Long-Run Saving Dynamics: Evidence from Unexpected Inheritances*

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Abstract

This paper makes two contributions to the consumption literature. First, we exploit inheritance episodes to provide novel causal evidence on the long-run effects of a large financial windfall on saving behavior. For identification, we combine a longitudinal panel of administrative wealth reports with variation in the timing of sudden, unexpected parental deaths. We show that after inheritance net worth converges towards the path established before parental death, with only a third of the initial windfall remaining after a decade. These dynamics are qualitatively consistent with convergence to a buffer-stock target. Second, we interpret these findings through the lens of a generalized consumption-saving framework. To quantitatively replicate this behavior, life-cycle consumption models require impatient consumers and strong precautionary saving motives, with implications for the design of retirement policy and the value of social insurance. This result also holds for two-asset models, which imply a high marginal propensity to consume.

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The fundamental goal of life-cycle consumption-saving models is to quantify the trade-off between consumption today and that in years and decades later. However, direct evidence on these long-run saving dynamics has previously not existed. This paper is the first to provide causal reduced-form evidence on these dynamics, interpret them through the lens of a structural framework, and show that they improve our understanding of the relative importance of precautionary and life-cycle saving motives.

Life-cycle consumption behavior has long been a central area of economic research (Modigliani and Brumberg, 1954 and Friedman, 1957; later Deaton, 1991, Carroll, 1997 and Gourinchas and Parker, 2002). Due to the lack of more direct evidence on long-run saving dynamics, the traditional approach has been to construct models that replicate accumulated levels of wealth at different ages. We show that this approach is not necessarily informative on long-run saving dynamics. Under standard assumption, calibrated models imply too slow depletion of large financial windfalls compared to what we observe in the data, even if the models are also calibrated to generate a high marginal propensity to consume out of small windfalls.

This paper thus contributes to the consumption literature in two ways. First, we provide novel reduced-form evidence on the long-run evolution of savings following a large financial windfall. We find that heirs quickly deplete their inheritance, and that net worth converges towards the path established before parental death. Only about a third of the initial increase in net worth remains nine years after parental death.

Second, we show that life-cycle consumption models can replicate the high depletion rate we observe while also matching the amount of wealth people accumulate over the life-cycle, but only for sufficiently impatient consumers with a stronger than usual precautionary saving motive. Consumers must be impatient enough to deplete two thirds of their inheritance within nine years. However, because impatience reduces accumulated wealth, these consumers must possess a strong precautionary motive to accumulate as much wealth over the life-cyle as we observe in the data.

This general result holds also for alternative models with heterogeneous preferences (Krueger, Mitman and Perri, 2016; Carroll et al., 2017) or liquid and illiquid assets (Kaplan and Violante, 2014). While these model adjustments can reproduce large short-run consumption responses out of small transitory shocks,[1] they are not sufficient to replicate empirical long-run saving dynamics. This robustness highlights the conceptual difference between marginal propensities to consume (MPCs), which the literature typically use as calibration moments, and long-run saving dynamics, which we in this paper are the first to use as additional calibration moments. If the precautionary saving motive is too weak, a two-asset model implying a MPC of 37 percent is worse at replicating the long-run saving dynamics we observe than a single-asset buffer-stock model, which implies a marginal propensity to consume of just 6 percent. As explained in detail by Kaplan and Violante (2014), the MPC is only large in two-asset models for small shocks because it is not optimal for the consumers to adjust their illiquid assets. For large shocks the transaction cost is negligible, and the two-asset model implies approximately the same MPC as a one-asset model.

To produce our first contribution, we exploit unexpected inheritance episodes and a unique panel dataset drawn from seventeen years of third-party reported Danish administrative records on individual wealth holdings. We identify the causal effect of inheritances by exploiting 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.[2]

Heirs respond to this sudden, salient, and sizable increase in available financial resources by decreasing their saving efforts in the ten years after inheriting, causing their net worth to converge back towards the path established before parental death. Moreover, the convergence patterns of different wealth components differ substantially. While heirs quickly deplete their excess of liquid assets, financing consumption or investments in real estate and financial instruments, accumulated wealth in housing equity, stocks, bonds, and mutual funds persists longer.

We draw general implications from these empirical results by analyzing them through a general structural consumption-saving framework, which extends the canonical buffer-stock model (Deaton, 1991; Carroll, 1997) to allow for inheritance expectations and a bequest motive (De Nardi, 2004; De Nardi and Yang, 2014). We show that standard parametrizations of the buffer-stock model—with the degree of

[1] A large and growing empirical literature documents such large responses (Shapiro and Slemrod, 2003; Johnson, Parker and Souleles, 2006; Parker et al., 2013; Fagereng, Holm and Natvik, 2016).

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

impatience and the strength of the bequest motive calibrated to match the life-cycle profile of median wealth—are unable to quantitatively reproduce the long-run saving dynamics we document.

Our empirical results on long-run saving dynamics imply impatient agents with a stronger than usual precautionary saving motive. Specifically, for a buffer-stock model our results imply a coefficient of relative risk aversion equal to 6.17. While higher than its standard value of 2 (Carroll, 1997; Aaronson, Agarwal and French, 2012; Berger and Vavra, 2015), this coefficient is not unreasonable.[3] Adjusting risk aversion is, however, not necessary for replicating our empirical findings. Amplifying the precautionary saving motive through alternative channels, such as the income risk faced by agents, or their beliefs about income risk, achieves the same result. These finding are consistent with recent evidence by Guvenen et al. (2016), who show that estimating a more general income process than the standard permanent-transitory process we use can triple the welfare cost of idiosyncratic income risk.

Regardless of the specification, buffer-stock and two-assets models able to replicate both the life-cycle wealth profile and the long-run saving dynamics imply a 25 to 50 percent increase in precautionary savings compared to a standard parametrization. Moreover, in these models agents start accumulating assets exclusively for retirement and bequest purposes only in the last 20 years before retirement. Life-cycle models are a commonly used tool for evaluating the design of social security, taxation, and pension systems (Heathcote, Storesletten and Violante, 2009). Our results thus imply that these evaluations should rest on models with higher than usual values assigned to private and social insurance mechanisms.

