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Jeppe Druedahl

Alessandro Martinello

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University of Copenhagen
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Long-Run Saving Dynamics: Evidence from Unexpected Inheritances

By Jeppe Druedahl and Alessandro Martinello*

We exploit inheritance episodes to provide novel causal evidence on long-run saving dynamics. For identification, we combine a panel of administrative wealth reports with the unexpected timing of sudden parental deaths. After inheritance, net worth converges towards the path established before parental death, and convergence is faster for liquid assets. Using a generalized structural framework, we show that buffer-stock and two-asset models can fit these dynamics, but only if agents are impatient enough and have both strong precautionary and post-retirement saving motives. Relative to standard calibrations, such agents have at least 50 percent higher precautionary savings for given total wealth.

Life-cycle consumption behavior has been a central area of research for the last half century (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. Incorporating illiquid assets (Kaplan and Violante, 2014) enables life-cycle models to match the empirical estimates of short-run consumption responses out of small transitory (Shapiro and Slemrod, 2003; Johnson, Parker and Souleles, 2006; Parker et al., 2013) and permanent (Aaronson, Agarwal and French, 2012) income shocks. However, while short-

* Martinello: Lund University and KWC and SFI, Tycho Brahe Väg 1, Lund, Sweden (Email: alessandro.martinello@nek.lu.se). Druedahl: CEBI, University of Copenhagen, Øster Farimagsgade 5, Copenhagen, Denmark (Email: jeppe.druedahl@econ.ku.dk). We are especially grateful to Paul Bingley, Martin Browning, Mette Ejrnæs, Niels Johannesen, Søren Leth-Petersen, Claus Thustrup Kreiner, Thomas Høgholm Jørgensen, Erik Öberg, Jonathan Parker, Luigi Pistaferri, and seminar participants at Università Cattolica of Milan, Copenhagen Business School, University of Copenhagen, Harvard University, Lund University, the Zeuthen Workshop and the Danish Central Bank for valuable comments and discussions. Jeppe Druedahl gratefully acknowledges financial support from the Danish Council for Independent Research in Social Sciences (FSE, grant no. 5052-00086B).

run consumption responses are key for counter-cyclical fiscal policies, most other policy questions on social security, retirement benefits, insurance, and taxation crucially require a good understanding of long-run saving dynamics.

Nevertheless, little empirical evidence exists on these long-run dynamics. As a consequence, the literature typically calibrates life-cycle models by matching only life-cycle wealth profiles. This paper is the first not only to provide causal empirical evidence of the long-run saving dynamics following a large financial windfall, but also to calibrate a life-cycle model able to match both the standard life-cycle wealth profiles and these novel dynamics, to which we refer as shock dynamics. By matching both wealth levels and shock dynamics, we draw new insights on consumption-saving behavior over the life-cycle.

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, and estimate the causal effect of large windfalls 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]

We analyze this experiment through the lens of a generalized structural model of buffer-stock behavior—augmented with inheritance expectations—which nests both the standard buffer-stock model (Deaton, 1991; Carroll, 1997) and a two-asset model (distinguishing between liquid and illiquid assets, Kaplan and Violante, 2014) as special cases. We assess under which conditions these models can replicate the long-run shock dynamics of saving estimated in our empirical section, and show that matching these dynamics is crucial for determining the relative roles of precautionary and post-retirement saving motives over the life-

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

cycle.

The paper contributes to the literature on life-cycle consumption and saving models by presenting and discussing two main novel findings. First, we show that heirs respond to a sudden, salient, and sizable increase in available financial resources by decreasing their saving efforts in the ten years after inheriting, and that the net worth of the heirs converges back towards the path established before parental death. Overall, only about a third of the initial increase in net worth remains nine years after 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 persist longer over time.

Second, we show that buffer-stock and two-asset models can fit both the life-cycle patterns of wealth levels and the shock dynamics of saving estimated in our empirical analysis. However, this fit is possible only for sufficiently impatient agents with both a strong precautionary saving motive (e.g., due to risk aversion, additional income and financial risk, and exaggerated beliefs about uncertainty) and additional motives to save for retirement besides consumption smoothing (e.g., bequests and longevity risk). High impatience is necessary for fitting the observed long-run shock dynamics of saving. Because high impatience implies less wealth accumulation, strong precautionary and post-retirement saving motives are necessary for matching the life-cycle profile of wealth. In our generalized structural framework we are able to adjust the precautionary and post-retirement saving motives independently and parsimoniously by exploiting parameters interpretable as reduced-form quantities.

Relative to standard parametrizations, models able to fit both the life-cycle profile of wealth and the long-run shock dynamics of saving imply that the level of precautionary savings increases by at least 50 percent holding total wealth constant. This higher fraction indicates that frictions in mechanisms able to counter income risk, such as financial markets and unemployment insurance, carry higher welfare costs. Similarly, rational agents begin to accumulate assets for retirement (and bequest) purposes much later in life.

Moreover, we show that wealth adjustment behavior after a sizable shock provides orthogonal information with respect to consumption responses at the margin. A standard two-asset model calibrated to our data—which implies an average short-run marginal propensity to consume (MPC) of 42 percent—is as unable to fit our causal estimates of long-run wealth adjustment dynamics as a standard buffer-stock model—which implies a short-run MPC of 16 percent. A calibrated buffer-stock model with strong precautionary and post-retirement saving motives is able to fit both wealth levels over the life-cycle and wealth dynamics after a large financial shock while implying an average MPC of 24 percent.[2]

This paper also complements the literature studying consumption responses out of liquidity (Gross and Souleles, 2002; Leth-Petersen, 2010) and wealth changes.[3] With respect to the shocks typically studied in this literature, 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 medium- and long-run effects, we complement the existing short-run estimates of the elasticity of consumption on wealth (Paiella and Pistaferri, 2016) and housing equity (Mian, Rao and Sufi, 2013; Kaplan, Mitman and Violante, 2016).

Inheritance provides more than a useful experiment for identifying how saving behavior reacts to financial windfalls. It also plays a critical role role as a vehicle of intergenerational wealth transmission (Bowles and Gintis, 2002; Boserup,

[2]A similarly calibrated two-asset model is also able to fit both wealth levels and shock dynamics of saving and implies an average MPC of 43 percent.

[3]Estimates 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.

Kopczuk and Kreiner, 2016) and driver of inequality (De Nardi, 2004; De Nardi and Yang, 2014). Shapiro (2004) states that U.S. babyboomers are *"in the midst of benefiting from the greatest inheritance of wealth in history"*, amounting to approximately \$9 trillion between 1990 and 2030 (Avery and Rendall, 1993, 2002). Piketty (2011) estimates that in 2010 the flow of inheritance was about 15 percent of national GDP in France.[4] Understanding how inheritances affect individual saving behavior can shed light on the impact of such colossal wealth flows on the aggregate saving rate of an economy.

The remainder of the paper is organized as follows. Section I describes the data we use in our analysis. Section II illustrates our identification strategy. Section III presents our estimates of the causal effect of inheritance on wealth accumulation in the long run. Section IV presents a general structural framework of buffer-stock behavior augmented with rational inheritance expectations. Section V presents our model calibrations and draws novel insights on the structure of saving motives in life-cycle models. Section VI concludes.

I. Data

This paper exploits Danish administrative register data from 1995 through 2012.[5] 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

[4]Even excluding the wealthiest 1 percent of the population, between 1995 and 2010 Danes transferred via inheritance an average of 26.5 billions Danish Kroner (DKK) every year, an amount equal to 1.6 percent of the 2010 country GDP. For further comparison, the 2009 Danish SP stimulus policy, designed to stimulate aggregate consumption in response to the 2008 recession, released into the economy 23.3 billion DKK net of taxes (Kreiner, Lassen and Leth-Petersen, 2013).

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

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.[6] We then use this measure to identify our 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. 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.

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

[6]Details on this calculation appear in Appendix D. This procedure for identifying heirs likely 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).

according to the WHO's ICD-10 codes, represent about 10 percent of all deaths in the sample.[7] 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—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.

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

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.

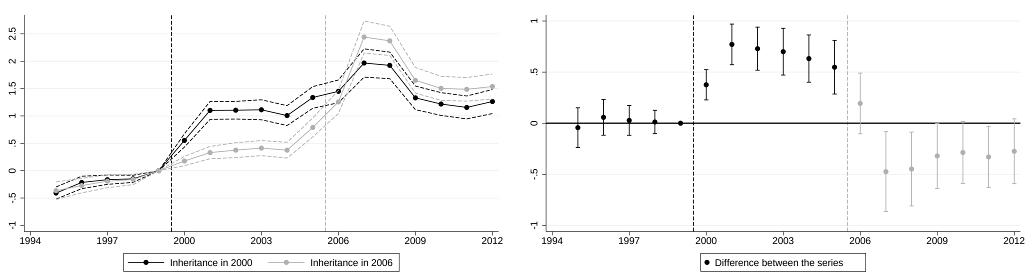
II. Identification

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., 2015; 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 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 may 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 expect—and thus react in advance to—parental death, we perform the main analysis on a sample of heirs inheriting because of sudden deaths, as defined in Section I. 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.



(a) Average net worth by year of inheritance (b) Difference in net worth between groups

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.

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. While after 2005 the control group is contaminated by its own treatment, before 2000 the wealth accumulation paths of the two groups are statistically indistinguishable, showing no evidence of anticipatory behavior.

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. 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 as

(1)

$$y_{i,t} = \gamma_{<-5}\mathbf{1}_{[t-\tau<-5]} + \sum_{n=-5}^{-2} \gamma_n^{pre}\mathbf{1}\left[t-\tau=n\right] + \sum_{n=0}^{9} \gamma_n^{post}\mathbf{1}\left[t-\tau=n\right] + \Lambda_{i,t} + \Psi_i + \varepsilon_{i,t},$$

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 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.[8] Second, we can include all available data in the same estimation, thereby exploiting more combinations across time of inheritance τ. More details on our identification strategy, and on how it nests the approach of Fadlon and Nielsen (2015), appear in Appendix A.

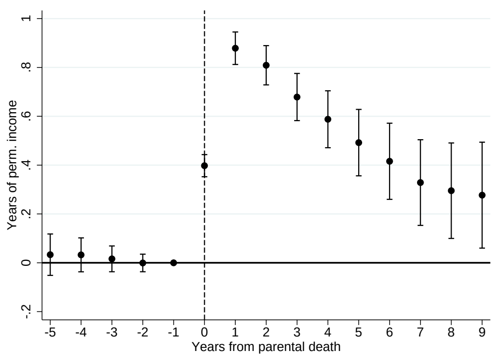
Our approach has two related consequences. First, effects for small n are identified by more combinations over τ. Our estimates are thus more precise as n approaches zero. Therefore, we focus on the first 10 years after parental death and exclude all observations for which $n > 9$, as after this period 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 by both performing a placebo estimation for individuals inheriting small or zero wealth and replicating our results while enforcing a (balanced) fixed control group over n (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 robustness check appears in Figure A.3 and Table A.1 in the Online Appendix.

III. The causal effect of inheritance

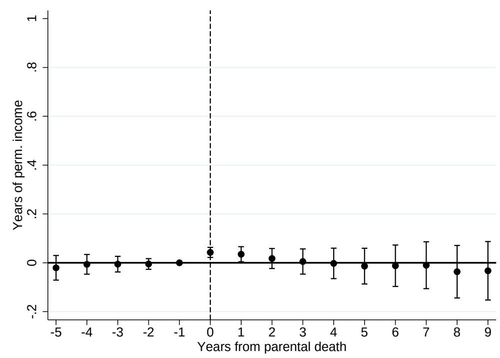
In this section, we estimate the causal effect of inheritance on long-run saving dynamics and demonstrate the robustness of our results to alternative explanations. We proceed in three steps. First, we present our main empirical results, obtained on the sample of heirs for whom our measure of potential 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 estimation on a sample of heirs for whom our measure of po-

[8]Intuitively, 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.

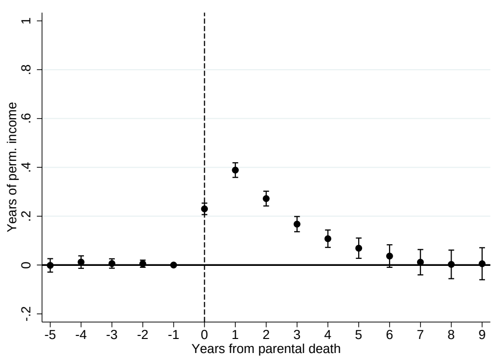
tential inheritance is smaller than a month of their permanent income. Third, we exclude the possibility that confounding factors such as endogenous labor supply responses or committed expenditures drive our results.



