}_{d_{T_R}=0}$.

The optimal consumption function then is

$$\bar{C}_{T_R}(\bar{M}_{T_R}, P_{T_R}) = \min \left\{ M_{T_R}, \frac{\gamma_1(\bar{M}_{T_R} + (1+\gamma_0)\bar{R}^{-1}\kappa P_{T_R})}{\bar{R}^{-1}(\beta_i \bar{R}\zeta)^{\frac{1}{\sigma}} + \gamma_1} \right\}$$

where $\gamma_0 \equiv \frac{1-(\bar{R}^{-1})^{T-T_R}}{1-\bar{R}^{-1}} - 1$ and $\gamma_1 \equiv \frac{1-\bar{R}^{-1}(\beta_i \bar{R})^{1/\sigma}}{1-(\bar{R}^{-1}(\beta_i \bar{R})^{1/\sigma})^{T-T_R}}$.

The value function is

$$\bar{V}_{T_R}(\bar{M}_{T_R}, P_{T_R}) = \begin{cases} \frac{C_{T_R}^{1-\sigma}}{1-\sigma} + \beta_i \frac{\zeta \gamma_1^{-1} C_{T_R+1}^{1-\sigma}}{1-\sigma} & \text{if } \rho = \sigma \\ ((1-\beta_i)C_{T_R}^{1-\sigma} + \beta_i(\gamma_2 C_{T_R+1})^{1-\sigma})^{\frac{1}{1-\sigma}} & \text{else} \end{cases}$$

where $\gamma_2 \equiv ((1-\beta)\zeta\gamma_1^{-1})^{\frac{1}{1-\sigma}}$ and

$$C_{T_R+1} \equiv \begin{cases} (\beta_i \bar{R}\zeta)^{\frac{1}{\sigma}} C_{T_R} & \text{if } C_{T_R} < \bar{M}_{T_R} \\ \gamma_1(1+\gamma_0\kappa)P_{T_R} & \text{else} \end{cases}$$

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

Jeppe Druedahl and Alessandro Martinello

May 8, 2018

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.

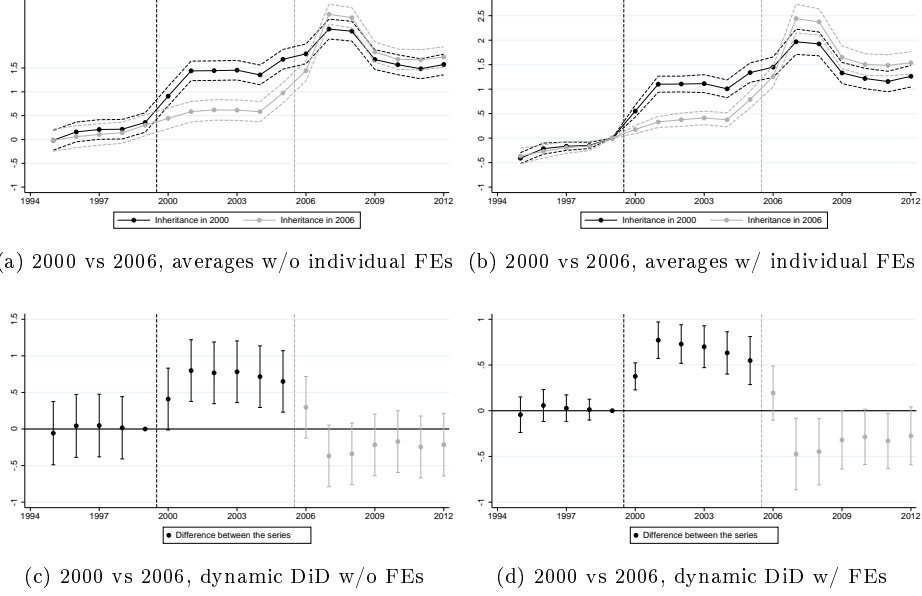
Maintaining the crucial property of separately controlling for time and group fixed effects, we extend this identification strategy in two ways. First, we add a minimal amount of structure to the model, allowing not only a more efficient extraction of information but also, under the same assumptions, 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



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

$$y_{it} = \Lambda_t + \Psi_\tau + \gamma_n + \varepsilon_{it} \quad (1)$$

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

¹For 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

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

where $\bar{y}_t^\tau = E[y_t^\tau]$. 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.