This paper also adds to the empirical literature studying consumption responses out of liquidity (Gross and Souleles, 2002; Leth-Petersen, 2010) and wealth changes.[4] Compared to the shocks exploited in this literature, our use of inheritance has the combined advantage of being a sizable, salient, and sudden windfall. Inheritance not only releases enough financial resources to allow intensive and extensive margin responses in both the financial (Andersen and Nielsen, 2011) and housing markets,

[3]Our result that a high level of risk aversion is needed to match the long-run saving dynamics aligns with the asset pricing model literature, where a high level of risk aversion is needed to explain observed risk premiums (Donaldson and Mehra, 2008).

[4]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.

but also requires no effort or any degree of financial sophistication for agents to be aware of it. Moreover, by focusing on long-run effects, we provide novel evidence compared to the existing short-run estimates of the elasticity of consumption on wealth (Paiella and Pistaferri, 2016) and housing equity (Mian, Rao and Sufi, 2013; Kaplan, Mitman and Violante, 2016).

Finally, this paper is related to a couple of recent papers using Scandinavian individual level data to look at the effect of inheritance on inequality in either Denmark (Boserup, Kopczuk and Kreiner, 2016) or Sweden (Elinder, Erixson and Waldenström, 2018; Nekoei and Seim, 2019). We differ from these papersby focusing on the implications for our understanding of long-run saving and consumption dynamics.

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

1 Data

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

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

tax and transfers over the previous five years. This data is often used as a example of administrative data perfectly suited for research purposes Chetty et al. (2010), and has extensively been used for this purpose. [6]

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.[7] 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 2010, and for whom our measure of potential inheritance is larger than their yearly permanent income. To estimate the effect of inheritance on saving dynamics, we use the net worth of these heirs as an outcome and the timing of parental death for identification.

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

In our analysis we focus on unexpected inheritances, defined as those due to a sudden death caused by either violent accidents (e.g. car crashes) or heart attacks for people with no known history of cardiac disease. These deaths, identified according to the WHO's ICD-10 codes, represent about 10 percent of all deaths in the sample.[8] 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

[6] One often cited drawback of this data is that housing values determined for tax purposes underestimate the value of housing, and therefore the level of wealth as measured in the register data. To assess the sensitivity of our identification strategy to this type of measurement error, in Appendix Figure G.5 we compare our main results with those obtained on an artificial measure of wealth where we inflate the value of each housing unit in our sample by 20%. The results on the two measures of wealth are virtually identical.

[7] Details on this calculation appear in Online Appendix F. 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). 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.

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

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

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

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

column pools all inheritance episodes in the sample. The second and third columns progressively select inheritance episodes that are unexpected and larger than one year of permanent income.

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

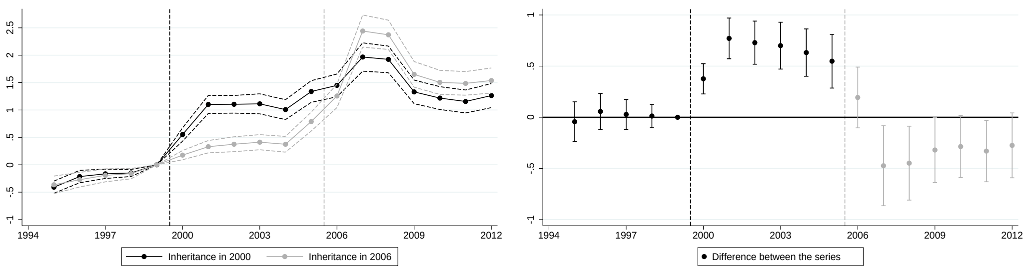
2 Identification

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

The first challenge stresses the danger of comparing the behavior of heirs with that of other individuals in the population, some of whom might already have inherited and thus do not expect another such windfall in their lifetime. While Andersen and Nielsen (2011, 2012) use a matching algorithm to find a suitable control group of non-heirs for their sample of heirs, this strategy relies heavily on the conditional independence assumption. To ensure the internal validity of our results, we focus instead on a homogeneous sample that by construction has similar expectations. All heirs in our sample inherit a comparable inheritance between 1996 and 2012, and all know that they will inherit at some point in the future. Thus they differ only in the timing of parental death. This identification strategy exploits the randomness in the timing of parental death and is similar to that used by Fadlon and Nielsen (2015) to estimate the effect of health shocks on household labor market supply and by Johnson, Parker and Souleles (2006), Agarwal, Liu and Souleles (2007), and Parker et al. (2013) to estimate the effect of tax rebates on short-term consumption.

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

To deal with the third challenge and show that parental death alone does not affect the wealth accumulation strategies of heirs, we replicate our analysis on a sample of heirs whose parents died with little or no wealth to leave as a bequest.



(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.

This placebo analysis reinforces the validity of our identification strategy. If parental death had an effect on savings over and beyond inheritance, then the placebo should capture this additional effect in the medium and long run.

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

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

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

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

Our estimating equation is thus that of an event study with separately identifiable year(-by-cohort) fixed effects.[9] However, while this approach maintains the identification argument and the assumptions (crucially, that of common trends) of a standard DiD, it has two advantages over the DiD approach. First, for a given comparison of inheritance-year groups, we exploit the ordered structure of dynamic effects to identify the effect of inheritance beyond the point in time at which the control group receives its inheritance.[10] Second, we can include all available data in the same estimation, thereby exploiting more combinations across time of inheritance τ_i.[11]

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

[9] That we estimate a single coefficient $\gamma_{<5}$ for all $n < -5$ makes the DiD assumption of common trends explicit, and allows us to separately identify year fixed effects and dynamic treatment effects up to a linear trend.

[10] 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.