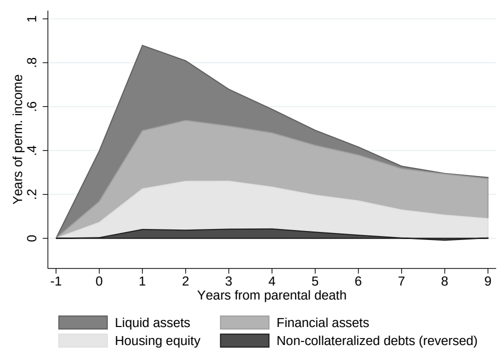
(a) Net worth, large inheritance



(b) Net worth, small or no inheritance (placebo)



(c) Liquid assets, large inheritance



(d) By wealth component, large inheritance

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.

Figure 2 presents the main empirical results of the paper. The scales of all vertical axes refer to years of permanent income.[9] The top left panel of Figure 2

[9] As shown later the normalization with permanent income is not important for our results but simplify

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.

To provide a first approximation of the dynamics of wealth held for precautionary motives, 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 into its different components, 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 components. 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). The full list of coefficients for all regressions appears in the Online Appendix. 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

the interpretation.

Table 2—The effect of inheritance on wealth accumulation

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

in both sets of results, demonstrating that these results do not depend on the permanent income normalization. While heirs deplete most of the initial burst of liquid wealth within five years of parental death, partly consuming it and partly investing it in housing equity, accumulated financial investments persist over time.[10]

Table 3—Dynamics of housing equity components

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

The effect of inheritance on the accumulation of housing equity is not as straightforwardly interpretable. Table 3 provides the necessary details to describe this convergence process by analyizing separately the components of housing equity. The table shows that although total housing value, if anything, increases over time following the shock, the sum of collateralized debt held increases more than proportionally. The response at the extensive margins provides the key mechanism: While the proportion of individuals owning 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

[10]Andersen and Nielsen (2011) show that financial market participation increases even if the inheritance does not include stocks held by the parent, suggesting that liquidity constraints prevent financial market participation.

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.

To demonstrate that invalid identification or parental death alone do not drive the wealth dissipation patterns shown in the top panel of Table 2, the bottom panel of Table 2 replicates the analysis on a sample of individuals receiving little or no inheritance. Panel B of Table 2 shows 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. (2015) 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 (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. (2015) 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

Table 4—Other budget incomings and outgoings

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

[a]These results are estimated on a sample restricted to individuals that are either married or in a registered partnership.

[b]These 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.

thereafter, for a cumulative impact of 2.5 percent of permanent income in five years.

Overall, labor supply and committed expenditures are unable to 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 calibrated to fit. Qualitatively, the observed patterns of wealth convergence are consistent with the predictions of the buffer-stock model under standard parameter choices. In this class of models, the combination of impatience and uncertainty about future income implies that individuals aim to hit a target ratio of precautionary savings relative to to their permanent income. If an individual's wealth is below this target, prudence dominates impatience and agents save; if wealth over income is above this target, impatience dominates prudence and agents deplete their savings. In the remainder of the paper, however, we show that the buffer-stock model under standard parameter choices implies quantitatively too little convergence.

IV. A general framework of life-cycle consumption and savings

This section describes the unified modeling framework we use to draw insights from the long-run shock 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 standard CRRA preferences. However, to take into account inheritance expectations, we augment this standard model with an exogenous process for receiving inheritance. We assume that the individuals are fully aware of this process and thus have rational expectations.

Our framework allows for flexibile adjustments of the strengths of the post-retirement and precautionary saving motives. To adjust the post-retirement saving motive independently, we introduce a reduced-form taste shifter that strengthens the motive to save for retirement due to, e.g., a bequest motive, non-modeled uncertainty, or longevity risk. This approach is similar to that adopted by Gourinchas and Parker (2002).[11]

To adjust the precautionary saving motive, possibilities include changing the risk individuals face or their beliefs about uncertainty. For example, Guvenen

[11]Explicitly modeling the post-retirement saving motive as a joy-of-giving bequest motive does not change the results of the paper.

et al. (2015) show that, relative to standard income processes, non-Gaussian income risk (especially excess kurtosis) amplifies the precautionary saving motive. House price and financial return risk have similar implications. To avoid these computationally more expensive extensions, we follow Kaplan and Violante (2014) and use Epstein-Zin preferences—which nest CRRA preferences as a special case. These preferences allow us to change the level of relative risk aversion without affecting the intertemporal elasticity of substitution. We thus interpret the relative risk aversion coefficient as a reduced-form proxy for the strength of the precautionary saving motive.

We allow for extensions of the baseline buffer-stock model in several additional directions. To approximate the full distribution of wealth over the life-cycle, we allow for heterogeneity in the discount factor.[12] To allow for heterogeneous saving dynamics across different asset types, we consider a two-asset version of the model with both liquid and illiquid assets as in Kaplan and Violante (2014) and Kaplan, Moll and Violante (2017).

A. The model

The economy is populated by a continuum of individuals indexed by i and working for T_R periods, $t \in \{1, 2, \ldots, T_R\}$. 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 and borrow in a liquid asset, A_t. Saving in the liquid asset provides a risk-free gross return of R, and borrowing in it costs a gross interest rate of $R_{-} > R$. The individual can borrow up to a fraction ω of

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

his permanent income P_t, but cannot retire with debt, such that

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

$$A_{T_R} \geq 0$$

In the two-asset versions of the model, the individual can additionally save in, but not borrow in, 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

$$Y_t = P_t \xi_t \tag{3}$$

$$P_t = G_{t-1} P_{t-1} \psi_t \tag{4}$$

where

$$\begin{aligned} \log \psi_t &\sim \mathcal{N}(-0.5\sigma_\psi^2, \sigma_\psi^2) \\ \log \xi_t &\sim \mathcal{N}(-0.5\sigma_\xi^2, \sigma_\xi^2), \end{aligned}$$

and G_{t-1} is the common deterministic age-specific growth factor of income.

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 the exact timing of parental death. 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. We 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

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

$$N_{t+1} = R_B B_t. \tag{6}$$

To model the post-retirement saving motive flexibly, we use the analytical solution to a perfect foresight problem without constraints or transaction costs to compute the consumption and value functions in the terminal period T_R (denoted $\overline{C}_{T_R}$ and $\overline{V}_{T_R}$ respectively). Specifically, we assume that agents live in retirement from period T_R to T with pension benefits as fraction, κ, of their permanent income at retirement, P_{T_R}, and that their utility function in retirement is scaled by the taste shifter $\zeta \geq 0$. As shown in Appendix B, ζ then controls the post-retirement saving motive. For $\zeta = 0$, there is thus no post-retirement saving motive, while for $\zeta = 1$, the only motive to save for retirement is consumption smoothing. Values of $\zeta > 1$ represent in a reduced-form expression additional saving motives due to, e.g., bequest or non-modeled uncertainty. Details appear in Appendix B.

B. Recursive formulation

Defining the post-decision value function

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

the recursive formulation of the model is

$$
\begin{aligned}
(8) \quad V_t(M_t, N_t, P_t, d_t) &= \max_{C_t, B_t} \begin{cases} C_t^{1-\rho}/(1-\rho) + \beta_i W_t & \text{if } \rho = \sigma \\ [(1-\beta_i) C_t^{1-\sigma} + \beta_i {W_t}^{1-\sigma}]^{\frac{1}{1-\sigma}} & \text{else} \end{cases} \\
& \text{s.t.} \\
A_t &= M_t - C_t + (N_t - B_t) - \mathbf{1}_{B_t \neq N_t} \lambda \\
M_{t+1} &= R(A_t) A_t + Y_{t+1} + H_t \mathbf{1}_{d_t=0} \mathbf{1}_{d_{t+1}=1} \\
N_{t+1} &= R_B B_t \\
\Pr[d_{t+1} = 1] &= \begin{cases} 1 & \text{if } d_t = 1 \\ \pi_t & \text{else} \end{cases} \\
B_t &\geq 0 \\
A_t &\geq -\omega P_t \\
A_{T_R} &\geq 0,
\end{aligned}
$$

where equations (3)-(4) specify the income process.

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 (2017), 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 B provides details on these methods.

C. *Calibration*

We calibrate the model in two steps. In the first step we externally fix all parameters except for the preference parameters ρ, σ, ζ,β, and Δ, which we internally calibrate in a second step (see Section V). The fixed and externally calibrated parameters appear in Table 5. The fit of the exogenous income and inheritance processes appears in Online Appendix C.

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	0.073	Jørgensen (2017)
σ_ξ	Std. of transitory shock	0.085	Jørgensen (2017)
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	0.6375	Externally calibrated
η	Growth rate of inheritance	1.01	Externally calibrated
	Single-asset buffer-stock model		
R	Return of *liquid* assets, *saving*	1.02	Kaplan, Moll and Violante (2017)
R_-	Return of *liquid* assets, *borrowing*	1.078	Kaplan, Moll and Violante (2017)
	Two-asset model		
R	Return of *liquid* assets, *saving*	1.02	Kaplan, Moll and Violante (2017)
R_-	Return of *liquid* assets, *borrowing*	1.078	Kaplan, Moll and Violante (2017)
R_B	Monetary return of *illiquid* assets	1.057	Kaplan, Moll and Violante (2017)
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.

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 chosen to match the profile in our data. Following the analysis in Jørgensen (2017) on Danish register data (using the method in Meghir and Pistaferri, 2004), we set the standard deviation of the permanent shocks equal to $\sigma_\psi = 0.073$, the standard deviations of the transitory shocks equal to $\sigma_\xi = 0.085$, and the retirement replacement rate equal to $\kappa = 0.90$.

We use the same interest rates as in Kaplan, Moll and Violante (2017). The individuals can borrow up to a fraction $\omega = 0.25$ of their annual permanent income. We set the fixed cost for illiquid asset adjustment λ as 2 percent of average yearly income, in line with the calibration choice by Kaplan and Violante (2014).

We choose the parameters for the timing of inheritance to match the life-cycle profile of inheritance receipts. This calibration gives us $\delta_H = 30$ as the age difference between child and parent, $\mu_H = 71$ 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

$$H_t = \eta^{(25+t)-45} \cdot (\Pi_{j=1}^{19} G_j) \cdot h_{45}, \tag{9}$$

where we choose $h_{45} = 0.64$ to match the median inheritance at age 45 relative to permanent income, and $\eta = 1.01$ 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 long-normal distribution, whose variance matches that in the data.

V. Characterization of long-run saving dynamics

This section connects our empirical results with our general theoretical framework by assessing its ability to match the empirical long-run shock dynamics of saving estimated in Section III. To highlight our focus on long-run convergence dynamics rather than short-run level changes, in this section we normalize all estimated and simulated coefficients by the increase in net worth estimated one year after the shock.[13] We begin by focusing on standard buffer-stock models, and then proceed to two-asset models according to the framework outlined in the previous section.

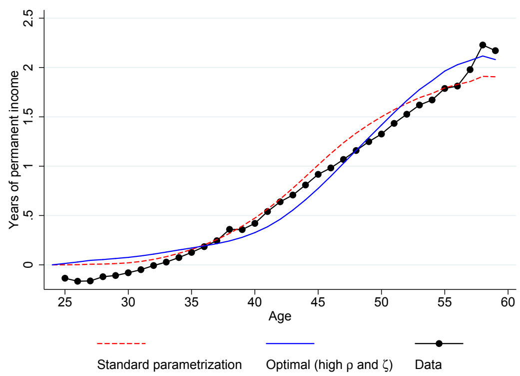
We first consider two different parametrizations of the buffer-stock model with Epstein-Zin preferences. The first one is a standard parametrization, for which we choose standard values for the preference parameters. Specifically, we assume that consumption smoothing is the sole driver of the post-retirement saving motive ($\zeta = 1$) and that the strength of the precautionary saving motive is as often assumed in the literature with $\rho = 2$ (Carroll, 1997; Aaronson, Agarwal and French, 2012; Berger and Vavra, 2015).[14] The second one is an optimal parametrization, for which we adjust the precautionary saving motive (through ρ) and the post-retirement saving motive (through ζ) to obtain the best possible fit of the empirical long-run shock dynamics of saving.

As stressed in the previous section, while the parameters ρ and ζ could be given strict structural interpretations, we prefer to interpret them as reduced-form indicators of precautionary saving motives and preferences for holding wealth after retirement age for purposes other than consumption smoothing (e.g., leaving a bequest) respectively. Both the standard and the optimal parametrizations share the externally calibrated parameters in Table 5, and we follow Kaplan and Violante (2014) in choosing an intertemporal degree of substantiation of $1/\sigma = 3/2$.[15] We initially assume that there is no preference heterogeneity ($\Delta = 0$) and choose the discount factor β (patience) to fit the profile of median net worth over the life-cycle observed in our data.