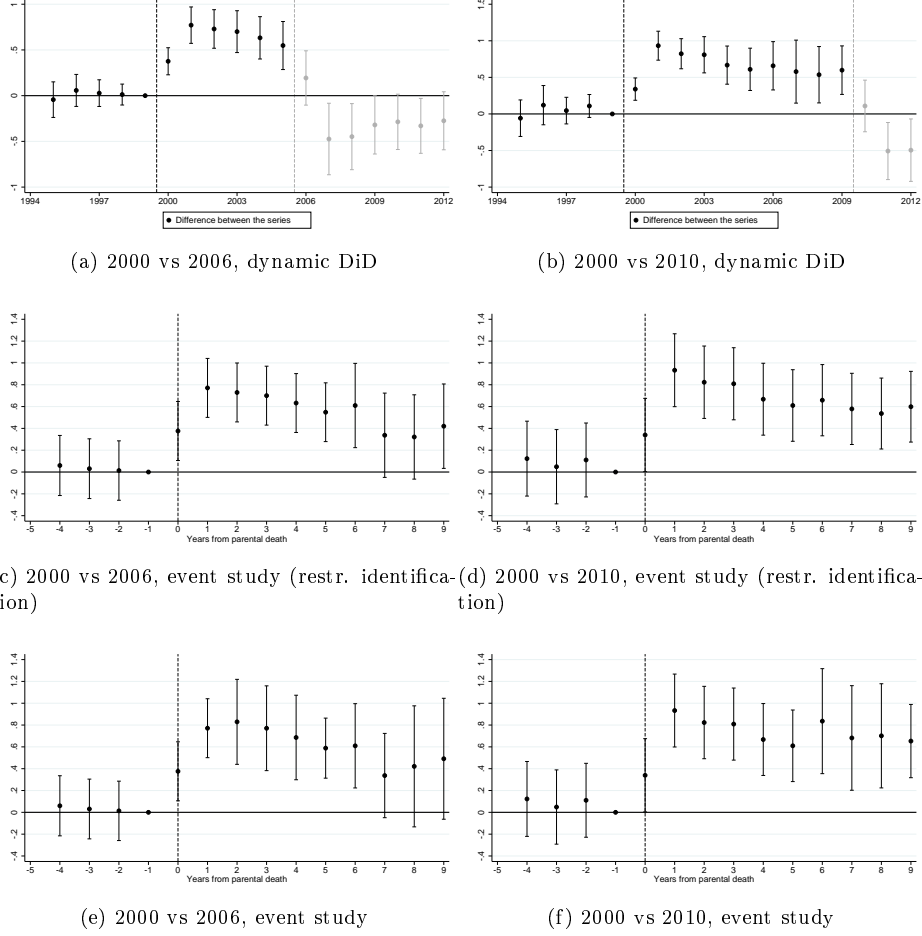
The relationship between γ_n^{FN} and γ_n in our descriptive equation (1) is straightforward. By substituting equation (1) in the FN estimator, we have that

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

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



sum of the real year effect plus the unidentified γ_{14} . In our analysis we thus restrict the estimation to $n \in \{-5, -4, \dots, 9\}$. 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

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

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

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 $E[\gamma_{\Delta+1}^{FN}] + \hat{\gamma}_1$. 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.

²In 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 $n < 0$.