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

3 The causal effect of inheritance

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

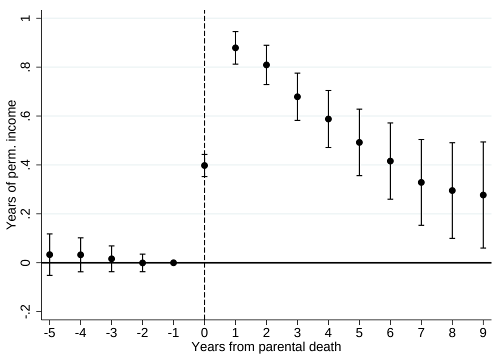
Figure 2 presents the main empirical results of the paper. The scales of all vertical axes refer to years of permanent income.[12] The top left panel of Figure 2 shows the effect of inheritance on net worth up to ten years after parental death. Heirs deplete most of the initial burst of wealth obtained through inheritance within six years of parental death, and continue a gradual convergence towards the path established before parental death throughout our estimation period.[13]

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

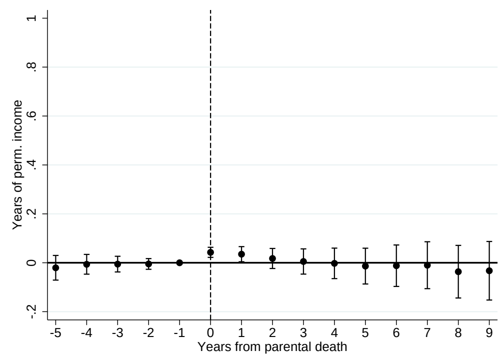
The top panel of Table 2 expands the results in Figure 2 for all wealth components. The table shows four $\hat{\gamma}_n \equiv (\gamma_n^{pre}, \gamma_n^{post})$ coefficients (from equation 1) describing, respectively, eventual anticipatory behavior one year before parental death, the burst of wealth due to inheritance one year after parental death, and the evolution of

[12]We show in Table 2 that the normalization with permanent income simplifies their interpretation but is not important for our results. First, in Online Appendix Figure D.2, we show that the permanent income profile for the individuals in our sample is close to flat after age 40. Second, in Appendix Figure G.4, we show that the convergence implied by the results on normalized and absolute wealth is virtually the same.When comparing our estimates to data simulated from a model in Section 5, we use the same type ofscaling with permanent income.

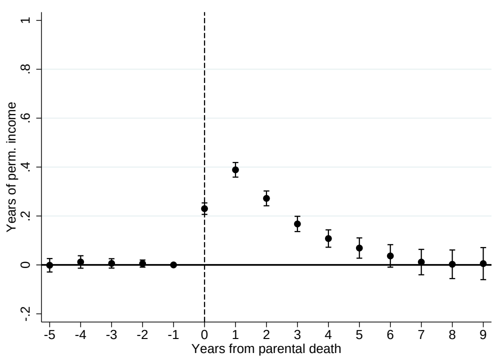
[13]Recent research confirms that similar results hold also in Sweden (Nekoei and Seim, 2019) and for lottery winnings (Cesarini et al., 2016).



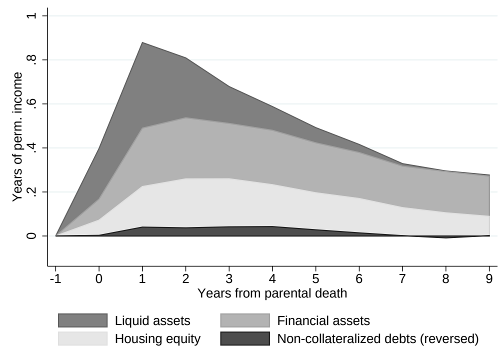
(a) Net worth, large inheritance



(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.

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

wealth components in the medium run (five years after parental death) and the long run (nine years after parental death).[14] Because inheritance is not always received in the same year of parental death, the effect of inheritance on accumulated wealth one year after parental death provides a reference for interpreting the start of the convergence process.

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

[14]The full list of coefficients for all regressions appears in Online Appendix G.

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

normalization.

The effect of inheritance on the accumulation of housing equity is not as straightforwardly interpretable. By separately analyzing the components of housing equity, Table 3 provides the necessary details to describe this convergence process. The table shows that although total housing value increases over time following parental death, mortgages increase more than proportionally. The response at the extensive margins provides the key mechanism: While the proportion of individuals owning any real estate increases by 5 percent after inheritance and remains stable in the following years, the number of people owning more than one real estate unit decreases over time after the initial jump due to inheritance. These patterns suggest that heirs sell excess housing units not only to finance consumption but also to upgrade their main estate and climb the property ladder, maxing out their mortgage debt and extracting housing equity in the process.

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

Table 4: Other budget incomings and outgoings

Years from shock	-2	1	5	9
	Panel A: Income and labor supply (1000DKK)			
Net disposable income	0.060	2.115	8.522	8.096
	(0.751)	(1.114)	(4.097)	(4.147)
Has earnings	0.002	-0.001	0.001	0.006
	(0.003)	(0.004)	(0.009)	(0.015)
Gross earnings	2.265	-2.974	1.297	7.086
	(1.521)	(2.038)	(5.370)	(8.860)
Gross 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 Online Appendix G. The coefficients are estimated according to equation (1) on a sample of unexpected inheritances larger than one year of the heir's permanent income. The specification includes individual and year-by-cohort fixed effects. Standard errors, clustered at the individual level, are shown in parentheses.

[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.

income one year after parental death, depleting it within a year.

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

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 contributions to individually managed pension funds increase on average of only 0.8 percent of permanent income one year after parental death and fade out quickly thereafter, for a cumulative impact of 2.5 percent of permanent income in five years.

We also verify that our results do not depend on a minority of extreme inheritance windfalls. We split our estimation sample in three subgroups according to potential inheritance, and replicate our estimation for each of them. While the estimated initial wealth windfall naturally increases with potential inheritance, the convergence patterns are the same across all subgroups. Although these estimates, which appear in Online Appendix G, support the validity of our empirical results, their structural interpretation is complicated by the heterogeneity of preferences, income dynamics and initial wealth levels across subgroups. As a consequence, in the remainder of the paper we focus on drawing general conclusions from the reduced-form results obtained in the full estimation sample.

Our causally estimated patterns represent a novel identified moment that life-cycle consumption models should be able to replicate. Qualitatively, the observed patterns of wealth convergence are consistent with convergence to a buffer-stock target. In the remainder of the paper we show that, quantitatively, standard parametrizations of life-cycle models imply too little convergence with respect to what we observe empirically.