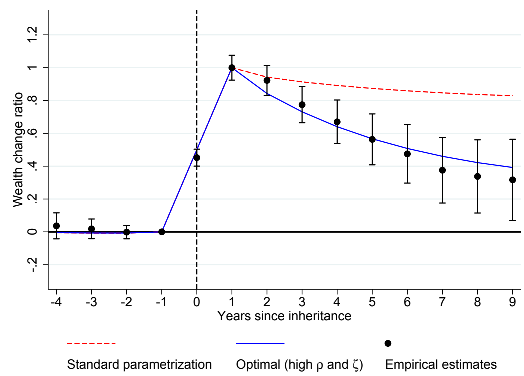
Figure 3 compares empirical and simulated profiles of both the median wealth level over the life-cycle and the long-run dynamic response to inheritance. The figure shows that although the standard parametrization is able to match precisely the evolution of median wealth over the life-cycle, it cannot fit the long-run shock

[13] γ_n/γ_1 in the notation of equation (1).
[14] Kaplan and Violante (2014) have $\rho = 4$.
[15] Appendix Table C.1 shows that this choice is not important for our results.

dynamics of saving following a large financial shock shown in panel (b). The inability to fit this empirical moment is related to the known discrepancy between the average MPCs implied by these models (12-16 percent in our calibrations) and the quasi-experimental evidence on fiscal stimulus payments, showing that US households spent about 25 percent of their tax rebates in the first quarter (Kaplan and Violante, 2014).



(a) Net worth over the life-cycle (median)



(b) Response to inheritance

FIGURE 3. LIFE-CYCLE ACCUMULATION (LEFT) AND SHOCK DYNAMICS (RIGHT) FIT OF THE STANDARD AND OPTIMAL CALIBRATION OF THE BUFFER-STOCK MODEL

Note: The figure compares the empirical and simulated life-cycle profiles of median net worth (left) and response to inheritance (right) for the standard and optimal parametrizations of the buffer-stock model presented in Section IV. We report simulations using Epstein-Zin preferences (with $\sigma = 2/3$). The tuning parameters ρ and ζ and the (implied) internally calibrated discount factor β appear in Table 6. The other fixed and externally calibrated model parameters appear in Table 5.

This standard parametrization implies patient consumers who do not react to financial windfalls as observed in the data.[16] However, Figure 3 shows that by increasing both precautionary (through ρ) and post-retirement (through ζ) saving motives a buffer-stock model can fit both the evolution of median net worth over the life-cycle and the shock dynamics implied by our causal estimates. The increased incentive to accumulate wealth due to ρ and ζ balances the lower

[16] In Figure C.3 in the Online Appendix, we show that even by removing inheritance expectations, and thus considering inheritance as a pure, unexpected wealth shock, the standard parametrization is unable to fit our estimated shock dynamics of saving in the long-run.

discount factor β necessary for agents to be willing to quickly dissipate large financial windfalls.

Varying both saving motives simultaneously is necessary for obtaining this fit. Figure 4 shows that for unbalanced precautionary and post-retirement saving motives a discount factor able to match the life-cycle profile of wealth levels does not exist. Even by choosing the discount factor β that best fits the life-cycle evolution of wealth, if the precautionary saving motive is too large with respect to the post-retirement saving motive rational agents will try to consume most of their wealth as retirement age approaches. If the post-retirement saving motive dominates, impatient rational agents will accumulate wealth only as retirement approaches.

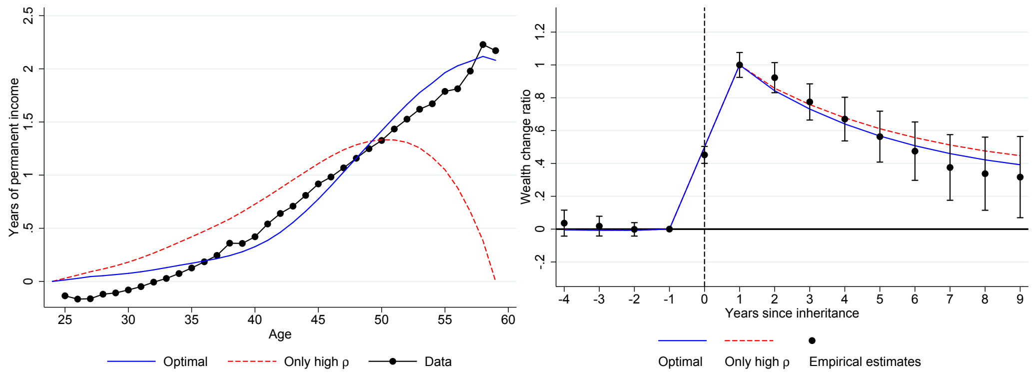
Table 6 formally summarizes and collects the results of Figures 3 and 4, showing the fit of alternative model parametrizations for both life-cycle level profiles and long-run shock dynamics of saving. In all models we internally calibrate β to best fit the life-cycle profile of median net worth. We choose the optimal ζ and ρ as the combination delivering the best aggregate fit in a grid search.[17]

Table 6 makes four important points. First, the table shows that the choice of Epstein-Zin preferences does not drive our results for the standard model parametrization. Both CRRA and Epstein-Zin preferences can precisely fit the life-cycle profile of median net worth, but are unable to fit the causally estimated dynamic responses to large financial shocks.[18]

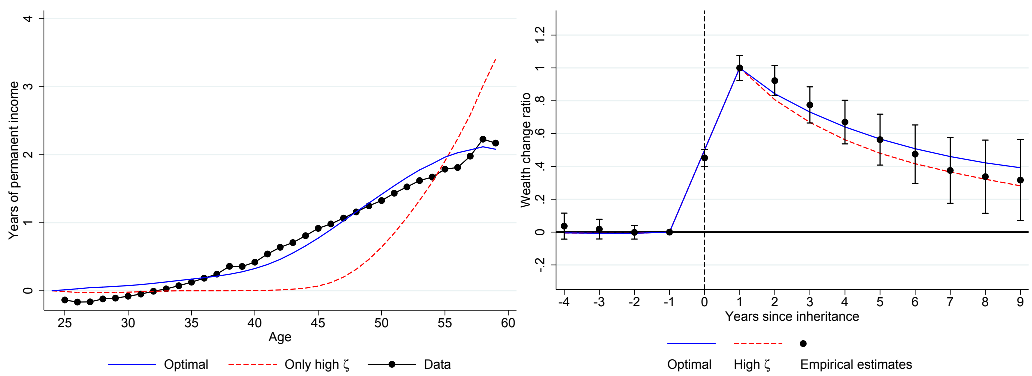
Second, the table shows that, holding every other model parameter constant, only by increasing ρ well beyond its typical range we can lower β enough to replicate our estimated saving dynamics. Note that ρ is in our model the only parameter capturing consumer's dislike for risk. As Guvenen et al. (2015) show, introducing higher-order income risk can also amplify the precautionary saving

[17]All values from the grid search are available in Online Appendix Table C.4 and C.5. Appendix B describes the details of our calibration strategy.

[18]Tables C.2 and C.3 in the Appendix show that because of the identity between ρ and σ, iterating over different values of ρ in models using CRRA preferences does not improve the fit of the model to the data.



(a) High precautionary saving motive alone



(b) High retirement saving motive alone

Figure 4. Life-cycle accumulation (left) and shock dynamics (right) fit of alternative calibrations of the buffer-stock model

Note: The figure compares the empirical and simulated life-cycle profiles of median net worth (left) and response to inheritance (right) for alternative parametrizations of the buffer-stock model presented in Section IV. The dashed lines show the simulated profiles according to the optimal parametrization (Figure 3). The fixed and externally calibrated parameters of the model appear in Table 5. The tuning parameters ρ and ζ and the (implied) internally calibrated discount factor β used for each alternative parametrization appear in Table 6.

Table 6—Parameters and fit of buffer-stock models

					Fit		
					Levels		Dynamics
Parametrization	ρ	ζ	β	MPC	Median	IQR	Net worth
			Panel A: CRRA preferences ($\sigma = \rho$)				
Standard	2.0	1.0	0.977	0.12	0.007	2.318	0.821
			Panel B: Epstein-Zin preferences ($\sigma = 2/3$)				
Standard	2.0	1.0	0.977	0.16	0.015	2.145	0.884
Increased prec. savings motive	25.0	1.0	0.926	0.23	0.377	2.803	0.059
Increased life-cycle savings motive	2.0	1.8	0.955	0.32	0.277	2.658	0.068
Optimal	25.0	1.8	0.917	0.24	0.017	2.095	0.032
			Panel C: Heterogenous Epstein-Zin preferences ($\sigma = 2/3$)				
Standard	2.0	1.0	[0.970;0.984]	0.19	0.027	0.061	0.508
Optimal	25.0	1.8	[0.896;0.942]	0.24	0.017	0.17	0.05

Note: The table shows how the different model specifications fit the life-cycle levels of wealth accumulation and the saving dynamics after a large financial shock. The first two columns of the table show the value of the free calibration parameters ρ (precautionary saving motive) and ζ (post-retirement saving motive). The third column shows the value of the internally calibrated discount factor β (or its range in the case of heterogeneous preferences), chosen to best fit the life-cycle profile of median wealth. The fourth column shows the implied average MPC in the model. The final three columns report the measures of fitness of the median and interquartile range of net worth over the life-cycle, and of the saving dynamics in the decade after a large financial shock. Wealth level fit are computed as mean squared errors from the age of 25 to the age of 59. The shock dynamics fit is calculated as the mean squared error weighted by the standard error of the empirical estimates, or $\sum_{n=2}^{9} \left(\hat{\gamma}_n^{data} - \hat{\gamma}_n^{model}\right)^2 \frac{\bar{\sigma}}{\hat{\sigma}_n}$, where $\bar{\sigma}$ is $\sum_{n=2}^{9} \hat{\sigma}_n/8$.

motive. Unobserved (and possibly incorrect) beliefs about risk have similar effects. We therefore prefer to interpret ρ as a reduced-form parameter rather than applying a strict structural interpretation.[19] Our results demonstrates the more general point that precautionary motives play a crucial and quantitatively dominant role in shaping individual saving strategies.

[19]Table C.1 in the Online Appendix supports this interpretation by showing that increasing the variance of income shocks while holding ρ constant improves the model fit in a similar fashion.

Third, the table shows that for high precautionary savings motives, post-retirement saving motives are necessary to fit the life-cycle profile of wealth accumulation. A ζ above one pushes agents to accumulate wealth approaching retirement even in the presence of high replacement rates, and is consistent with the empirical evidence showing that agents keep accumulating assets during retirement (Nardi, French and Jones, 2016), for example in order to leave a bequest (De Nardi, 2004; De Nardi and Yang, 2014).

Fourth, the table shows that, even allowing for heterogeneous discount factors. the standard model cannot fit our estimated shock dynamics. Heterogeneous preferences contribute only in explaining heterogeneities in wealth accumulation over the life-cycle, as shown by the increased fit of the interquartile range of wealth accumulation over the life-cycle in Panel C.

A. Two-asset models

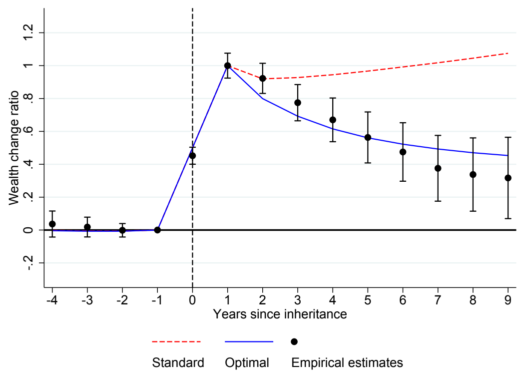
We have shown that, by combining low patience and strong precautionary and post-retirement saving motives, buffer-stock models can match not only the levels but also the shock dynamics of wealth accumulation over the life-cycle. In this subsection we show that the same intuition applies for more complex and computationally expensive two-asset models (Kaplan and Violante, 2014).