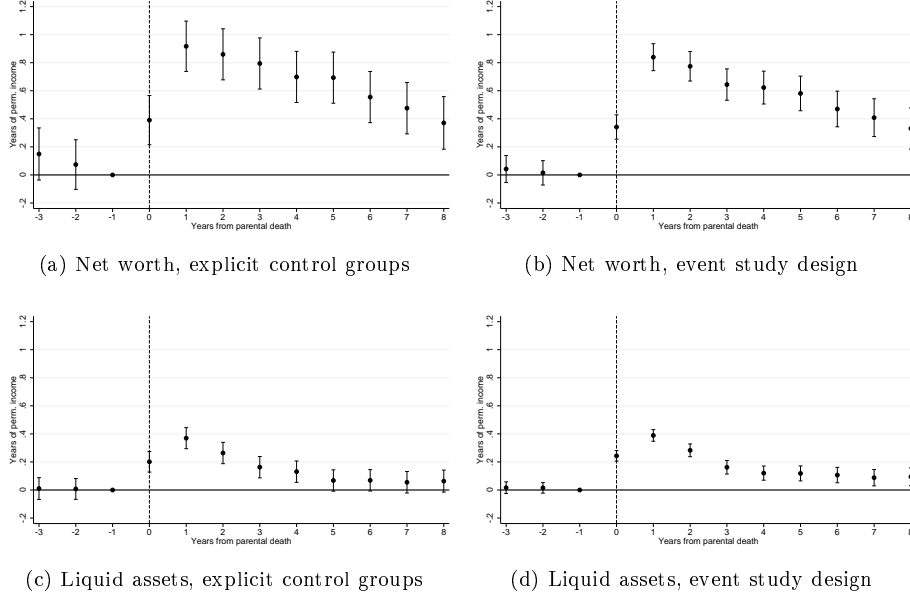
c Allowing for multiple Δ

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



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

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

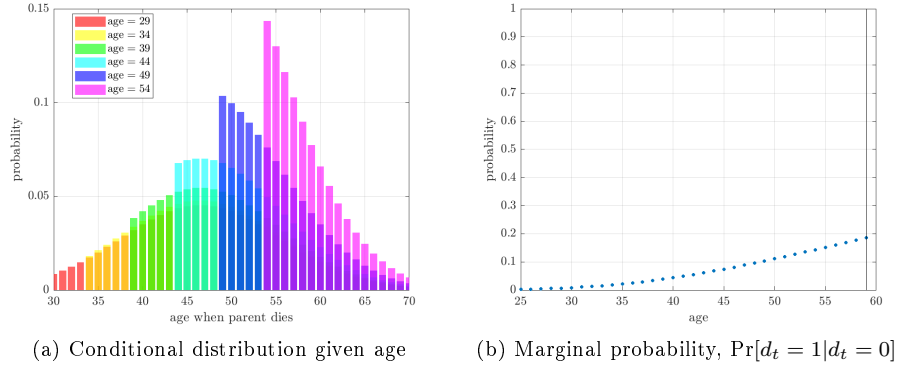


Figure D.1: Inheritance process

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

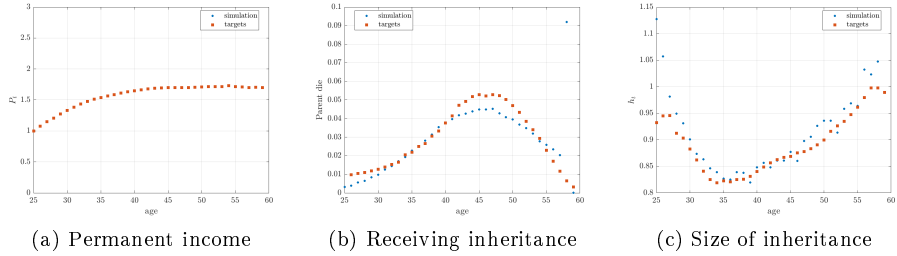


Figure D.2: Fit of external calibration

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 [†]	1.50	0.50	1.14 [†]	0.007 [‡]	0.369	0.06
0.965 [†]	2.00	0.50	1.20 [†]	0.006 [‡]	0.281	0.06
0.951 [†]	4.00	0.50	1.38 [†]	0.006 [‡]	0.070	0.09
0.940 [†]	6.00	0.50	1.49 [†]	0.009 [‡]	0.032	0.12
0.932 [†]	8.00	0.50	1.54 [†]	0.014 [‡]	0.045	0.14
0.927 [†]	10.00	0.50	1.57 [†]	0.021 [‡]	0.060	0.16
0.968 [†]	1.50	0.80	1.15 [†]	0.006 [‡]	0.440	0.05
0.963 [†]	2.00	0.80	1.23 [†]	0.006 [‡]	0.361	0.06
0.946 [†]	4.00	0.80	1.49 [†]	0.006 [‡]	0.128	0.08
0.932 [†]	6.00	0.80	1.66 [†]	0.007 [‡]	0.048	0.10
0.923 [†]	8.00	0.80	1.76 [†]	0.010 [‡]	0.031	0.12
0.914 [†]	10.00	0.80	1.85 [†]	0.016 [‡]	0.032	0.14
0.965 [†]	1.50	1.50	1.19 [†]	0.006 [‡]	0.519	0.05
0.958 [†]	2.00	1.50	1.29 [†]	0.006 [‡]	0.453	0.05
0.933 [†]	4.00	1.50	1.75 [†]	0.005 [‡]	0.209	0.07
0.914 [†]	6.00	1.50	2.11 [†]	0.006 [‡]	0.104	0.09
0.898 [†]	8.00	1.50	2.41 [†]	0.008 [‡]	0.056	0.10
0.885 [†]	10.00	1.50	2.68 [†]	0.011 [‡]	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
<i>Panel A: Targeting Life-Cycle Profile (LCP) only</i>									
Fixed risk aversion (ρ)	0.965 [†]	1.50	1.50	1.19 [†]	1.00	1.00	0.006 [‡]	0.519	0.05
	0.955 [†]	2.00	2.00	1.34 [†]	1.00	1.00	0.005 [‡]	0.491	0.05
	0.893 [†]	4.00	4.00	2.83 [†]	1.00	1.00	0.005 [‡]	0.361	0.06
	0.805 [†]	6.00	6.00	8.41 [†]	1.00	1.00	0.004 [‡]	0.242	0.07
<i>Panel B: Targeting both life-cycle profile (LCP) and Long-Run Dynamics (LRD)</i>									
Free perceived risk ($\tilde{\alpha}$)	0.766 [†]	4.00	4.00	15.11 [†]	1.68 [†]	1.00 [†]	0.017 [‡]	0.025 [‡]	0.14
Free risk (α)	0.833 [†]	4.00	4.00	5.31 [†]	1.00	1.38 [†]	0.009 [‡]	0.031 [‡]	0.10

NOTE. † internally calibrated parameter. ‡ targeted moment.

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

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

NOTE. † internally calibrated parameter. ‡ targeted moment.

Table D.4: Robustness: External calibration

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

NOTE. † internally calibrated parameter. ‡ targeted moment.

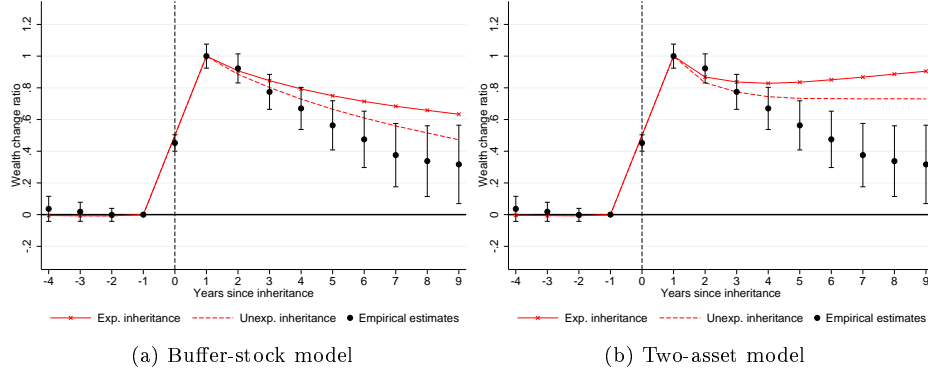


Figure D.3: Long-run saving dynamics without inheritance expectations

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.