4 A general consumption-saving framework

This section describes the modeling framework we use to draw insights from the long-run dynamics of saving estimated in the previous section. Our starting point is the single-asset buffer-stock consumption model of Deaton (1991, 1992) and Carroll

(1992, 1997, 2012), with a flexible retirement value function similar to that of Gourinchas and Parker (2002). We account for inheritance expectations by augmenting the standard model with an exogenous process for receiving inheritance. We assume that the agents are fully aware of this process and thus have rational expectations.

We further generalize this model by considering both heterogeneity in the discount factor[15] and a two-asset version of the model distinguishing between liquid and illiquid assets as in Kaplan and Violante (2014) and Kaplan, Moll and Violante (2018). These two extensions strengthen the baseline model's ability to match short-run saving dynamics (i.e., the marginal propensity to consume). They further allow us to fit the distribution of wealth over the life-cycle, and to investigate heterogeneous saving dynamics across asset types.

4.1 The model

The economy is populated by a continuum of individuals indexed by i and working for T_R periods, $t \in \{1, 2, \ldots, T_R\}$. 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 in and borrow from a liquid asset, A_t. Saving in the liquid asset provides a risk-free gross return of R, and borrowing from it costs a gross interest rate of $R_{-} > R$. The individual can borrow up to a fraction ω of his permanent income P_t, but cannot retire with debt, such that

$$\begin{aligned} A_t &\geq -\omega P_t. \qquad (2) \\ A_{T_R} &\geq 0 \end{aligned}$$

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

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

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

$$
\begin{aligned}
Y_t &= P_t \xi_t && (3)\\
P_t &= G_{t-1} P_{t-1} \psi_t && (4)
\end{aligned}
$$

where

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

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

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

$$
\begin{aligned}
M_{t+1} &= R(A_t)A_t + Y_{t+1} + H_t \mathbf{1}_{d_t=0} \mathbf{1}_{d_{t+1}=1} && (5)\\
N_{t+1} &= R_B B_t. && (6)
\end{aligned}
$$

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

4.2 Recursive formulation

Defining the post-decision value function

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

the recursive formulation of the model is

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

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

4.3 Calibration

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

Individuals enter the model at age 25, work until age 60 ($T_R = 35$), and die at age 85 ($T = 60$). The average earnings profile during working life (regulated by G_t) is chosen to match the profile in our estimation sample. Using the method in Meghir and Pistaferri (2004), we estimate the standard deviation of the permanent shocks to be $\sigma_\psi = 0.120$, and the standard deviations of the transitory shocks to be $\sigma_\xi = 0.087$ in our estimation sample. Following Jørgensen (2017), we set the retirement replacement rate equal to $\kappa = 0.90$.

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

We choose the parameters regulating the timing of inheritance by matching the life-cycle profile of inheritance receipts. This calibration gives us $\delta_H = 30$ as the age difference between child and parent, and $\mu_H = 71$ and $\sigma_H = 8$ as the mean and standard deviation of death age of the parent. For the size of the inheritance we assume that $H_t = \eta^{(25+t)-45} \cdot h_{45}$, where we choose $h_{45} = 0.93$ to match the average inheritance at age 45 relative to permanent income, and $\eta = 1.00$ to match the life-cycle profile of inheritances.

To calibrate the initial states, we model the initial distribution of permanent income as a log-normal distribution, whose variance matches that observed in our estimation sample. 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

Table 5: Fixed and externally calibrated parameters

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

NOTE.The table shows the externally calibrated parameters that we fix for all our model iterations. All externally calibrated parameters are inferred from our estimation sample, and not the full population. In the fourth column we report the source of these parameters.

assigning zero wealth to 70 percent of all agents, and some (illiquid) assets to the remaining 30 percent independently of income. We model the initial distribution of assets for these 30 percent as a log-normal distribution, whose variance matches that in the data.

5 Implications for consumption-saving behavior

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

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

However, the implied long-run saving dynamics differ sharply across these different parametrizations. In our second step, we show that specifications with high impatience, a strong precautionary saving motive, and strong retirement saving and bequest motives imply much faster convergence of wealth to the path established before the shock. Whether the strength of the precautionary saving motive is due to risk aversion, income risk, or perceived income risk does not affect our results.

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

Table 6 collects our main results. The top panel of the table shows that different combinations of preference parameters deliver very similar life-cycle profiles of wealth. In each row, we set an intertemporal elasticity ($1/\sigma$) of 1.5 and a relative risk aversion coefficient (ρ) of either 1.5, 2, 4 or 6. For each of these choices, we internally calibrate the discount factor (β) and the strength of the retirement saving and bequest motives (through the utility shifter ζ) to replicate the life-cycle profile of median wealth.[16]

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

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

Table 6: Replicating long-run saving dynamics

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

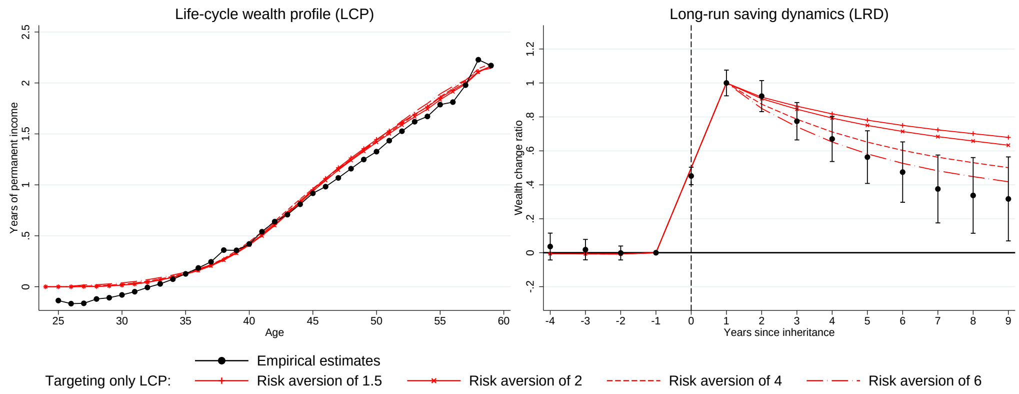
NOTE. The table shows preference and scaling parameters, fit measures and the implied marginal propensity to consume for alternative parametrizations of the buffer-stock model from Section 4. The remaining model parameters are shown in Table 5. β is the discount factor. ρ is the relative risk aversion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

† internally calibrated parameter. ‡ targeted moment.