Section III shows that the housing market plays an important role in shaping the differential shock dynamics of liquid and illiquid wealth. Although modeling housing markets in detail is not the focus of this paper, two-asset models provide a convenient approximation of these mechanisms: By separating liquid and illiquid net worth, we are able to test the model predictions about the dynamic adjustments of both total and liquid wealth.[20]

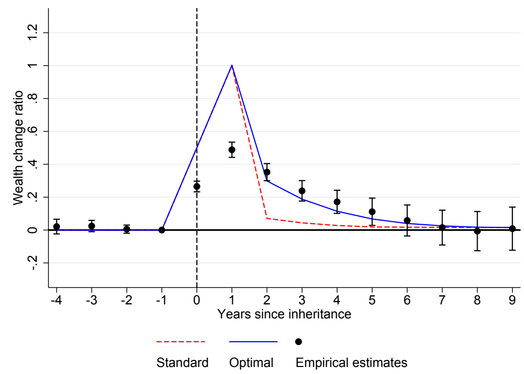
As in our analysis of the buffer-stock model, we evaluate the fit of the shock dynamics of both a two-asset model with standard parameters and the two-asset model resulting from a grid search over combinations of precautionary and post-

[20]Empirically, we define liquid wealth as the difference between liquid assets and uncollateralized debts.

retirement saving motives. For both models we internally calibrate the discount factor to match the median wealth levels over the life-cycle.



(a) Net worth



(b) Liquid worth

FIGURE 5. SHOCK DYNAMICS IN TWO-ASSET MODELS

Note: The figure compares the empirical and simulated long-run saving dynamics following a large financial shock of total and liquid worth for the two-asset version of the model presented in Section IV. The tuning parameters ρ and ζ and the (implied) internally calibrated discount factor β appear in Table 7. The other fixed and externally calibrated model parameters appear in Table 5.

TABLE 7—PARAMETERS AND FIT OF TWO-ASSET MODELS

					Fit		
					Levels	Dynamics	
Parametrization	ρ	ζ	β	MPC	Median	Net worth	Liquid
Standard	2.0	1.0	0.946	0.45	0.009	1.666	0.428
Optimal	30.0	1.6	0.888	0.43	0.008	0.081	0.029

Note: The table shows how the different model specifications fit the life-cycle levels of wealth accumulation and the saving dynamics after a large financial shock in two-asset models. The structure of the table mirrors that of Table 6.

Figure 5 and Table 7 demonstrate that the same intuition as in the single-asset model holds for the two-asset model. Only combining strong precautionary and post-retirement saving motives with low patience can the two-asset model fit both the levels and the shock dynamics of wealth accumulation. Remarkably, although we target net worth saving dynamics in our grid search, the shock dynamics fit of liquid assets also greatly improves for the optimal parametrization.[21]

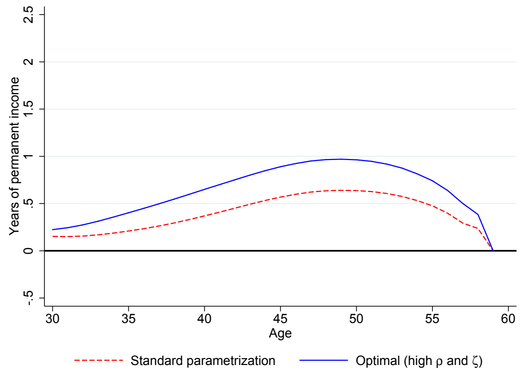
Furthermore, Table 7 stresses how long-run saving dynamics provide orthogonal information with respect to consumption decisions. While, in one-asset models, moving from the standard to the optimal parametrization increases the implied MPC, the optimal two-asset parametrization implies a marginally lower MPC than the standard model.

B. Implications for precautionary and retirement savings

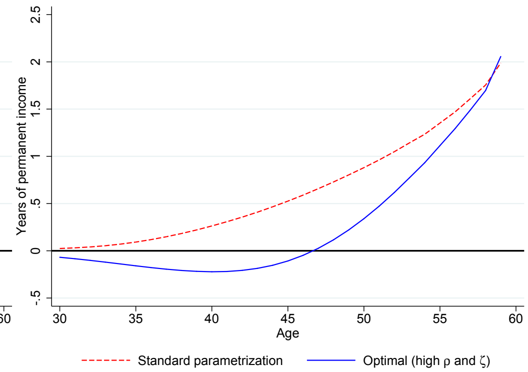
The implications of models with enhanced impatience, precautionary saving motives, and post-retirement saving motives differ sharply from those of models with more standard parametrizations. If, for a given wealth level, agents hold a higher fraction of wealth for precautionary purposes, then frictions in mechanisms able to counter income risk, such as financial markets and unemployment insurance, carry higher welfare costs. In the remainder of this section we focus on the change across the standard and optimal parametrizations of the relative importance of precautionary and retirement saving motives over the life-cycle.

Typically, empirical data do not directly measure the proportion of wealth accumulated for precautionary purposes. However, with a structural model at hand we can decompose the fraction of total wealth held only for precautionary purposes across different specifications. Given two identical groups of agents, exposed to the same shocks throughout their life-cycle, we assume that consumers in one of the two groups have no motive to save for retirement ($\zeta = 0$). Because agents in this group do not receive any utility from wealth held during and after retirement, they save only for precautionary purposes and consume all their remaining wealth during the last period. Figure 6 indicates the average wealth held by this group as wealth held for precautionary purposes, and the difference in the average

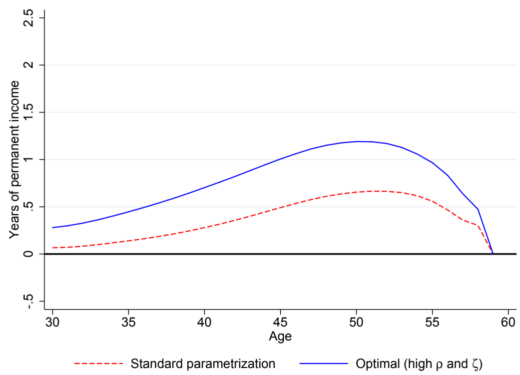
[21] The simulated spike in liquid assets one year after inheritance is due to the the mechanics of the model. While in the model heirs receive inheritance at the end of the year in liquid assets and cannot convert it into illiquid assets until the next period, in reality heirs can immediately turn part of the inheritance in illiquid assets, or even directly inherit illiquid assets.



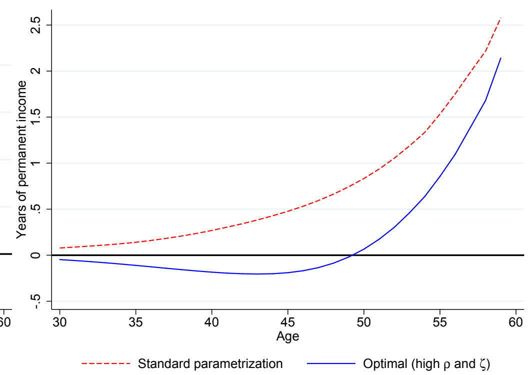
(a) Buffer-stock model, precautionary savings



(b) Buffer-stock model, post-retirement savings



(c) Two-asset model, precautionary savings



(d) Two-asset model, post-retirement savings

FIGURE 6. STRUCTURAL DECOMPOSITION OF WEALTH HELD FOR PRECAUTIONARY (LEFT) AND POST-RETIREMENT MOTIVES (RIGHT)

Note: Using the preference parameters listed in Tables 6 and 7, we calculate wealth accumulated for precautionary motives by simulating the counterfactual wealth profile for the same agents if they had no motive to save for retirement ($\zeta = 0$). These agents, exposed to exactly the same shocks, have no incentive to hold any wealth by the end of the last working year. We calculate wealth held for post-retirement motive as the average difference between the baseline accumulated wealth and that in the counterfactual.

wealth held by the two groups as wealth held for retirement purposes (for both consumption smoothing during retirement and bequest motives).

The figure shows the difference in saving motives between the calibrated models with standard preferences and those with optimal preferences. With optimal parametrizations consumers save at least 50 percent as much for precautionary motives (twice as much in the two-asset model), implying a higher value to mechanisms able to smooth income risk than the value implied by standard preferences. Moreover, agents begin accumulating assets exclusively reserved for post-retirement purposes only towards the end of their working life. This finding 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 smaller effects on younger agents (Chetty et al., 2014).

VI. 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 shock 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 committed expenditures (e.g., pension savings or family growth) and labor supply 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 only by allowing for impatient agents with very strong precautionary savings motives and additional post-retirement saving motives (e.g., bequests or longevity risk) these models can fit both empirical long-run shock dynamics of saving and life-cycle wealth levels. Our optimal 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 late in their working life. Second, as wealth held for precautionary purposes is much 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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Online Appendices to: "Long-Run Saving Dynamics: Evidence from Unexpected Inheritances"

By Jeppe Druedahl and Alessandro Martinello

This document contains (A) details on the identification strategy, (B) details on the solution method and our internal calibration strategies, (C) additional figures and tables for the model simulations, (D) information about access to administrative data and the definitions of the wealth variables used in the analysis and (E) additional robustness checks and the full list of γ_n coefficients estimated in the empirical section of the paper.

A. 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 A.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.

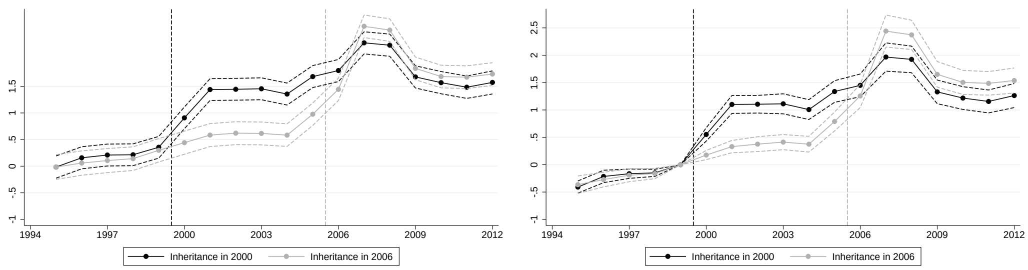
We show these extensions in three steps. First, we show that the FN DiD estimator and our estimation strategy in a restricted dataset estimate the exact same effects. Second, we show how the additional structure imposed by our strategy allows us to extract information more efficiently from the data, 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 as τ.[1] We describe the wealth holdings at year t of an individual i inheriting at

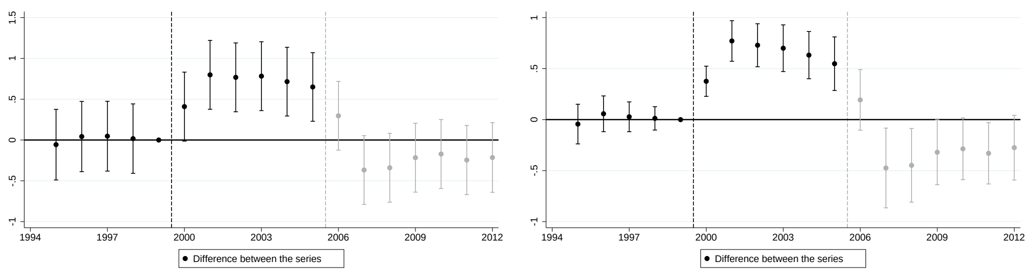
[1] For simplicity, we replace individual and cohort-by-year fixed effects Ψ_i and $\Lambda_{i,t}$ with the aggregated fixed effects by the time of inheritance Ψ_τ and year fixed effects Λ_t. Figure A.1 shows that the inclusion of more granular fixed effects greatly reduces the amount of unexplained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

Figure A.1. Improving precision with individual FEs



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

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



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

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

time τ as

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

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

Under the assumption of parallel trends, we can compare the FN DiD estimator for $\gamma_n^{FN} \mid 0 < n < \Delta$ with the quantity γ_n obtained by estimating equation (1) on a sub-sample of our data. More specifically, consistently with FN, we restrict our sample to two groups of individuals inheriting a fixed number Δ of years apart (e.g. comparing people inheriting in 2000 and 2006, with $\Delta = 6$) and explicitly assigning a placebo shock at time τ_1 to people inheriting at time $\tau_2 = \tau_1 + \Delta$.

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

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

where $\bar{y}_t^{\tau} = E\left[y_t^{\tau}\right]$. The top two panels of Figure A.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 A.2, and show that, after an initial increase, the average wealth holdings of treatment and control groups converge over time.

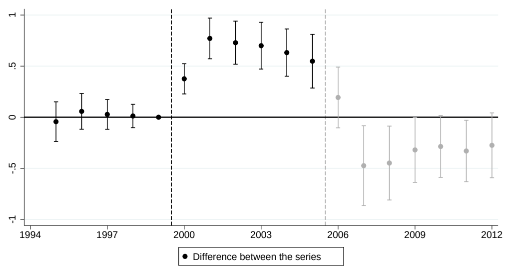
The relationship between γ_n^{FN} and γ_n in our descriptive equation (1) is straightforward. By substituting equation (1) in the FN estimator, we have that

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

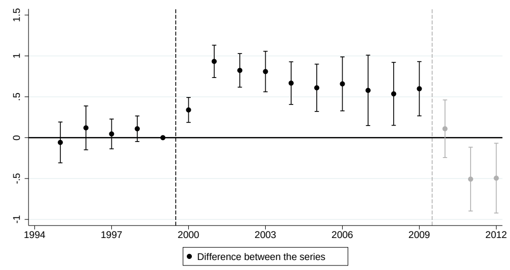
Under the identifying assumption of parallel trends, with respect to γ_{-1} we have that, for $n < \Delta$, $\gamma_{-1-\Delta} = \gamma_{n-\Delta} = \gamma_{-1} = 0$. Thus, γ_n converges to γ_n^{FN}.