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

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

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

and the value function for adjustment is

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

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

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

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

$$C_t^{-\sigma} = \beta R \mathbb{E}_t \left[C_{t+1}^{-\sigma} V_{t+1}^{\sigma-\rho} \right] W_t^{\rho-\sigma}, \quad C_t < M_t \quad (6)$$

$$C_t^{-\sigma} = \beta R \mathbb{E}_t \left[C_{t+1}^{-\sigma} V_{t+1}^{\sigma-\rho} \right] W_t^{\rho-\sigma}, \quad C_t \in (M_t, M_t + \omega P_t) \quad (7)$$

$$C_t = M_t + \omega_t P_t \quad (8)$$

$$C_t = M_t. \quad (9)$$

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

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

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

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

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

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

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

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

where

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

We also interpolate $\mathbb{E}_t [C_{t+1}^{-\sigma} V_{t+1}^{\sigma-\rho}]$ 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

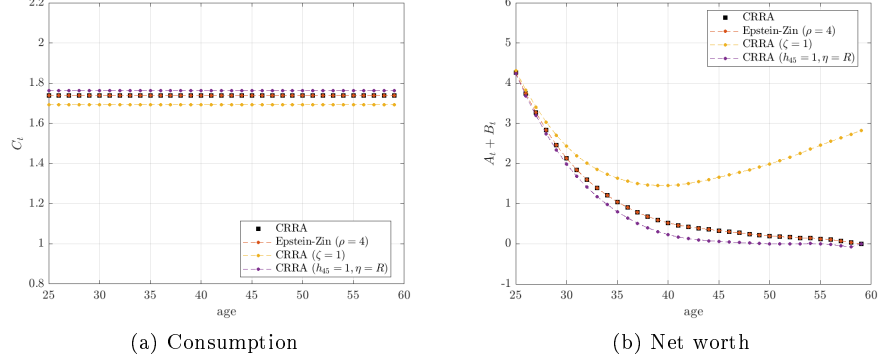


Figure E.1: Buffer-stock: Constant consumption

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 $\eta = R$.

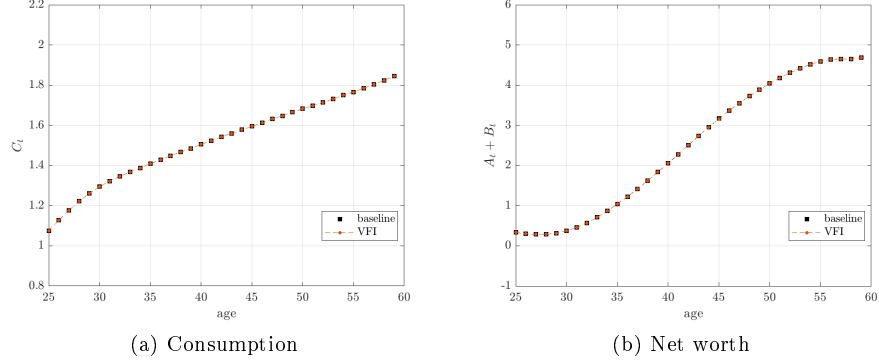


Figure E.2: Buffer-stock model: VFI

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 $\zeta \rightarrow 0$ agents save less and less for retirement, specifically $\lim_{\zeta \rightarrow 0} A_{TR} = 0$.

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 $\lambda \rightarrow 0$

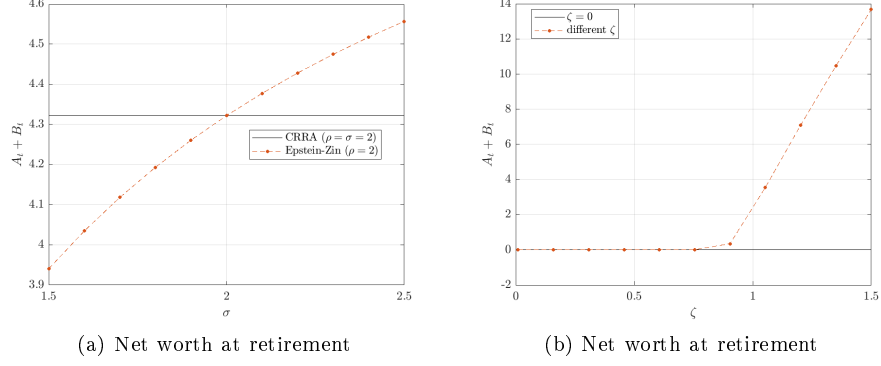


Figure E.3: Buffer-stock model: Varying σ and ζ

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 $\zeta = 1$.