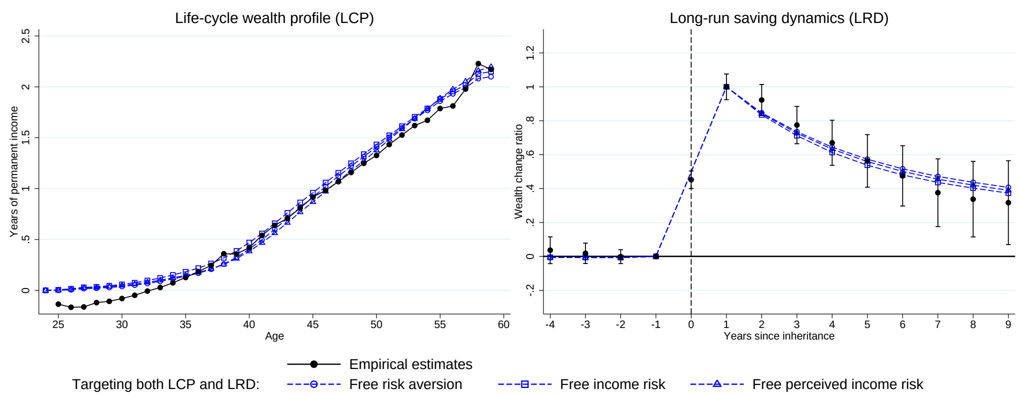
of wealth. The top-left plot of Figure 3 shows this result graphically.

However, these alternative parametrizations imply sharply different long-run saving dynamics. These differences are evident both graphically in the top-right panel of Figure 3, and in the eighth column (LRD) of Table 6—which reports the weighed mean squared difference between our empirical estimates and estimates on simulated data from the model. For the standard choice of a relative risk aversion coefficient of 2 (Carroll, 1997; Aaronson, Agarwal and French, 2012; Berger and Vavra, 2015), the model implies that the amount of the initial shock left after under a decade is twice as large as what we estimate empirically. However, the gap between the empirical and the simulated dynamics decreases in the high risk aversion specifications, for which the calibrated discount factor is lower and the motive to save for retirement and bequests is stronger.[17]

[17] All specifications appearing in Table 6 have Epstein-Zin preferences. Under the more restrictive as-



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



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

Figure 3: Replicating long-run saving dynamics

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

These results show that the long-run saving dynamics provide orthogonal information relative to the life-cycle profile. In other words, by evaluating a model by its ability to replicate not only the life-cycle wealth profile, but also the empirical long-run saving dynamics, we are able to exclude a large set of potential parametrizations. In the first row of Panel B of Table 6 we explicitly exploit this additional information, and also calibrate the relative risk aversion coefficient by simultaneously targeting

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

the life-cycle profile of wealth and the long-run saving dynamics. The resulting risk aversion coefficient of 6.17 is higher than the standard value of 2, but within the range of usual choices (e.g., Favilukis, Ludvigson and Van Nieuwerburgh, 2017, use a risk aversion coefficient equal to 8). Similarly, while the value of the discount factor β (0.94) is within the range of reasonable parameter values, it decreases with respect to the standard case.

Adjusting risk aversion is however not necessary for replicating the empirical long-run saving dynamics. Amplifying the precautionary saving motive through alternative channels equivalently allows the model to simultaneously replicate the life-cycle profile of wealth and the long-run saving dynamics. We prove this result by fixing the degree of risk aversion, and instead calibrate the standard deviations of shocks in the income process (via the scaling parameter α) or the agent's beliefs about these standard deviations (via the scaling parameter $\tilde{\alpha}$). For ρ equal to 4, we show that a 21 percent increase in the standard deviation of income shocks, or a 25 percent perceived increase in these standard deviations, is sufficient to replicate the convergence we observe in the data holding the fit of the life-cycle profile of wealth constant.[18] This result also holds for standard CRRA preferences, for which we need a 38 percent increase in the standard deviation of income shocks to fit the data.[19]

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

Figure 4 shows that, with respect to the standard case, models able to fit both the life-cycle profile of wealth and the long-run saving dynamics imply substantially

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

[19]This result appear in table D.2 in the Online Appendix.

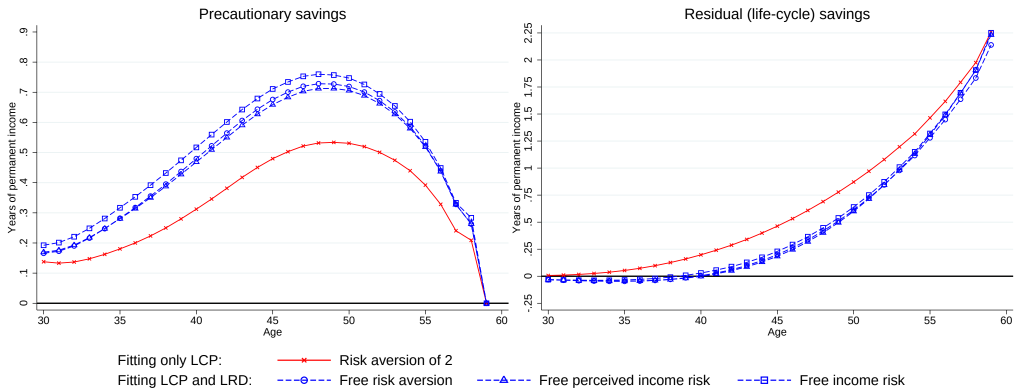


Figure 4: Structural decomposition of wealth held for precautionary (left) and life-cycle motives (right)

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

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

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

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

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

5.1 Extensions to the buffer-stock model

We have shown that the long-run saving dynamics we estimate in our data identify buffer-stock models with a strong precautionary saving motive. In this subsection, we show that the same conclusion generalizes to common extensions of the standard buffer-stock model, such as a two-asset model and a model with preference heterogeneity. These extensions allow us to capture more complex empirical features, such as the increase in the interquartile range of wealth over the life-cycle, and the high marginal propensity to consume documented, among others, by Shapiro and Slemrod (2003), Johnson, Parker and Souleles (2006) and Parker et al. (2013). Nonetheless, we find that for both extensions a stronger than usual precautionary saving motive is necessary to simultaneously replicate the observed life-cycle profile of wealth and long-run saving dynamics.

