Old Age Savings and House Price Shocks*

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Abstract

Elderly households hold most of their wealth in housing, maintain high levels of wealth throughout their retirement, and often leave bequests. The value of their houses are subject to potentially large shocks. To what extent do these shocks affect their savings, consumption, and bequests? Answering this question requires separating precautionary savings, bequest motives, and the desire to remain in one's home. I develop and estimate a structural model of retirement savings decisions with realistic risks, housing, and heterogeneity in bequest preferences. I combine data on wealth composition, exogenous policy changes, and subjective bequest probabilities to separately identify the different motives for holding wealth. Estimated bequest motives differ across the households and roughly half of the sample has no bequest motive. House price changes are quantitatively important and a large fraction of increases are passed on to future generations. I use the estimated model to evaluate the current structure of disregard eligibility for (Medicaid-like) programs that insure retirees. I find that for every pound it costs the government, increasing the disregards for liquid assets provides far more value than increasing the disregards for houses.

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1 Introduction

Across the OECD the over 65 population has grown by over 40% in the last 25 years and is projected to continue to rise. These older households hold lots of wealth, even at advanced ages, primarily in the form of houses, and often leave bequests. Houses, however, are complex assets. First, they are risky. Some cohorts experience substantial house value increases, while others drops and stagnation. Second, houses provide a consumption flow, are illiquid, and are often exempt from tests on assets that determine eligibility for important government insurance programs.

This paper aims at understanding the role of housing in retirement. I estimate a dynamic life-cycle model of consumption, savings, and portfolio choice for older households using panel data on household choices, beliefs, and the risks they face. To the best of my knowledge, this is the first paper that allows for extensive and intensive margins of housing adjustment, a rich set of risks in retirement, including aggregate risks, and heterogeneity in bequest motives. Estimating the model with rich micro data and exploiting quasi-experimental variation in tax regimes over time allows me to separately identify and quantify the demand for housing and its illiquidity separately from other savings motives. I use this rich framework to understand portfolio rebalancing in retirement and the effect of housing and changes to house prices on the dynamics of saving among the elderly. Furthermore, I use the estimated model to quantify the intergenerational transmission of house price shocks and evaluate the distinction between housing and liquid wealth in the means testing of government Long Term Care (LTC) insurance.

I develop a model that incorporates differences in assets and preference heterogeneity in bequest motives. Households choose between investing in housing, risk-free liquid wealth, or consuming today. Focusing on the role of preference heterogeneity and the characteristics that make these asset classes different requires that I accurately model the set of risks facing households. Each member of the household faces uncertainty over their health status, mortality, costs from long term care needs, and uncertainty over aggregate house price levels. These rich sources of risks also determine a household's desire for liquidity, consumption, and savings for a bequest over different horizons, and consequently their demand for different assets.

Separately identifying precautionary savings motives, the desire to remain in one's home, and a bequest motive when there are many reasons households may hold wealth, let alone with heterogeneous bequest motives, presents a considerable empirical challenge.[1] To do so, I employ a new strategy that combines exogenous variation in the tax system with data on wealth composition and a measure of household subjective expectations within a structural framework. Incorporating subjective probabilities of leaving an inheritance into the estimation provides an additional source of information about

[1]See, for instance, De Nardi et al. (2010, 2016a); Ameriks et al. (2011, 2018); Lockwood (2018).

the heterogeneous preferences of individual households and the full path of future saving behaviour over longer horizons.

I study the financial behaviour of retirees in England during a period which saw numerous reforms to both estate and residential property transaction tax schedules as well as large changes in house prices. Transaction taxes create an implicit tax on home equity adjustment, or downsizing, and variation in the tax schedule over time generates quasi-experimental variation in this implicit tax. I examine how these implicit taxes distort the home moving decisions of retirees. Using a quasi-experimental design, I estimate the decrease in household mobility and adjustments of home equity in response to increases in the transaction tax burden. I use data covering the period between 2002 and 2014, simulating households through the various reforms to their budget constraint and realizations of aggregate house prices. This is key to identifying the different costs households face when adjusting their portfolio. I validate the model against the reduced form evidence and show that it reproduces household responses to changes in the financial incentives to adjust their housing stock - a key model mechanism. Retirees in the UK and the US have similar medical expenditure risk driven by LTC related needs, similar life expectancies, and are covered by similar public programs. Thus, my results are also useful to understand retirement savings and their implications in many countries.