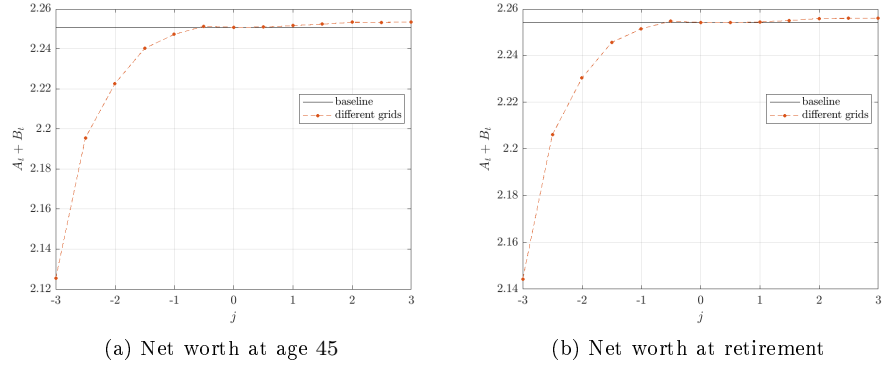


Figure E.4: Buffer-stock model: Grids

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 $\#_A = 150 + j \cdot 40$.

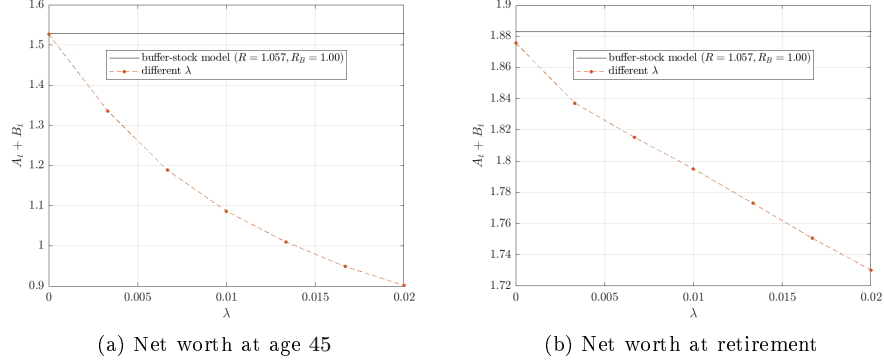


Figure E.5: Two-asset model: $\lambda \rightarrow 0$

Note. This figure shows average net worth at age 45 and retirement when $\lambda \rightarrow 0$ 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.

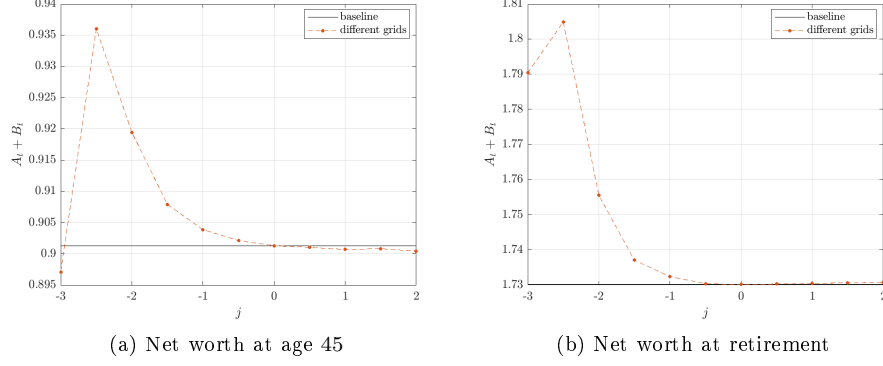


Figure E.6: Two-asset model: Grids

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 $\#_A = 100 + j \cdot 30$.

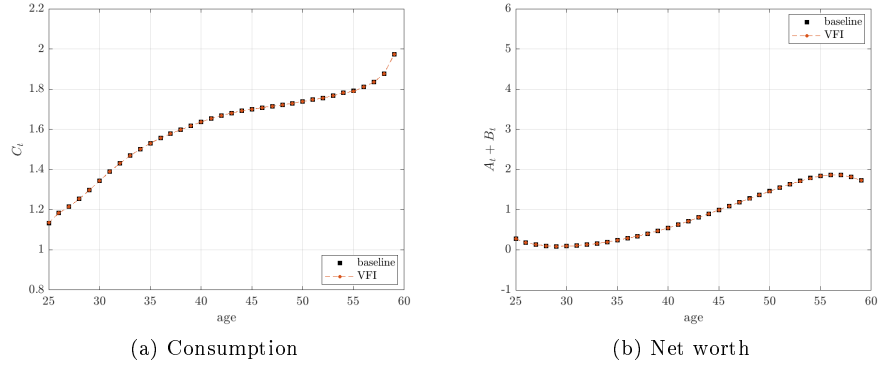
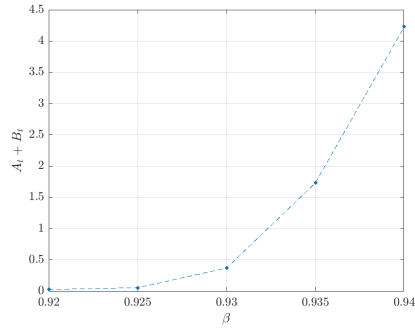
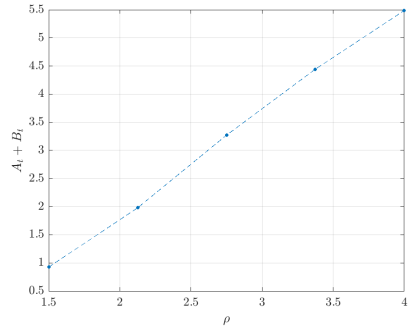