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

Panel B shows that introducing heterogeneous impatience slightly improves the ability of the model to replicate the empirical long-run dynamics of savings. However, consistently with the results of Table 6, the model with heterogeneous patience fails to replicate the empirical long-run saving dynamics with a standard risk aversion parameter of 2. Moreover, the fit of the long-run dynamics improves as the degree of risk aversion increases, holding constant the fit of the life-cycle wealth

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

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

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

† internally calibrated parameter. ‡ targeted moment.

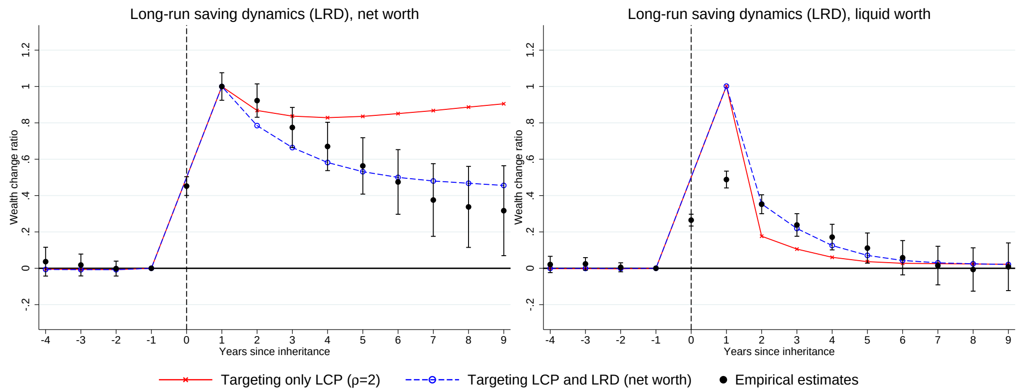


Figure 5: Two-asset model: Long-run saving dynamics of net worth (left) and net liquid worth (right)

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

profile. By simultaneously targeting the life-cycle profile of wealth, the increase in the interquartile range of wealth, and the long-run saving dynamics, we calibrate a relative risk aversion coefficient of 6.82, in line with our results for the buffer-stock model with homogeneous preferences.

In the third panel of the table, we extend the model with an illiquid asset (Kaplan and Violante, 2014). This extension enables the model to produce a high marginal propensity to consume (MPC), and thus replicate the short-run dynamics documented in the empirical literature. However, for the same degree of risk aversion, the two-asset model is less capable of replicating the observed long-run saving dynamics compared to the single-asset model, which implies a much smaller MPC. This difference stresses the qualitative difference between short- and long-run dynamics in consumption-saving models. Moreover, our main results apply also to the two-asset model: As the precautionary saving motive increases, the fit of long-run saving dynamics improves. Simultaneously targeting the life-cycle profile of wealth and the long-run saving dynamics, we obtain a calibrated risk aversion coefficient of 8.57. Remarkably, such a model is also able to closely replicate the (non-targeted) empirical dynamics of net liquid worth. The empirical and simulated long-run saving dynamics for the two-asset model appear in Figure 5.

5.2 Additional robustness checks

We conduct a series of additional robustness checks by investigating the implications of changing each of the externally calibrated parameters in Table 5. These robustness checks appear in Online Appendix Table D.4, except thoseshowing that our results are not sensitive to the choice of the intertemporal elasticity of substitution ($1/\sigma$), which appear in Appendix Table D.1. We find that changing the parameters affecting the borrowing constraint (R_{-},ω), or the inheritance process (μ_H, σ_H, h_{45}, η),[20] only marginally affect the combination of impatience (β), risk aversion (ρ), and retirement saving and bequest motive (ζ) necessary to simultaneously match both the life-cycle wealth profile and the long-run saving dynamics observed empirically. Changing the replacement rate in retirement (κ) affects the scaling of the utility shifter for the strength of the retirement saving and bequest motives (ζ), and changing the interest rate (R) implies an change in the opposite direction of the discount factor (β). However, the calibrated degree of risk aversion does not change substantially.

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

6 Conclusions

Long-run saving dynamics are a crucial component of life-cycle consumption and saving models. This paper identifies and characterize the long-run dynamics of savings, and exploits these identified moments to calibrate structural consumption models, as advocated by Nakamura and Steinsson (2018).

We combine a unique panel dataset drawn from seventeen consecutive years of Danish administrative records with large inheritances due to sudden parental

[20] Online Appendix Figure D.3 shows that assuming that inheritance is completely unexpected slightly improves the model's fit of the long-run saving dynamics. This resultsalso suggests thatinheritance can be thought as something close to an actual unexpected windfall.

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. This convergence differs markedly across wealth components, with excess liquid assets being consumed or converted in other saving vehicles within six years. Endogenous labor supply and committed expenditures (e.g., pension savings or family growth) do not drive these results.

We analyze these results through the lens of a structural model of life-cycle consumption and savings. We show that only by allowing for impatient agents with a stronger than usual precautionary saving motive can consumption-saving models fit both the empirical long-run dynamics of saving and life-cycle wealth levels. This results hold also for models with heterogeneity in preferences and two-asset models, highlighting the conceptual difference between short- and long-run saving dynamics. We show that the two-asset model can fit the different shock dynamics of both net and liquid worth.

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

References

Aaronson, Daniel, Sumit Agarwal, and Eric French. 2012. "The Spending and Debt Response to Minimum Wage Hikes." *The American Economic Review*, 102(7): 3111–3139.

Agarwal, Sumit, Chunlin Liu, and Nicholas S. Souleles. 2007. "The Reaction of Consumer Spending and Debt to Tax Rebates—Evidence from Consumer Credit Data." *Journal of Political Economy*, 115(6): pp. 986–1019.

Agarwal, Sumit, John C Driscoll, Xavier Gabaix, and David Laibson. 2009. "The age of reason: Financial decisions over the life cycle and implications for regulation." *Brookings Papers on Economic Activity*, 2009(2): 51–117.