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 sum of the real year effect plus the unidentified γ_{14}. In our analysis we thus restrict the

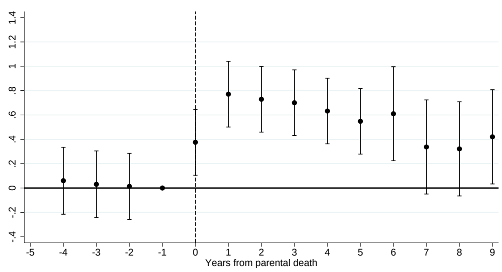
Figure A.2. Estimation of γ_n for net worth using pairs of τ groups



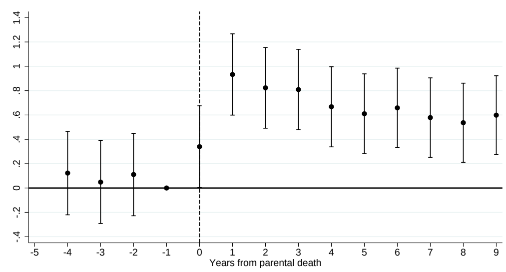
(a) 2000 vs 2006, dynamic DiD



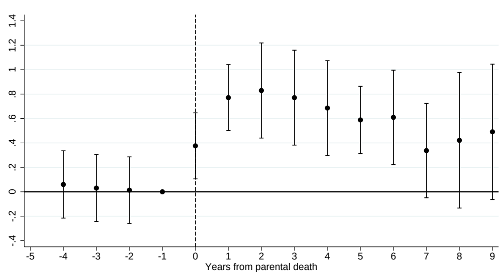
(b) 2000 vs 2010, dynamic DiD



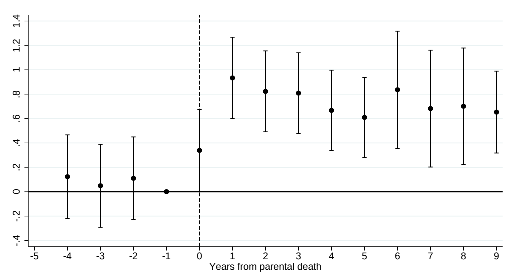
(c) 2000 vs 2006, event study (restr. identification)



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



(e) 2000 vs 2006, event study



(f) 2000 vs 2010, event study

estimation to $n \in \{-5, -4, \ldots, 9\}$. Notice that in practice we can recover the exact FN estimator in an event study by substituting γ_n with a separate dummy for observations in group τ_2 for all n, thus using group τ_2 exclusively as a control.

b. Identifying γ_n for $n \geq \Delta$

The advantage of imposing a minimal structure and estimating equation (1) instead of an explicit difference-in-difference estimator is that, by sacrificing some of the intuition, under the same assumptions we are able to simultaneously estimate all identifiable γ_n. To see this, we can use the FN estimator in (2) to estimate $\gamma_{\Delta+1}$. In the left panes of Figure A.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 A.2, second-to-last panel) is

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

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

By estimating (1) instead we estimate simultaneously all γ_n coefficients. As Section A.b shows that γ_1 is identified, $\gamma_{\Delta+1}$ is also identified as $E\left[\gamma_{\Delta+1}^{FN}\right] + \hat{\gamma}_1$. The coefficient $\gamma_{\Delta+1}$ is thus identified separately from year and group fixed effects. The bottom four panels of Figure A.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 A.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 A.2 estimates equation (1), augmented with individual fixed effects, with no data restrictions. In the third row, all identifiable γ_n coefficients are estimated simultaneously.

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

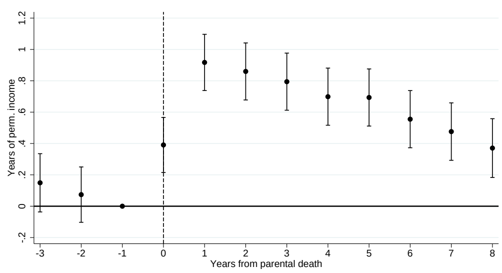
c. Allowing for multiple Δ

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

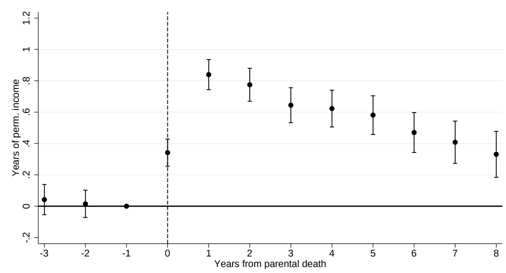
We highlight this point in Figure A.3, which compares estimates obtained by the FN estimator (on a balanced panel) with those obtained estimating equation (1) on the same data. In the left panels of Figure A.3 we thus impose $\Delta = 9$ and estimate the effect of inheriting between 1999 and 2001 explicitly 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 A.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.

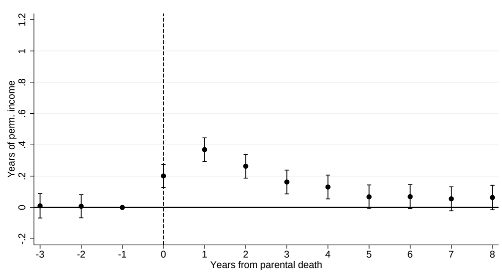
Figure A.3. Comparison of explicit control group (FN, balanced panel) versus event study design (this paper, varying control groups), estimated on individuals inheriting in 1999-2001 and 2008-2010



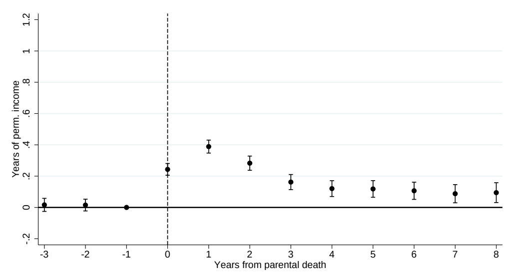
(a) Net worth, explicit control groups



(b) Net worth, event study design



(c) Liquid assets, explicit control groups



(d) Liquid assets, event study design

The figure shows not only that the convergence paths estimated by the two approaches are virtually identical, but also that by exploiting the structure of the dynamic response (and thereby using more information), the event study approach improves the precision of the empirical estimates. This improvement in precision occurs primarily for coefficients for which more combination of inheritance year provide identification, i.e. for n close to zero. Figure A.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 A.1.

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

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

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

B. Solution algorithm and internal calibration

The appendix firstly contains a detailed description of the approach we take to compute the value and consumption functions at retirement. It next presents the details of our various internal calibration strategies. Finally, it contains additional information on the solution algorithm, its implementation and some validation tests.

a. Terminal value function

We construct the terminal value function as the analytical solution to the following perfect foresight problem in retirement

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

where $\overline{R} = R$ in the buffer-stock model and $\overline{R} = R_b$ in the two-asset model, and

$$
(4) \qquad \overline{M}_{T_R} = M_{T_R} + N_{T_R} + H_{T_R} \mathbf{1}_{d_{T_R}=0}
$$

The Euler-equation for this problem is

$$
(5) \qquad \frac{C_{t+1}}{C_t} = \left(\beta_i \overline{R} \frac{\zeta_{t+1}}{\zeta_t}\right)^{\frac{1}{\sigma}}
$$

From period $T_R + 1$ and onward the problem is both perfect foresight and free of intraperiod constraints. This implies that we can analytically solve for the consumption function

$$
\begin{aligned}
C_{T_R+1} &= \gamma_1 \left[\overline{M}_{T_R+1} + \gamma_0 \kappa P_{T_R}\right] \\
&= \gamma_1 \left[\overline{R}(K_{T_R} - C_{T_R}) + (1+\gamma_0)\kappa P_{T_R}\right]
\end{aligned} \tag{6}
$$

where

$$
\begin{aligned}
\gamma_0 &\equiv \frac{1-(\overline{R}^{-1})^{T-T_R}}{1-\overline{R}^{-1}} - 1 \\
\gamma_1 &\equiv \frac{1-\overline{R}^{-1}(\beta_i \overline{R})^{1/\sigma}}{1-\left[\overline{R}^{-1}(\beta_i \overline{R})^{1/\sigma}\right]^{T-T_R}}
\end{aligned}
$$

Next, the value function in period $T_R + 1$ is then given by

$$
\overline{V}_{T_R+1}(\overline{M}_{T_R+1}, P_{T_R}) = \begin{cases} \frac{\zeta\gamma_2 C_{T_R+1}^{1-\sigma}}{1-\sigma} & \text{if } \rho = \sigma \\ ((1-\beta_i)\zeta\gamma_2)^{\frac{1}{1-\sigma}} C_{T_R+1} & \text{else} \end{cases} \tag{7}
$$

where

$$
\gamma_2 \equiv \frac{1-\left(\beta_i^{\frac{1}{\sigma}} \overline{R}^{\frac{1-\sigma}{\sigma}}\right)^{T-T_R}}{1-\left(\beta_i^{\frac{1}{\sigma}} \overline{R}^{\frac{1-\sigma}{\sigma}}\right)}
$$

Here we have used the general result that without risk the value function under Epstein-Zin preferences, V_t^{EZ}, is related to the value function under CRRA preferences, V_t^{CRRA}, by the monotone transformation

$$
V_t^{EZ} = \left((1-\beta_i)(1-\sigma)V_t^{CRRA}\right)^{\frac{1}{1-\sigma}}
$$

If the Euler-equation is satisfied in period T_R, we therefore have that

$$\frac{C_{T_R+1}}{C_{T_R}} = \left(\beta_i \overline{R}\zeta\right)^{\frac{1}{\sigma}} \Leftrightarrow C_{T_R} = \frac{\gamma_1 \left[\overline{M}_{T_R} + (1+\gamma_0)\,\overline{R}^{-1}\kappa P_{T_R}\right]}{\overline{R}^{-1}(\beta_i \overline{R}\zeta)^{\frac{1}{\sigma}} + \gamma_1}$$

The Euler-equation is both necessary and sufficient for all interior consumption choices and we can therefore conclude that the optimal consumption function in period T_R must be

$$(8) \qquad \overline{C}_{T_R}(\overline{M}_{T_R}, P_{T_R}) \;=\; \min\left\{ M_{T_R}, \frac{\gamma_1 \left[\overline{M}_{T_R} + (1+\gamma_0)\,\overline{R}^{-1}\kappa P_{T_R}\right]}{\overline{R}^{-1}(\beta_i \overline{R}\zeta)^{\frac{1}{\sigma}} + \gamma_1} \right\}$$

The value function in period T_R then finally becomes

$$(9) \qquad \overline{V}_{T_R}(\overline{M}_{T_R}, P_{T_R}) = \begin{cases} \frac{C_{T_R}^{1-\sigma}}{1-\sigma} + \beta_i \frac{\zeta\gamma_2 C_{T_R+1}^{1-\sigma}}{1-\sigma} & \text{if } \rho = \sigma \\ \left[(1-\beta_i) C_{T_R}^{1-\sigma} + \beta_i \left(\gamma_3 C_{T_R+1}\right)^{1-\sigma}\right]^{\frac{1}{1-\sigma}} & \text{else} \end{cases}$$

where

$$\gamma_3 \;\equiv\; ((1-\beta)\zeta\gamma_2)^{\frac{1}{1-\sigma}}$$

and

$$(10) \qquad C_{T_R+1} \equiv \begin{cases} (\beta_i \overline{R}\zeta)^{\frac{1}{\sigma}} C_{T_R} & \text{if } C_{T_R} < \overline{M}_{T_R} \\ \gamma_1(1+\gamma_0\kappa) P_{T_R} & \text{else} \end{cases}$$

b. Calibration procedures

We use three different internal calibration methods in the paper. In all of them we use a simulated method of moments approach targeting central life-cycle moments from age 25 to age 59. To calculate the simulated moments, we simulate a panel of 100.000 individuals.

1) **Calibration of only β:** In this case, we minimize the squared distance between the median life-cycle profile of net worth in the true and simulated data. We start from a vector of starting values in a suitable domain, pick the one delivering the best fit, and start a Nelder-Mead solver from there.

2) **Calibration of β and Δ.** In this case, we additionally target the squared distance between the increase in the interquartile range of net worth in the true and simulated data. We again use a Nelder-Mead solver and start from the β calibrated for the model with homogeneous preferences and $\Delta = 0$.