Figure E.7: Two-asset model: VFI

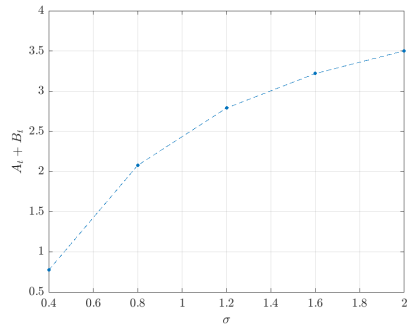
NOTE. This figure shows life-cycle profiles of average consumption and average net worth from a two-asset model with the calibration from the main text and $\sigma = 2/3$, $\beta = 0.935$, $\rho = 2$ and $\zeta = 1$.



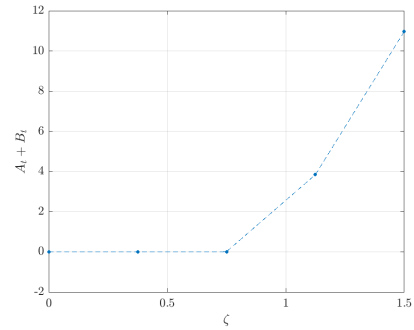
(a) β



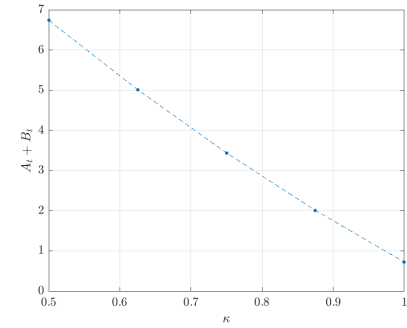
(b) ρ



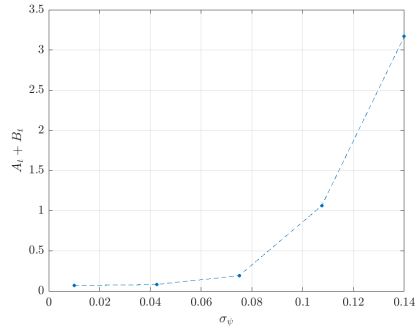
(c) σ



(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

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

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*.

³This 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 - OBLGAEELD- PANTGAEELD	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	BANKGAEELD	The sum of all debts not associated to a bond granted by banks in Denmark
Financial wealth	finw	KURSANP + KUR- SAKT + 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- FRYD + AKTIEINDK - SKATMVIALT_NY ERHVERVSINDK	Income available for consumption after taxes and transfers
Labor income		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 (0.024)	0.826 (0.046)	0.560 (0.095)	0.539 (0.152)
– Liq. assets	0.044 (0.006)	0.416 (0.019)	0.222 (0.021)	0.251 (0.033)
– Housing equity	-0.060 (0.022)	0.143 (0.038)	0.141 (0.084)	0.115 (0.134)
– Fin. investments	-0.001 (0.005)	0.190 (0.016)	0.124 (0.019)	0.105 (0.030)
– Unc. debts	0.015 (0.011)	-0.077 (0.018)	-0.072 (0.040)	-0.068 (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 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 than 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.