Andersen, Steffen, and Kasper Meisner Nielsen. 2011. "Participation Constraints in the Stock Market: Evidence from Unexpected Inheritance Due to Sudden Death." *Review of Financial Studies*, 24(5): 1667–1697.

Andersen, Steffen, and Kasper Meisner Nielsen. 2012. "Ability or Finances as Constraints on Entrepreneurship? Evidence from Survival Rates in a Natural Experiment." *Review of Financial Studies*, 25(12): 3684–3710.

Avery, Robert, and Michael Rendall. 2002. "Lifetime Inheritances of Three Generations of Whites and Blacks." *American Journal of Sociology*, 107(5): pp. 1300–1346.

Berger, David, and Joseph Vavra. 2015. "Consumption Dynamics During Recessions." *Econometrica*, 83(1): 101–154.

Bernheim, B Douglas, Andrei Shleifer, and Lawrence H Summers. 1985. "The strategic bequest motive." *Journal of Political economy*, 93(6): 1045–1076.

Boserup, Simon H., Wojciech Kopczuk, and Claus T. Kreiner. 2016. "The Role of Bequests in Shaping Wealth Inequality: Evidence from Danish Wealth Records." *American Economic Review*, 106(5): 656–661.

Browning, Martin, Mette Gørtz, and Søren Leth-Petersen. 2013. "Housing Wealth and Consumption: A Micro Panel Study." *The Economic Journal*, 123(568): 401–428.

Cagetti, Marco. 2003. "Wealth Accumulation over the Life Cycle and Precautionary Savings." *Journal of Business & Economic Statistics*, 21(3): 339–353.

Carroll, CD, Jiri Slacalek, Kiichi Tokuoka, and Matthew N White. 2017. "The distribution of wealth and the marginal propensity to consume." *Quantitative Economics, forthcoming*.

Carroll, Christopher D. 1992. "The buffer-stock theory of saving: Some macroeconomic evidence." *Brookings Papers on Economic Activity*, 2: 61–156.

Carroll, Christopher D. 1997. "Buffer-Stock Saving and the Life Cycle/Permanent Income Hypothesis." *The Quarterly Journal of Economics*, 112(1): 1–55.

Carroll, Christopher D. 2006. "The method of endogenous gridpoints for solving dynamic stochastic optimization problems." *Economics Letters*, 91(3): 312–320.

Carroll, Christopher D. 2012. "Theoretical Foundations of Buffer Stock Saving." Working Paper.

Cesarini, David, Erik Lindqvist, Matthew J. Notowidigdo, and Robert Östling. 2017. "The Effect of Wealth on Individual and Household Labor Supply: Evidence from Swedish Lotteries." *American Economic Review*, 107(12): 3917–3946.

Cesarini, David, Erik Lindqvist, Robert Östling, and Björn Wallace. 2016. "Wealth, Health, and Child Development: Evidence from Administrative Data on Swedish Lottery Players." *The Quarterly Journal of Economics*, 131(2): 687–738.

Chetty, Raj, David Card, Martin Feldstein, and Emmanuel Saez. 2010. "Expanding Access to Administrative Data for Research in the United States." National Science Foundation White Paper.

Chetty, Raj, John N. Friedman, Søren Leth-Petersen, Torben Heien Nielsen, and Tore Olsen. 2014. "Active vs. Passive Decisions and Crowd-Out in Retirement Savings Accounts: Evidence from Denmark." *The Quarterly Journal of Economics*, 129(3): 1141–1219.

Deaton, Angus. 1991. "Saving and Liquidity Constraints." *Econometrica*, 59(5): pp. 1221–1248.

Deaton, Angus. 1992. *Understanding Consumption.* Oxford University Press.

De Nardi, Mariacristina. 2004. "Wealth Inequality and Intergenerational Links." *The Review of Economic Studies*, 71(3): 743–768.

De Nardi, Mariacristina, and Fang Yang. 2014. "Bequests and heterogeneity in retirement wealth." *European Economic Review*, 72: 182–196.

Donaldson, John, and Rajnish Mehra. 2008. "CHAPTER 2 - Risk-Based Explanations of the Equity Premium." In *Handbook of the Equity Risk Premium. Handbooks in Finance*, , ed. Rajnish Mehra, 37–99. San Diego:Elsevier.

Druedahl, Jeppe. 2018. "A Fast Nested Endogenous Grid Method for Solving General Consumption-Saving Models." Working Paper.

Druedahl, Jeppe, and Thomas Høgholm Jørgensen. 2017. "A general endogenous grid method for multi-dimensional models with non-convexities and constraints." *Journal of Economic Dynamics and Control*, 74: 87–107.

Elinder, Mikael, Oscar Erixson, and Daniel Waldenström. 2018. "Inheritance and wealth inequality: Evidence from population registers." *Journal of Public Economics*, 165: 17–30.

Fadlon, Itzik, and Torben Heien Nielsen. 2015. "Household Responses to Severe Health Shocks and the Design of Social Insurance." National Bureau of Economic Research Working Paper 21352.

Fagereng, Andreas, Martin Blomhoff Holm, and Gisle James James Natvik. 2016. "MPC Heterogeneity and Household Balance Sheets." Social Science Research Network SSRN Scholarly Paper ID 2861053, Rochester, NY.

Favilukis, Jack, Sydney C. Ludvigson, and Stijn Van Nieuwerburgh. 2017. "The Macroeconomic Effects of Housing Wealth, Housing Finance, and Limited Risk Sharing in General Equilibrium." *Journal of Political Economy*, 125(1): 140–223.

Fella, Giulio. 2014. "A generalized endogenous grid method for non-smooth and non-concave problems." *Review of Economic Dynamics*, 17(2): 329–344.

Francesconi, Marco, Robert A. Pollak, and Domenico Tabasso. 2015. "Unequal Bequests." National Bureau of Economic Research Working Paper 21692.

Friedman, Milton. 1957. *A theory of the consumption function.* Princeton university Press for NBER.

Gourinchas, Pierre-Olivier, and Jonathan A. Parker. 2002. "Consumption over the Life Cycle." *Econometrica*, 70(1): 47–89.