The model matches two new key facts that I document in the data. First, that primary residences constitute the majority of household wealth and that passive saving due to house price appreciation masks the deccumulation of housing wealth through downsizing. Because housing is less liquid and historically has experienced long periods of large appreciation it is especially attractive for those wishing to leave as a bequest. Second, that different households report systematically different expectations about leaving bequests, outcomes which are likely to reflect differences in the amount these households plan to leave. This reinforces important evidence supporting that bequest motives exist and are heterogeneous across households (Laitner and Juster, 1996; Kopczuk and Lupton, 2007).

Armed with a carefully estimated model that matches these and other important facts, I quantify household responses to changes in different sources of retirement wealth and to what extent house price run-ups are shared with younger generations. I find that over a third of house price shocks at age 70 are passed on to future generations as a bequest while almost 70% of a liquid wealth shock is passed on as bequests (both of these results are larger than existing estimates such as those in Altonji and Villanueva, 2003). Increases in housing and liquid wealth have opposite effects on liquidity constraints. This changes the incentives to access wealth held in housing leading to very different downsizing behaviour and bequests.

My estimated model parameters indicate that bequest motives are very heterogeneous. Around half the population have zero, or close to zero, estimated bequest motives, while the remaining population have positive and quantitatively important bequest motives. These differences in bequest preferences affect how households deaccumulate wealth in retirement and, in particular, how strongly they respond to changes in their portfolio.

I use my estimated model to evaluate the extent to which asset disregards (in housing and other assets) affect government provided insurance against the risk of large LTC expenses. I take the current structure of disregards and eligibility for these (Medicaid-like) benefits in the UK as given. I simulate retirees through a set of reforms that eliminate disregards for specific assets to isolate how the insurance provided by these programs is affected by the specific design of the asset testing. Comparing across these different scenarios, I find that for every pound it costs the government increasing the disregards for liquid assets provides more value than increasing the housing disregards. Asset tests that determine eligibility treat housing and other assets differently in the UK system, as well as Medicaid in the US, and is a feature of many tax and transfer systems. My results suggest that this is an important policy instrument.

Related Literature This paper contributes to four important strands of the literature. Firstly, it contributes to an established literature exploring the so-called "retirement saving puzzle" and quantifying various savings motive for the elderly. I make a significant contribution to a second, highly related, literature analysing the distribution of household bequest motives. There is a large literature on the role of housing wealth in savings decisions to which this paper is closely related. Finally, incorporating quasi-experimental variation and self reported subjective probabilities into the identification of a large structural model contributes to the nascent literature attempting to provide more robust and transparent identification.

I incorporate both the important precautionary and bequest savings channels from earlier work on the retirement savings puzzle, combining it with rich heterogeneity in assets choices and preferences. In estimating the different savings motives in retirement, I combine self reported probabilities of leaving an inheritance (a widely available survey instrument) with a rich asset structure and quasi-experimental variation. Ameriks et al. (2018) instead combine panel data on the liquid component of household portfolios with specially designed *strategic survey question* on bequests and long term care-in effect, stated choice. I exploit the self insurance information in the composition of household portfolios between liquid and illiquid assets. Inkmann and Michaelides (2012), De Nardi et al. (2016a), and Lockwood (2018) all estimate quantitatively important and prevalent bequest motives as a feature that rationalizes household under-utilization of insurance products (life insurance, Medicaid participation and long term care insurance respectively). The allocation of wealth across assets with different self insurance capacities uses similar variation in household precautionary incentives and provides a potential alternative explanation for this underutilization.[2]