b Extended main results

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

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

n	Net worth	Liq. assets	Housing equity	Fin. invest.	Unc. Debts
-5	0.033 (0.043)	-0.001 (0.014)	0.020 (0.038)	-0.001 (0.012)	-0.016 (0.020)
-4	0.032 (0.035)	0.012 (0.013)	0.014 (0.031)	-0.001 (0.010)	-0.007 (0.016)
-3	0.016 (0.027)	0.006 (0.010)	-0.002 (0.024)	-0.003 (0.007)	-0.015 (0.012)
-2	-0.001 (0.018)	0.005 (0.007)	-0.002 (0.017)	-0.004 (0.005)	0.000 (0.008)
0	0.398 ** (0.023)	0.230 ** (0.012)	0.069 ** (0.018)	0.096 ** (0.008)	-0.003 (0.008)
1	0.879 ** (0.034)	0.389 ** (0.015)	0.184 ** (0.027)	0.265 ** (0.014)	-0.040 ** (0.014)
2	0.809 ** (0.041)	0.272 ** (0.015)	0.222 ** (0.035)	0.278 ** (0.015)	-0.037 * (0.017)
3	0.679 ** (0.049)	0.168 ** (0.016)	0.218 ** (0.044)	0.251 ** (0.016)	-0.042 + (0.022)
4	0.588 ** (0.059)	0.108 ** (0.018)	0.191 ** (0.052)	0.247 ** (0.018)	-0.043 + (0.025)
5	0.492 ** (0.069)	0.069 ** (0.021)	0.168 ** (0.061)	0.227 ** (0.021)	-0.028 (0.030)
6	0.416 ** (0.080)	0.037 (0.024)	0.156 * (0.070)	0.209 ** (0.024)	-0.014 (0.034)
7	0.329 ** (0.089)	0.012 (0.026)	0.127 (0.078)	0.188 ** (0.026)	-0.001 (0.038)
8	0.295 ** (0.100)	0.003 (0.030)	0.114 (0.087)	0.187 ** (0.030)	0.009 (0.043)
9	0.277 * (0.111)	0.005 (0.033)	0.088 (0.096)	0.182 ** (0.033)	-0.002 (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 (10.506)	-0.244 (3.100)	8.742 (8.671)	2.570 (4.159)	2.358 (4.157)
-4	11.386 (8.504)	3.503 (2.998)	9.168 (7.156)	0.241 (2.529)	1.526 (3.237)
-3	6.974 (6.352)	1.396 (2.054)	4.203 (5.478)	-1.142 (1.819)	-2.517 (2.318)
-2	1.181 (4.305)	0.960 (1.614)	1.896 (3.886)	-1.071 (1.294)	0.603 (1.681)
0	78.209 ** (5.314)	44.604 ** (2.359)	12.270 ** (4.221)	20.807 ** (1.863)	-0.528 (1.631)
1	188.284 ** (8.065)	80.823 ** (3.118)	40.775 ** (6.508)	59.363 ** (3.270)	-7.322 ** (2.587)
2	186.560 ** (10.328)	62.046 ** (3.380)	52.279 ** (8.577)	67.027 ** (3.991)	-5.208 (3.269)
3	160.557 ** (12.707)	41.127 ** (3.722)	55.515 ** (11.038)	61.062 ** (4.344)	-2.853 (4.888)
4	146.127 ** (15.665)	30.115 ** (4.247)	49.737 ** (13.095)	61.659 ** (5.160)	-4.616 (4.880)
5	126.459 ** (18.418)	21.212 ** (4.962)	44.694 ** (15.290)	57.147 ** (5.866)	-3.405 (5.670)
6	110.028 ** (21.231)	15.414 ** (5.687)	41.578 * (17.782)	54.762 ** (6.895)	1.726 (6.768)
7	89.426 ** (23.952)	10.212 (6.243)	33.924 + (20.020)	51.030 ** (7.642)	5.740 (7.677)
8	78.007 ** (26.613)	8.250 (7.157)	29.610 (22.269)	51.859 ** (8.778)	11.711 (9.133)
9	70.358 * (29.577)	6.012 (7.828)	22.554 (24.628)	49.784 ** (9.809)	7.991 (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 (0.026)	0.007 (0.007)	-0.014 (0.022)	0.001 (0.004)	0.015 (0.015)
-4	-0.006 (0.021)	0.008 (0.006)	-0.004 (0.018)	0.000 (0.004)	0.011 (0.012)
-3	-0.006 (0.016)	0.006 (0.005)	0.001 (0.015)	0.000 (0.003)	0.012 (0.010)
-2	-0.005 (0.011)	0.007 (0.004)	-0.004 (0.010)	-0.000 (0.002)	0.008 (0.006)
0	0.043 ** (0.011)	0.031 ** (0.005)	-0.002 (0.010)	0.004 * (0.002)	-0.010 + (0.006)
1	0.035 * (0.016)	0.022 ** (0.006)	0.001 (0.014)	0.010 ** (0.003)	-0.001 (0.009)
2	0.018 (0.021)	0.008 (0.006)	-0.003 (0.018)	0.007 + (0.003)	-0.005 (0.012)
3	0.005 (0.026)	0.001 (0.008)	-0.014 (0.023)	0.008 + (0.004)	-0.010 (0.015)
4	-0.002 (0.032)	-0.007 (0.009)	-0.010 (0.028)	0.008 (0.005)	-0.007 (0.018)
5	-0.014 (0.037)	-0.004 (0.011)	-0.019 (0.032)	0.009 (0.006)	-0.001 (0.021)
6	-0.012 (0.043)	-0.002 (0.012)	-0.025 (0.037)	0.007 (0.006)	-0.008 (0.024)
7	-0.010 (0.049)	-0.010 (0.014)	-0.020 (0.042)	0.006 (0.007)	-0.014 (0.028)
8	-0.037 (0.055)	-0.016 (0.015)	-0.038 (0.047)	0.008 (0.008)	-0.010 (0.031)