3) **Calibration of β, ζ and ρ:** For a suitable grid over ζ and ρ we apply the calibration method from approach (1) above to each combination. The calibrated ζ and ρ are chosen based on summing the squared distance between the median life-cycle profile of net worth in the true and simulated data and the squared distance between the impulse response profile of net worth in the true and simulated data weighted by the standard error of the empirical estimates. β is chosen conditionally on ζ and ρ to achieve the best life-cycle fit. This nested calibration approach has the central benefit that it limits the possibility of trading a better fit of the impulse response profile for a worse fit of the life-cycle profile. Closely matching the life-cycle profile is of central importance for our purposes.

c. Choice-specific value functions

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

$$V_t(M_t, P_t, N_t, d_t) = \max_{z_t \in \{0,1\}} v_t(M_t, P_t, N_t, d_t, z_t), \tag{11}$$

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

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

and the value function for adjustment is

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

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

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

d. EGM for non-adjusters

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

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

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

In the buffer-stock model the Euler-equations (14) and (15) 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 (2017) 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).

e. Reducing the state space for adjusters

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

$$
\begin{aligned}
\text{(18)} \qquad \tilde{v}_t(X_t, P_t, d_t) &= \max_{C_t, B_t} \begin{cases} C_t^{1-\rho}/(1-\rho) + \beta_i W_t & \text{if } \rho = \sigma \\ [(1-\beta_i) C_t^{1-\sigma} + \beta_i W_t^{1-\sigma}]^{\frac{1}{1-\sigma}} & \text{else} \end{cases} \\
& \text{s.t.} \\
A_t &= X_t - C_t - B_t - \omega P_t \\
B_t &\geq 0.
\end{aligned}
$$

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

$$
\begin{aligned}
v_t(M_t, P_t, N_t, d_t, 1) &= \tilde{v}_t(X_t, P_t, d_t) \\
&\text{s.t.} \\
X_t &= M_t + N_t - \lambda + \omega P_t.
\end{aligned} \tag{19}
$$

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

$$
\begin{aligned}
\tilde{v}_t(X_t, P_t, d_t) &= \max_{s_t \in [0,1]} \begin{cases} C_t^{1-\rho}/(1-\rho) + \beta_i {W_t}^{1-\sigma}) & \text{if } \rho = \sigma \\ [(1-\beta_i)C_t^{1-\sigma} + \beta_i W_t]^{\frac{1}{1-\sigma}} & \text{else} \end{cases} \\
&\text{s.t.} \\
M_t &= (1 - s_t)X_t - \omega P_t \\
N_t &= s_t X_t \\
C_t &= C_t^{\star}(M_t, N_t, P_t, d_t, 0) \\
A_t &= M_t - C_t^{\star} \\
B_t &= N_t.
\end{aligned} \tag{20}
$$

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.

f. 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

$$W_t(\bullet) \quad = \quad \beta \mathbb{E}_t \left[\begin{cases} v_{t+1}(\bullet, 0)^{1-\rho} & \text{if } z^{\star}_{t+1}(\bullet) = 0 \\ \tilde{v}_{t+1}(\bullet)^{1-\rho} & \text{if } z^{\star}_{t+1}(\bullet) = 1 \end{cases} \right]^{\frac{1}{1-\rho}} \tag{21}$$

where

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

We also interpolate $\mathbb{E}_t \left[C_{t+1}^{-\sigma} V_{t+1}^{\sigma-\rho} \right]$ from equations (14)-(15) 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 $\#_M = 200$, $\#_X = 120$ and $\#_A = \#_N = 100$ and $\#_P = 60$. For the buffer-stock model we instead use $\#_M = 600$ and $\#_A = 300$, but keep $\#_P = 60$.

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 (20) 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). The code was run on a Intel(R) Core(TM) i7-4770 CPU with 8 processors (4 cores) and 32 GB of RAM.

g. Code validation

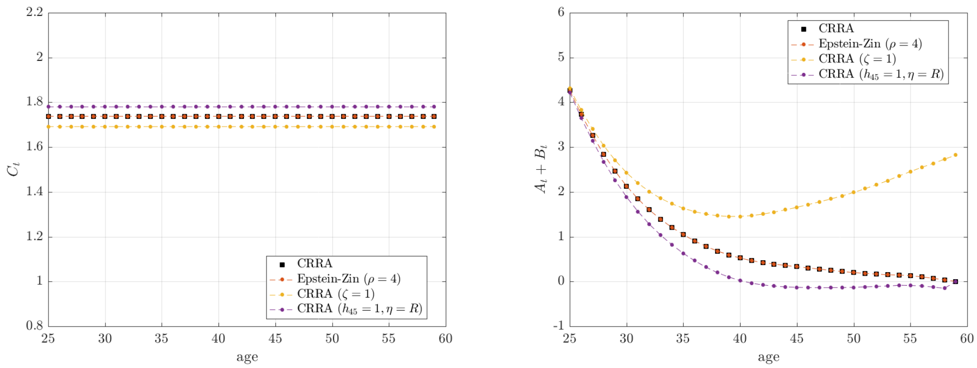
In this section we show that the code package developed for this paper delivers robust simulation results, which also aligns with theoretical results when available.

Figure B.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 $R = \beta^{-1} = \frac{1}{0.975}$,
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



(a) Consumption

(b) Net worth

FIGURE B.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 $\beta = 0.975$, ,$\sigma = \rho = 2$, $\zeta = 0$, $\sigma_\psi = \sigma_\varepsilon = 0$, $R = \beta^{-1}$, $\omega = 2$, $h_{45} = 0$ and the remaining parameters as in the main text. In the simulation all agents are born wealthy with $A_0 = 5$.

1) Epstein-Zin preferences with $\rho \neq \sigma$.

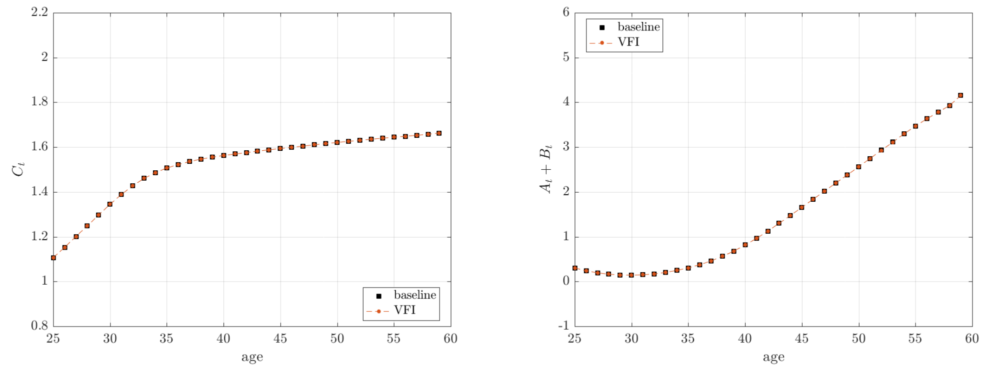
2) Active post-retirement saving motive, $\zeta > 0$.

3) Some inheritance, $h_{45} > 0$, if and only if $\eta = R$.

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 B.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.

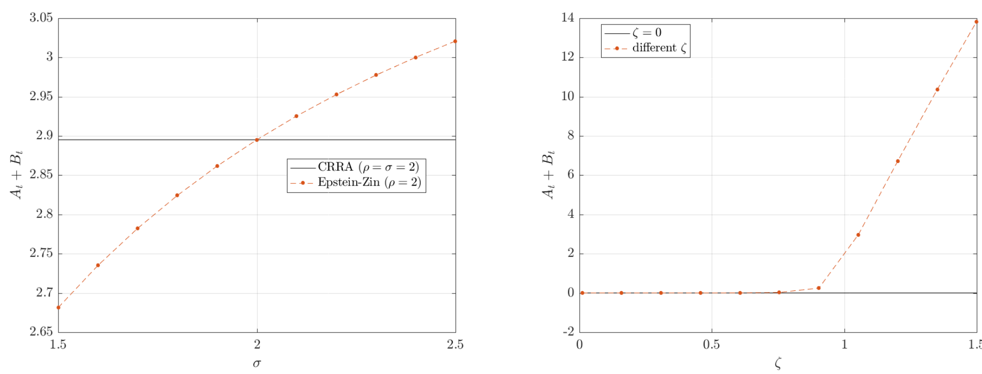
Figure B.3 shows average net worth at retirement when varying σ and ζ. First, we see that when $\rho = \sigma$ then model is the same with CRRA and Epstein-Zin preferences. Second, we see that when $\zeta \to 0$ agents save less and less for retirement, specifically $\lim_{\zeta \to 0} A_{T_R} = 0$.



(a) Consumption (b) Net worth

FIGURE B.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 $\sigma = 2/3$, $\beta = 0.975$, $\rho = 2$ and $\zeta = 1$.



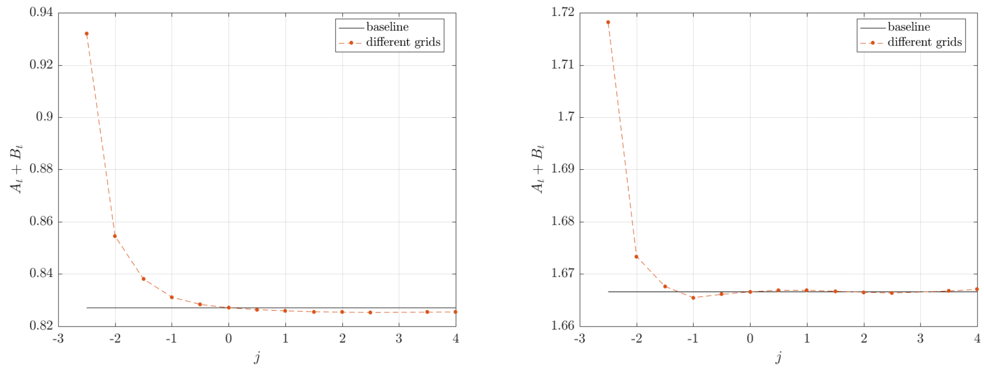
(a) Net worth at retirement (b) Net worth at retirement

FIGURE B.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 $\sigma = 2/3$, $\beta = 0.975$, $\rho = 2$ and $\zeta = 1$.

Figure B.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 B.5 shows that when $\lambda \to 0$ then

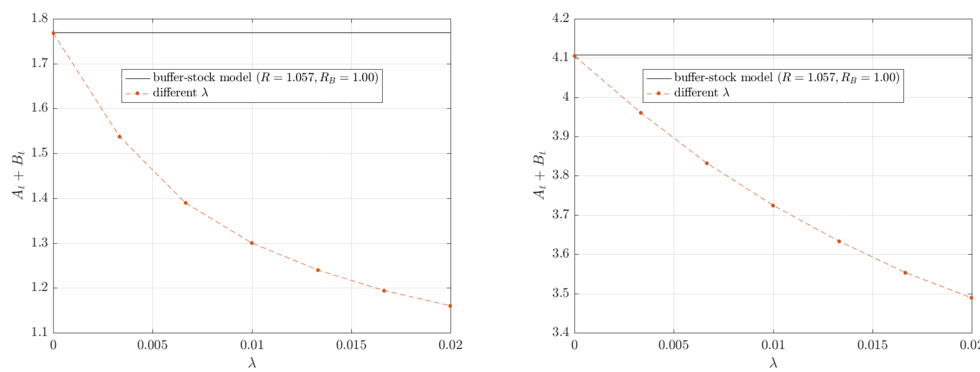


(a) Net worth at age 45 (b) Net worth at retirement

Figure B.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 $\sigma = 2/3$, $\beta = 0.975$, $\rho = 2$ and $\zeta = 1$. Grids are specified as $\#_M = 600 + j \cdot 100$, $\#_P = 60 + j \cdot 20$ and $\#_A = 300 + j \cdot 100$,.

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.

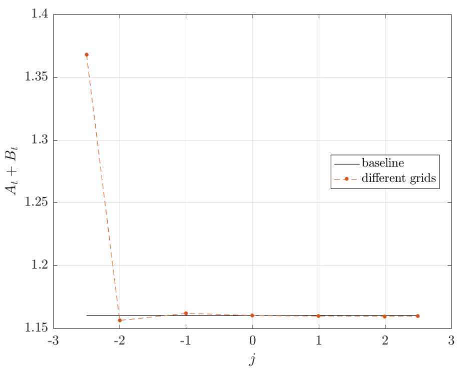


(a) Net worth at age 45 (b) Net worth at retirement

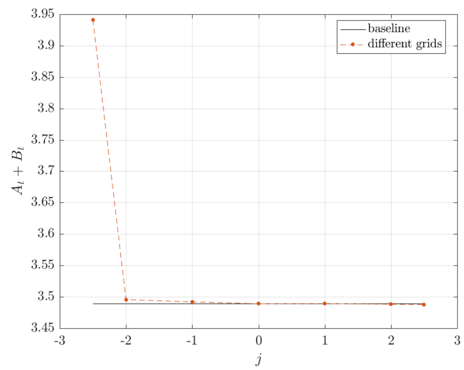
Figure B.5. Two-asset model: $\lambda \to 0$

Note: This figure shows average net worth at age 45 and retirement when $\lambda \to 0$ starting from a two-asset model with the calibration from the main text and $\sigma = 2/3$, $\beta = 0.945$, $\rho = 2$ and $\zeta = 1$.