I provide a link between the precautionary savings focused retirement savings literature and the literature exploring heterogeneity in household bequest motives by combining an estimation of heterogeneous bequest motives with a state of the art structural model. I estimate a latent distribution of household bequest motives while also allowing for a richer environment of empirically relevant risks in retirement and a more flexible approach to estimating the bequest motive. I allow both the overall strength of the bequest motive and the extent to which they are a luxury to vary across households in addition to the extensive margin of the linear bequest motive in Hurd (1989) and Kopczuk and Lupton (2007). Put differently, I allow for variation even among households who do have a bequest motive. Ameriks et al. (2016) allow for variation in the strength of the bequest motive out of financial wealth estimated directly from variation in responses to strategic survey questions, but without choice data and do not study the non-financial component of household portfolios.

To understand the role of housing wealth in retirement separately from other assets, I present new descriptive evidence on the lifetime frequency and size of housing adjustments by retirees. In the short run, households retain capital gains and their housing wealth tracks house price movements. Similarly to Fagereng et al. (2019), failing to distinguish between active and passive saving when asset prices change can substantially overstate household savings rates. Despite this short run correlation, adjustments to their housing wealth are large and common over the entire retirement period. This paper explores how the housing wealth effect[3] interacts with different sources of idiosyncratic risks as well as its implications for future generations. I extend the housing decision faced by households by modelling adjustments to their housing stock on the intensive margin and capture the active rebalancing of the portfolios held by retirees. Nakajima and Telyukova (2018a) and Cocco and Lopes (2018), who both model retirees' decisions to remain in their own home, have the closest asset structure to this paper among studies focussed on wealth in retirement.[4]

[2]Since Yaari (1965), several studies have explored the role of idiosyncratic risk in old age with Hurd (1989) suggesting that mortality risk is the primary empirical driver of savings in retirement or, as in Palumbo (1999), that medical expenses faced by retired households are necessary to explain their limited deccumulation. Studies in this tradition argue that risk averse households maintain wealth and exhibit slow deccumulation because of high levels of precautionary savings and that bequests are accidental. De Nardi et al. (2010) examine the role of precautionary savings motives using a structural model and find that longevity and medical expenditure risk dominate for the majority of single households. While much of this literature focuses on the United States, evidence from Dutch (Alessie et al., 1999), Norwegian (Kvaerner, 2017), Swedish (Nakajima and Telyukova, 2018b) or other cross country comparisons (Blundell et al., 2016) emphasises similar motives. See De Nardi et al. (2016b) for an extensive review of this literature

[3]An increase in household expenditures in response to an increase in home values. An inexhaustive list of contributions explicitly exploring the size and heterogeneity of this expenditure response using micro data include Mian et al. (2013); Kaplan et al. (2016); Aladangady (2017); Berger et al. (2018); Guren et al. (2018).

[4]A parallel literature in household finance, including Love (2010) and Hubener et al. (2016), finds that

Finally, this paper contributes to a literature focussed on the credible identification of structural models. Exploiting exogenous policy variation in estate taxation and housing transaction taxes in the estimation of bequest motives (building on Voena (2015) and Blundell et al. (2016)) complements the instrumental variable approach proposed by Lee and Tan (2017). Additionally, the identification approach in this paper uses elicited self reported probabilities of leaving a bequest in the future as dependent variables and also to classify unobserved preference heterogeneity. van der Klaauw and Wolpin (2008) and van der Klaauw (2012) demonstrate the value of using non-choice data as outcome variables in identifying dynamic discrete choice structural models while Pantano and Zheng (2013) shows how they can be used to identify household level fixed effects. Hendren (2013) uses subjective probabilities to infer differences in household private information or unobserved risk types.

The remainder of this paper proceeds as follows. Section 2 describes the data used in this paper and presents descriptive results. The quasi-experimental tax variation is described in detail in Section 3. Section 4 describes the model and Section 5 detail the identification and estimation of the model. Estimation results are given in Section 6 and 7 discusses the implications of the results. Section 8 empirically evaluates means tested long term care benefits. Finally, Section 9 concludes.