9	-0.033 (0.061)	-0.007 (0.018)	-0.037 (0.052)	0.007 (0.009)	-0.004 (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 (5.883)	1.293 (1.616)	-1.938 (5.064)	-0.472 (1.043)	2.397 (3.321)
-4	-0.462 (4.713)	0.939 (1.268)	0.779 (4.088)	-0.846 (0.847)	1.334 (2.723)
-3	-0.609 (3.694)	1.410 (1.095)	1.217 (3.409)	-0.628 (0.637)	2.608 (2.211)
-2	-1.204 (2.557)	1.096 (0.892)	-0.132 (2.432)	-0.493 (0.435)	1.675 (1.466)
0	7.136 ** (2.436)	5.507 ** (0.982)	-1.543 (2.401)	0.668 + (0.404)	-2.504 + (1.370)
1	6.577 + (3.682)	4.361 ** (1.323)	-2.360 (3.457)	1.831 ** (0.652)	-2.744 (2.060)
2	4.997 (4.892)	2.272 (1.569)	-3.012 (4.490)	1.371 + (0.823)	-4.366 (2.809)
3	0.876 (6.553)	-0.446 (2.274)	-6.958 (5.932)	1.604 (1.039)	-6.676 + (3.863)
4	-1.229 (7.906)	-2.040 (2.647)	-7.355 (7.113)	1.596 (1.245)	-6.570 (4.719)
5	-4.812 (9.280)	-0.346 (3.204)	-11.742 (8.186)	0.952 (1.391)	-6.324 (5.530)
6	-5.145 (10.699)	-0.555 (3.544)	-13.151 (9.451)	0.608 (1.564)	-7.953 (6.386)
7	-3.804 (12.177)	-1.959 (4.019)	-12.429 (10.743)	0.369 (1.741)	-10.215 (7.166)
8	-10.433 (13.634)	-3.777 (4.527)	-17.311 (11.958)	0.489 (1.985)	-10.165 (8.041)
9	-10.757 (14.990)	-3.263 (4.973)	-19.560 (13.279)	0.620 (2.208)	-11.446 (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 (0.038)	-0.062 (0.056)	0.001 (0.010)	0.002 (0.005)	-0.082 ⁺ (0.043)
-4	0.014 (0.031)	-0.034 (0.046)	0.005 (0.008)	0.005 (0.004)	-0.049 (0.036)
-3	-0.002 (0.024)	-0.027 (0.035)	0.005 (0.006)	0.003 (0.003)	-0.025 (0.026)
-2	-0.002 (0.017)	-0.018 (0.022)	0.004 (0.004)	0.002 (0.002)	-0.016 (0.016)
0	0.069 ** (0.018)	0.128 ** (0.024)	0.023 ** (0.004)	0.025 ** (0.003)	0.059 ** (0.018)
1	0.184 ** (0.027)	0.318 ** (0.039)	0.052 ** (0.006)	0.042 ** (0.004)	0.133 ** (0.028)
2	0.222 ** (0.035)	0.369 ** (0.051)	0.059 ** (0.008)	0.044 ** (0.005)	0.147 ** (0.037)
3	0.218 ** (0.044)	0.373 ** (0.064)	0.061 ** (0.010)	0.042 ** (0.006)	0.155 ** (0.046)
4	0.191 ** (0.052)	0.364 ** (0.078)	0.053 ** (0.012)	0.040 ** (0.007)	0.174 ** (0.056)
5	0.168 ** (0.061)	0.347 ** (0.090)	0.050 ** (0.015)	0.038 ** (0.008)	0.179 ** (0.066)
6	0.156 * (0.070)	0.353 ** (0.104)	0.048 ** (0.017)	0.033 ** (0.009)	0.197 ** (0.075)
7	0.127 (0.078)	0.353 ** (0.117)	0.052 ** (0.019)	0.030 ** (0.010)	0.226 ** (0.085)
8	0.114 (0.087)	0.350 ** (0.130)	0.053 * (0.021)	0.028 * (0.011)	0.236 * (0.096)
9	0.088 (0.096)	0.387 ** (0.144)	0.050 * (0.024)	0.028 * (0.013)	0.300 ** (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 * (2.443)	6.996 + (4.030)	8.259 * (3.908)	0.001 (0.002)	0.000 (0.002)
-4	1.283 (1.490)	4.733 (3.207)	5.068 (3.151)	0.000 (0.002)	0.000 (0.001)
-3	1.130 (1.160)	3.609 (2.525)	3.399 (2.443)	-0.001 (0.002)	0.001 (0.001)
-2	0.060 (0.751)	2.265 (1.521)	2.399 + (1.438)	0.000 (0.001)	-0.001 (0.001)
0	0.667 (0.742)	-0.920 (1.421)	-1.534 (1.347)	0.000 (0.001)	0.003 ** (0.001)
1	2.115 + (1.114)	-2.974 (2.038)	-3.878 * (1.946)	-0.002 (0.001)	0.008 ** (0.002)
2	5.137 ** (1.773)	-0.274 (2.797)	-2.925 (2.709)	-0.003 (0.002)	0.005 ** (0.002)
3	5.863 ** (1.863)	1.791 (3.735)	-0.455 (3.601)	-0.003 (0.002)	0.003 * (0.002)
4	7.259 ** (2.596)	0.933 (4.589)	-0.795 (4.463)	-0.004 (0.003)	0.001 (0.002)
5	8.522 * (4.097)	1.297 (5.370)	-1.291 (5.221)	-0.003 (0.003)	0.001 (0.002)
6	10.783 * (4.605)	3.894 (6.323)	0.887 (6.105)	-0.002 (0.004)	0.001 (0.002)
7	7.019 * (3.407)	3.912 (7.007)	0.380 (6.794)	-0.001 (0.004)	0.001 (0.002)
8	7.630 * (3.702)	5.203 (7.992)	1.239 (7.757)	-0.002 (0.005)	0.002 (0.003)
9	8.096 + (4.147)	7.086 (8.860)	0.930 (8.521)	-0.004 (0.005)	-0.000 (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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