Figure B.5 shows that grids denser than in the baseline does not affect the implied average net worth at age 45 or at retirement. Figure B.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 B.8 shows that varying β, ρ, σ, ζ, κ, and σ_ψ imply results in line with economic intuition.



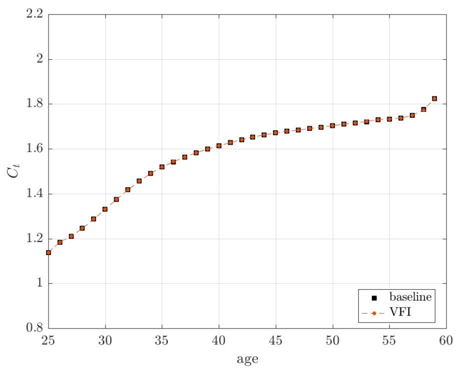
(a) Net worth at age 45



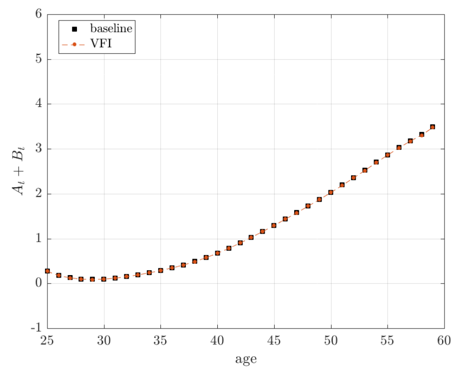
(b) Net worth at retirement

Figure B.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 $\sigma = 2/3$, $\beta = 0.945$, $\rho = 2$ and $\zeta = 1$. Grids are specified as $\#_M = 200 + j \cdot 70$, $\#_X = 200 + j \cdot 50$, $\#_P = 60 + j \cdot 20$, $\#_N = 100 + j \cdot 30$, and $\#_A = 100 + j \cdot 30$.



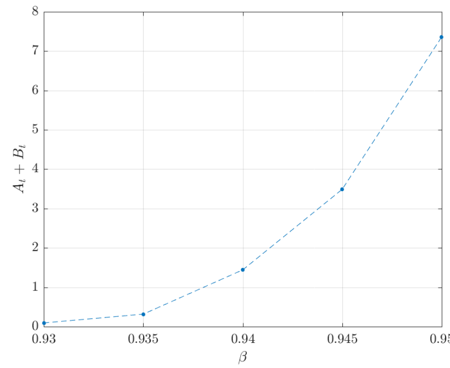
(a) Consumption



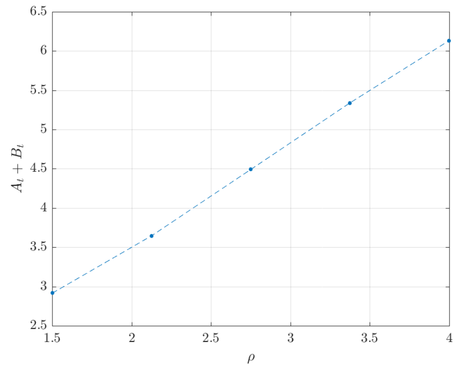
(b) Net worth

FIGURE B.7. TWO-ASSET MODEL: VFI

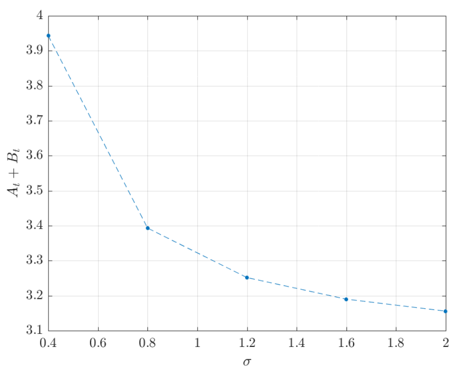
Note: This figure shows life-cycle profiles of average consumption and average net worth from a two-asset model with the calibration from the main text and $\sigma = 2/3$, $\beta = 0.945$, $\rho = 2$ and $\zeta = 1$.



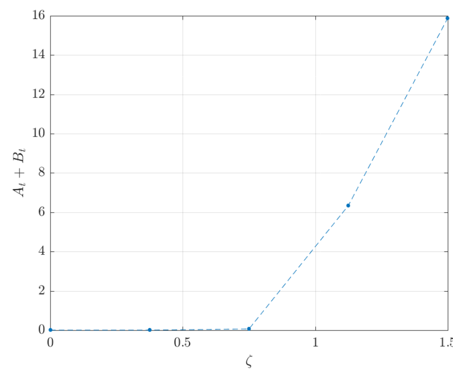
(a) β



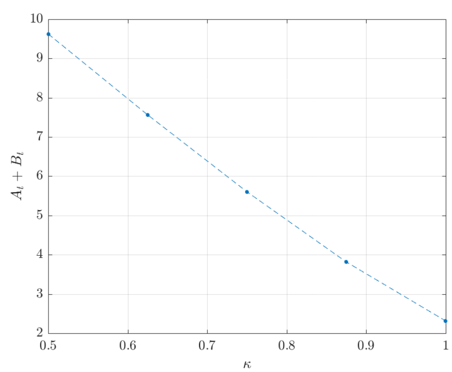
(b) ρ



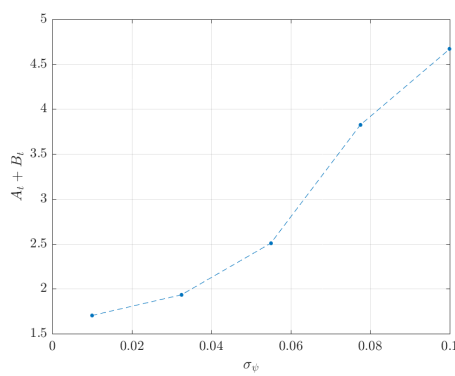
(c) σ



(d) ζ



(e) κ



(f) σ_ψ

FIGURE B.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 $\sigma = 2/3$, $\beta = 0.945$, $\rho = 2$ and $\zeta = 1$.

C. Additional Figures and Tables

a. *Outcomes*

Table C.1 shows central model outcomes for the various specifications.

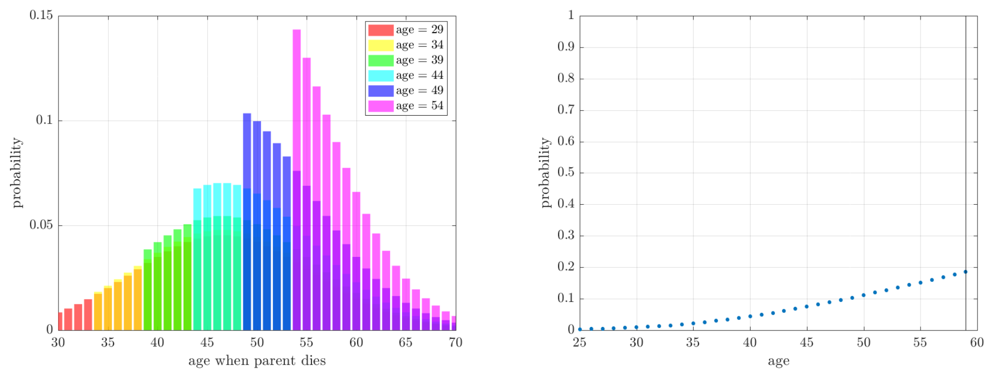
Table C.1—Selected outcomes

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
β	0.977	0.977	0.917	0.977	0.919	0.946	0.888
Δ				0.007	0.023		
ρ	2.0	2.0	25.0	2.0	25.0	2.0	30.0
ζ	1.0	1.0	1.8	1.0	1.8	1.0	1.6
σ	2.000	0.667	0.667	0.667	0.667	0.667	0.667
Assets	A_t	A_t	A_t	A_t	A_t	A_t, B_t	A_t, B_t
	life-cycle moments						
A_t/P_t (median) at age 35	0.07	0.15	0.17	0.20	0.18	-0.01	0.03
A_t/P_t (median) at age 45	0.87	0.96	0.71	1.04	0.72	-0.00	0.03
A_t/P_t (median) at age 55	1.84	1.77	1.94	1.72	1.96	-0.00	0.03
$(A_t + B_t)/P_t$ (median) at age 35						0.01	0.18
$(A_t + B_t)/P_t$ (median) at age 45						0.84	0.82
$(A_t + B_t)/P_t$ (median) at age 55						1.89	1.87
Share of $B_t > 0$ at age 35						0.38	0.47
Share of $B_t > 0$ at age 45						0.79	0.69
Share of $B_t > 0$ at age 55						0.95	0.91
	working age households						
Avg. MPC	0.12	0.16	0.24	0.19	0.24	0.45	0.43
25th	0.04	0.04	0.11	0.04	0.09	0.26	0.29
50th	0.05	0.05	0.16	0.05	0.16	0.37	0.37
75th	0.19	0.15	0.29	0.26	0.32	0.68	0.54
Share of $A_t = -\omega P_t$	0.02	0.00	0.00	0.00	0.00	0.03	0.02
Share of $A_t \in (-\omega P_t, 0)$	0.15	0.02	0.01	0.03	0.02	0.38	0.11
Share of $A_t = 0$	0.07	0.14	0.14	0.16	0.15	0.44	0.38

Note: This table shows selected outcomes for the different main parametrizations.

b. External calibration fit

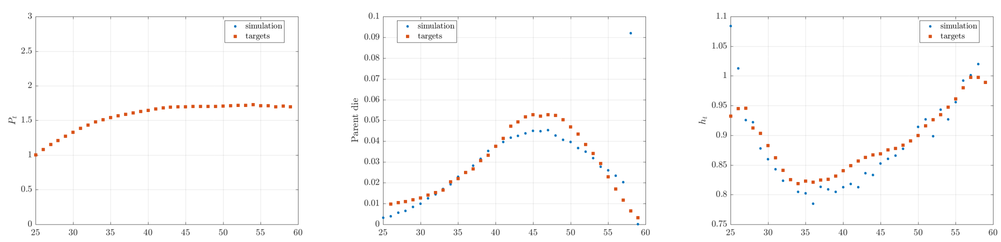
Figure C.1 shows central properties of the inheritance process common across all model specifications. Figure C.2 shows the fit of the externally calibrated parameters related to the income and inheritance processes.



(a) Conditional distribution given age (b) Marginal probability, $\Pr[d_t = 1 | d_t = 0]$

FIGURE C.1. INHERITANCE PROCESS

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



(a) Permanent income (b) Receiving inheritance (c) Size of inheritance

FIGURE C.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 median size of the received inheritance relative to permanent income.

c. Robustness

Table C.2 shows that the main results are robust to changing each of the fixed or externally calibrated parameters. The baseline specification is the buffer-stock model with homogeneous parameters. The discount factor is re-calibrated for each parameter change targeting the life-cycle profile of median net worth as in the main text.

Neither of the rows in Table C.2 produce a substantial improvement in the fit of the long-run shock dynamics of saving without deteriorating the fit of the life-cycle profile of median net worth. In two situations we see a considerable improvement in the fit of the long-run shock dynamics of saving; when the variance of the permanent shocks σ_ψ is increased, and when the replacement rate κ is reduced. In both cases, however, the fit of the life-cycle profile of median net worth substantially deteriorates. These effects are fully aligned with our main results. Increasing σ_ψ is similar to increasing risk aversion ρ, while reducing κ strengthens the motive to save for retirement and this is thus similar to increasing the post-retirement saving motive taste shifter ζ.