Gross, David B., and Nicholas S. Souleles. 2002. "Do Liquidity Constraints and Interest Rates Matter for Consumer Behavior? Evidence from Credit Card Data." *The Quarterly Journal of Economics*, 117(1): 149–185.

Guvenen, Fatih, Fatih Karahan, Serdar Ozkan, and Jae Song. 2016. "What Do Data on Millions of U.S. Workers Reveal about Life-Cycle Earnings Risk?" National Bureau of Economic Research Working Paper 20913.

Heathcote, Jonathan, Kjetil Storesletten, and Giovanni L. Violante. 2009. "Quantitative Macroeconomics with Heterogeneous Households." *Annual Review of Economics*, 1(1): 319–354.

Holtz-Eakin, Douglas, David Joulfaian, and Harvey S. Rosen. 1993. "The Carnegie Conjecture: Some Empirical Evidence." *The Quarterly Journal of Economics*, 108(2): 413–435.

Imbens, Guido W., Donald B. Rubin, and Bruce I. Sacerdote. 2001. "Estimating the Effect of Unearned Income on Labor Earnings, Savings, and Consumption: Evidence from a Survey of Lottery Players." *The American Economic Review*, 91(4): pp. 778–794.

Iskhakov, Fedor, Thomas H. Jørgensen, John Rust, and Bertel Schjerning. 2017. "The endogenous grid method for discrete-continuous dynamic choice models with (or without) taste shocks." *Quantitative Economics*, 8(2): 317–365.

Jappelli, Tullio, and Luigi Pistaferri. 2010. "The Consumption Response to Income Changes." *Annual Review of Economics*, 2(1): 479–506.

Johnson, David S., Jonathan A. Parker, and Nicholas S. Souleles. 2006. "Household Expenditure and the Income Tax Rebates of 2001." *American Economic Review*, 96(5): 1589–1610.

Jørgensen, Thomas H. 2017. "Life-Cycle Consumption and Children: Evidence from a Structural Estimation." *Oxford Bulletin of Economics and Statistics*, 79(5): 717–746.

Juster, F. Thomas, Joseph P. Lupton, James P. Smith, and Frank Stafford. 2006. "The Decline in Household Saving and the Wealth Effect." *Review of Economics and Statistics*, 88(1): 20–27.

Kaplan, Greg, and Giovanni L Violante. 2014. "A model of the consumption response to fiscal stimulus payments." *Econometrica*, 82(4): 1199–1239.

Kaplan, Greg, Benjamin Moll, and Giovanni L. Violante. 2018. "Monetary Policy According to HANK." *American Economic Review*, 108(3): 697–743.

Kaplan, Greg, Kurt Mitman, and Giovanni L. Violante. 2016. "Non-durable Consumption and Housing Net Worth in the Great Recession: Evidence from Easily Accessible Data." National Bureau of Economic Research Working Paper 22232.

Krueger, Dirk, Kurt Mitman, and F Perri. 2016. "Macroeconomics and Heterogeneity, Including Inequality." forthcoming in Handbook of Macroeconomics, Vol. 2.

Leth-Petersen, Søren. 2010. "Intertemporal Consumption and Credit Constraints: Does Total Expenditure Respond to an Exogenous Shock to Credit?" *The American Economic Review*, 100(3): 1080–1103.

Lettau, Martin, and Sydney Ludvigson. 2001. "Consumption, aggregate wealth, and expected stock returns." *Journal of Finance*, 56(3): 815–849.

Lettau, Martin, Sydney C Ludvigson, and others. 2004. "Understanding Trend and Cycle in Asset Values: Reevaluating the Wealth Effect on Consumption." *American Economic Review*, 94(1): 276–299.

Meghir, C, and Luigi Pistaferri. 2004. "Income variance dynamics and heterogeneity." *Econometrica*, 72(1): 1–32.

Mian, Atif, Kamalesh Rao, and Amir Sufi. 2013. "Household Balance Sheets, Consumption, and the Economic Slump." *The Quarterly Journal of Economics*, 128(4): 1687–1726.

Modigliani, Franco, and R Brumberg. 1954. "Utility Analysis and the Consumptio Function: An Interpretation of Cross-Section Data." In *Post-Keynesian Economics*. , ed. K Kurihara and News Brunswick, 338–436. Rutgers University Press.

Nakamura, Emi, and Jón Steinsson. 2018. "Identification in Macroeconomics." *Journal of Economic Perspectives*, 32(3): 59–86.

Nekoei, Arash, and David Seim. 2019. "How do Inheritances Shape Wealth Inequality? Theory and Evidence from Sweden." Social Science Research Network SSRN Scholarly Paper ID 3192778, Rochester, NY.

Paiella, Monica, and Luigi Pistaferri. 2016. “Decomposing the Wealth Effect on Consumption.” *The Review of Economics and Statistics*.

Parker, Jonathan A., Nicholas S. Souleles, David S. Johnson, and Robert McClelland. 2013. “Consumer Spending and the Economic Stimulus Payments of 2008.” *American Economic Review*, 103(6): 2530–2553.

Shapiro, Matthew D., and Joel Slemrod. 2003. “Consumer Response to Tax Rebates.” *The American Economic Review*, 93(1): pp. 381–396.

Zagorsky, JayL. 2013. “Do People Save or Spend Their Inheritances? Understanding What Happens to Inherited Wealth.” *Journal of Family and Economic Issues*, 34(1): 64–76.

A Robustness of the empirical results: DiD and balanced samples

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

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

NOTE. The table compares the saving dynamics estimated on the sample of heirs inheriting between 1999 and 2001, and between 2008-2010. The first and fourth column use the identification strategy of the paper, estimating equation (1) in the paper on the full sample. The second and fifth column use the DiD identification strategy of Fadlon and Nielsen (2015), assigning an explicit control group to each inheritance year (e.g., the control group for heirs inheriting in 1999 is heirs inheriting in 2008). The third and sixth column replicate this estimation strategy on a strictly balanced sample.

B Terminal consumption and value functions

From period T_R onward the recursive problem is

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

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

The optimal consumption function then is

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

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

The value function is

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

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

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