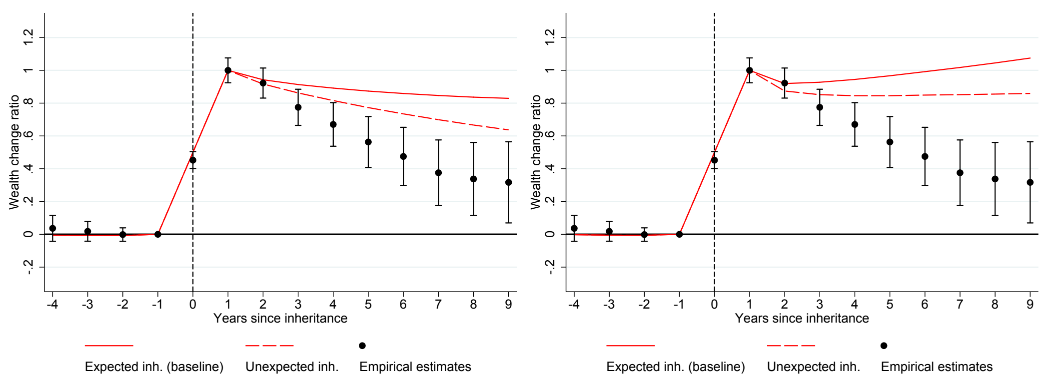
Table C.3 and Table C.4 shows the fit of the life-cycle wealth levels and long-run shock dynamics of saving for a grid of values of ρ and ζ under the restriction of CRRA preferences (i.e. $\sigma = \rho$). The discount factor is re-calibrated for each combination of ρ and ζ; notice that β is sometimes calibrated to be very low when ρ is high implying a very low intertemporal elasticity of substitution. We see that there is no combination of ρ and ζ that simultaneously deliver an acceptable fit of the wealth levels and the long-run shock dynamics. This shows that we need the separation of risk aversion and the intertemporal elasticity substitution Epstein-Zin preferences provide.

Table C.5 and Table C.6 show the fit of the life-cycle wealth levels and long-run shock dynamics of saving for a grid of values of ρ and ζ under the baseline parametrization of the buffer-stock model from the main text. The discount factor is re-calibrated for each combination of ρ and ζ. We see that simultaneously high

ρ and ζ are required to get an acceptable fit of both the the life-cycle wealth levels and long-run shock dynamics of saving.

Figure C.3 shows the shock dynamics fit for the standard parametrizations of buffer-stock and two-assets models with and without inheritance expectations. Without expectations inheritance can be interpreted as a pure unexpected income shock, comparable to a lottery winning. The figure shows that for both sets of models, although an unexpected shock in general accelerates the convergence, the standard model parametrization is unable to fit our estimated shock dynamics of saving. Moreover, the difference between the two simulated responses can be interpreted as bounding the average saving dynamics if only a fraction of agents had rational expectations about inheritance.

Figure C.3. Fit of standard parametrizations in models with and without inheritance expectations



(a) Buffer-stock model

(b) Two-assets model

Table C.2—Robustness - buffer-stock model (various)

	Change	β	Fits: Levels Median	Fits: Dynamics Net worth
1	$\sigma = 0.30$	0.977	0.046	1.005
2	$\sigma = 0.50$	0.977	0.019	0.922
3	$\sigma = 0.70$	0.977	0.013	0.879
4	$\sigma = 0.90$	0.977	0.010	0.853
5	$\sigma_\psi = 0.04$	0.981	0.009	0.738
6	$\sigma_\psi = 0.06$	0.979	0.009	0.841
7	$\sigma_\psi = 0.08$	0.976	0.018	0.888
8	$\sigma_\psi = 0.10$	0.973	0.046	0.787
9	$\sigma_\psi = 0.12$	0.970	0.099	0.547
10	$\sigma_\psi = 0.14$	0.966	0.169	0.297
11	$\sigma_\xi = 0.04$	0.977	0.014	0.979
12	$\sigma_\xi = 0.06$	0.977	0.013	0.941
13	$\sigma_\xi = 0.08$	0.977	0.013	0.895
14	$\sigma_\xi = 0.10$	0.977	0.014	0.848
15	$\sigma_\xi = 0.12$	0.977	0.016	0.795
16	$\sigma_\xi = 0.14$	0.977	0.019	0.742
17	$\kappa = 0.40$	0.962	0.182	0.045
18	$\kappa = 0.60$	0.970	0.065	0.293
19	$\kappa = 0.80$	0.975	0.009	0.698
20	$\kappa = 1.00$	0.979	0.042	1.039
21	$R = 1.01$	0.987	0.017	0.825
22	$R = 1.04$	0.959	0.009	0.975
23	$R_- = 1.04$	0.977	0.010	0.901
24	$R_- = 1.08$	0.977	0.013	0.884
25	$\omega = 0.00$	0.977	0.014	0.885
26	$\omega = 0.50$	0.977	0.013	0.884
27	$\mu_H = 70.00$	0.977	0.033	0.804
28	$\mu_H = 85.00$	0.978	0.008	1.060
29	$\sigma_H = 6.00$	0.977	0.016	0.950
30	$\sigma_H = 12.00$	0.977	0.013	0.894
31	$h_{45} = 0.40$	0.977	0.018	0.805
32	$h_{45} = 0.80$	0.977	0.013	0.906
33	$\eta = 1.00$	0.977	0.014	0.953
34	$\eta = 1.02$	0.977	0.012	0.826

Note: The baseline specification is the buffer-stock model with homogeneous parameters. The discount factor is re-calibrated for each parameter change targeting the life-cycle profile of median net worth as in the main text.

Table C.3—Robustness - CRRA preferences I ($\sigma = \rho$ and ζ)

				Fits	
				Levels	Dynamics
	$\rho = \sigma$	ζ	β	Median	Net worth
1	2	1.0	0.977	0.007	0.821
2	5	1.0	0.962	0.031	1.077
3	10	1.0	0.926	0.327	1.134
4	15	1.0	0.752	0.441	0.452
5	20	1.0	0.570	0.448	0.255
6	25	1.0	0.399	0.453	0.130
7	30	1.0	0.260	0.459	0.061
8	35	1.0	0.160	0.464	0.029
9	2	1.2	0.972	0.015	0.653
10	5	1.2	0.953	0.014	0.987
11	10	1.2	0.915	0.261	1.119
12	15	1.2	0.752	0.441	0.452
13	20	1.2	0.570	0.448	0.255
14	25	1.2	0.399	0.453	0.130
15	30	1.2	0.260	0.459	0.061
16	35	1.2	0.160	0.464	0.029
17	2	1.4	0.967	0.034	0.516
18	5	1.4	0.946	0.009	0.903
19	10	1.4	0.906	0.210	1.106
20	15	1.4	0.752	0.441	0.452
21	20	1.4	0.570	0.448	0.255
22	25	1.4	0.399	0.453	0.130
23	30	1.4	0.260	0.459	0.061
24	35	1.4	0.160	0.464	0.029
25	2	1.6	0.962	0.056	0.407
26	5	1.6	0.939	0.010	0.825
27	10	1.6	0.898	0.172	1.090
28	15	1.6	0.752	0.441	0.452
29	20	1.6	0.570	0.448	0.255
30	25	1.6	0.399	0.453	0.130
31	30	1.6	0.260	0.459	0.061
32	35	1.6	0.160	0.464	0.029

Note: The baseline specification is the buffer-stock model with homogeneous parameters. The discount factor is re-calibrated for each parameter change targeting the life-cycle profile of median net worth as in the main text.

Table C.4—Robustness - CRRA preferences II ($\sigma = \rho$ and ζ)

				Fits	
				Levels	Dynamics
	$\rho = \sigma$	ζ	β	Median	Networth
33	2	1.8	0.958	0.078	0.322
34	5	1.8	0.933	0.014	0.755
35	10	1.8	0.891	0.142	1.072
36	15	1.8	0.752	0.441	0.452
37	20	1.8	0.570	0.448	0.255
38	25	1.8	0.399	0.453	0.130
39	30	1.8	0.260	0.459	0.061
40	35	1.8	0.160	0.464	0.029
41	2	2.0	0.954	0.101	0.253
42	5	2.0	0.928	0.020	0.692
43	10	2.0	0.885	0.117	1.054
44	15	2.0	0.752	0.441	0.452
45	20	2.0	0.570	0.448	0.255
46	25	2.0	0.399	0.453	0.130
47	30	2.0	0.260	0.459	0.061
48	35	2.0	0.160	0.464	0.029
49	2	2.2	0.951	0.123	0.203
50	5	2.2	0.923	0.028	0.635
51	10	2.2	0.879	0.098	1.035
52	15	2.2	0.752	0.441	0.452
53	20	2.2	0.570	0.448	0.255
54	25	2.2	0.399	0.453	0.130
55	30	2.2	0.260	0.459	0.061
56	35	2.2	0.160	0.464	0.029

Note: The baseline specification is the buffer-stock model with homogeneous parameters. The discount factor is re-calibrated for each parameter change targeting the life-cycle profile of median net worth as in the main text.

Table C.5—Robustness - buffer-stock model (ρ and ζ) I

				Fits	
				Levels	Dynamics
	$\rho = \sigma$	ζ	β	Median	Networth
1	2	1.0	0.977	0.013	0.884
2	5	1.0	0.970	0.103	0.970
3	10	1.0	0.959	0.374	0.708
4	15	1.0	0.945	0.415	0.255
5	20	1.0	0.935	0.390	0.130
6	25	1.0	0.926	0.377	0.059
7	30	1.0	0.918	0.376	0.029
8	35	1.0	0.911	0.383	0.040
9	2	1.2	0.971	0.043	0.388
10	5	1.2	0.965	0.008	0.613
11	10	1.2	0.954	0.084	0.537
12	15	1.2	0.945	0.185	0.365
13	20	1.2	0.938	0.244	0.250
14	25	1.2	0.932	0.290	0.162
15	30	1.2	0.927	0.339	0.097
16	35	1.2	0.914	0.367	0.029
17	2	1.4	0.966	0.130	0.105
18	5	1.4	0.960	0.052	0.265
19	10	1.4	0.949	0.008	0.335
20	15	1.4	0.940	0.041	0.227
21	20	1.4	0.933	0.073	0.153
22	25	1.4	0.927	0.102	0.100
23	30	1.4	0.922	0.136	0.061
24	35	1.4	0.917	0.177	0.036
25	2	1.6	0.960	0.214	0.031
26	5	1.6	0.954	0.130	0.077
27	10	1.6	0.945	0.031	0.167
28	15	1.6	0.936	0.009	0.121
29	20	1.6	0.928	0.017	0.080
30	25	1.6	0.922	0.030	0.055
31	30	1.6	0.917	0.049	0.036
32	35	1.6	0.912	0.075	0.028

Note: The baseline specification is the buffer-stock model with homogeneous parameters. The discount factor is re-calibrated for each parameter change targeting the life-cycle profile of median net worth as in the main text.

Table C.6—Robustness - buffer-stock model (ρ and ζ) II

				Fits	
				Levels	Dynamics
	$\rho = \sigma$	ζ	β	Median	Networth
33	2	1.8	0.955	0.284	0.068
34	5	1.8	0.949	0.207	0.031
35	10	1.8	0.940	0.090	0.063
36	15	1.8	0.931	0.031	0.056
37	20	1.8	0.924	0.019	0.039
38	25	1.8	0.917	0.020	0.032
39	30	1.8	0.912	0.026	0.029
40	35	1.8	0.907	0.039	0.034
41	2	2.0	0.949	0.339	0.155
42	5	2.0	0.944	0.273	0.071
43	10	2.0	0.935	0.156	0.032
44	15	2.0	0.926	0.077	0.033
45	20	2.0	0.919	0.047	0.032
46	25	2.0	0.913	0.040	0.034
47	30	2.0	0.907	0.038	0.040
48	35	2.0	0.903	0.041	0.052
49	2	2.2	0.944	0.383	0.252
50	5	2.2	0.939	0.326	0.151
51	10	2.2	0.931	0.219	0.058
52	15	2.2	0.922	0.131	0.045
53	20	2.2	0.914	0.088	0.052
54	25	2.2	0.908	0.074	0.060
55	30	2.2	0.903	0.068	0.068
56	35	2.2	0.898	0.064	0.082

Note: The baseline specification is the buffer-stock model with homogeneous parameters. The discount factor is re-calibrated for each parameter change targeting the life-cycle profile of median net worth as in the main text.

D. 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 D.1 and D.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 D.3.[3]

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

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

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

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

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

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

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

Table D.1—Wealth variables definitions

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

Table D.2—Other outcome variables definitions

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

Table D.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.

E. Extended empirical results

a. Further empirical robustness checks

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

Table E.1—The role of liquidity constraints

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

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

b. Extended main results

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

Table E.2—Extended results: Table 2, normalized values

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

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

Table E.3—Extended results: Table 2, absolute values

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

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

Table E.4—Extended results: Table 2, placebo, normalized values

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

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

Table E.5—Extended results: Table 2, placebo, absolute values

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

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

Table E.6—Extended results: Table 3

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

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

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

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

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

Table E.8—Extended results: Table 4, household outcomes

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

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

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