2 Data & Key Facts

This section first discusses the dataset used in the paper, the English Longitudinal Study of Ageing (ELSA). Then, it outlines the key facts on the evolution of wealth in retirement and, in particular, housing wealth that this paper aims to understand.

2.1 Data

ELSA is a biennial longitudinal survey that contains a representative sample of the non-institutionalized English population aged 50 and over. ELSA is an ageing survey modelled on the US Health and Retirement Study (HRS). It collects detailed panel data on demographics, earnings, health, wealth levels and portfolios through a combination face to face interviews and supplementary questionnaires. ELSA begins in 2002/03 and I use data collected in the first 7 waves.

To construct the sample, I keep only households where the head is above the age of 65 (the state pension age for men) and who do not report large labour income (those in excess of pension credit levels, a means tested benefit which tops up household income for those out of work and eligible for state pensions) and abstract from labour decisions

marital status and household demographics are important determinants of household portfolio allocations over the life cycle.

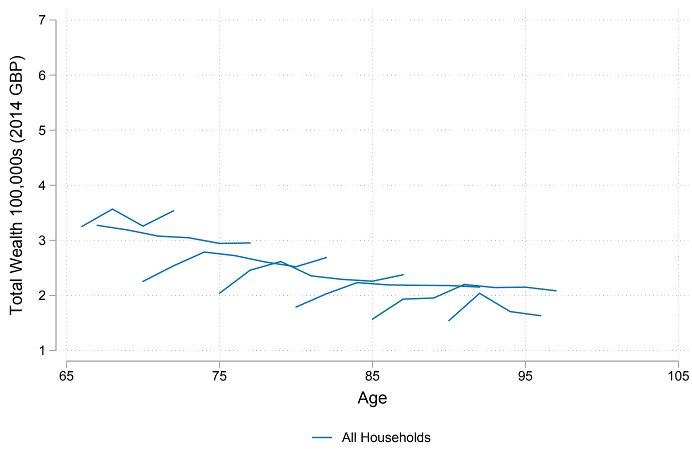


Figure 1: Mean Total Wealth by Cohort

around retirement. Following De Nardi et al. (2018), I allow for household composition changes only at death and drop households when either a new individual enters or leaves the household before death - this drops all households who either divorce or remarry during the sample period. I make use of the original sample cohort and households that are included as new entrants because, even if attrition is differential, these new households are included to maintain the representative sample as the survey ages.

In the next part of this section, I show how the savings of retired households and the major components of their portfolio have evolved over time. I present statistics for within group means by cohort (and, as discussed below, stratified by additional data) where I top-code wealth moments at the within group 95th percentile and drop cells with fewer than 15 observations to mitigate the impact of outliers. A subset of the moments presented here also comprise the moments used when estimating the model (discussed in more detail in section 5).

2.2 Key Facts

Figure 1 plots the mean total wealth, or net worth, of households by age for several five-year birth cohorts in ELSA. Total wealth is the sum of housing wealth and liquid wealth. Housing wealth consists of the value of their primary residence. Following Berger et al. (2018) mortgage debt is included in liquid (or non-housing) wealth. Liquid wealth additionally includes savings and current accounts, bonds/gilts, premium bonds, shares, trusts, and other physical assets less credit card debt, private debt and any other outstanding loans or debts.[5]

[5]Specifically savings accounts include savings accounts with a bank or building society as well as TESSA, all forms of ISA, PEPs, National Savings Accounts and life insurance savings. Following Berger et al. (2018) mortgage debt, secondary residences and other properties are included in liquid (or non-housing) wealth. I drop retirees who directly own businesses.

Comparing across birth cohorts, mean total wealth appears to decline moderately with age. By the time that they reach their late 90s, the oldest birth cohort hold about 40% less wealth than the youngest birth cohort at age 70. However, within each birth cohort mean wealth remains at high levels for much of their retirement and exhibits little signs of deccumulation For all but the youngest birth cohort, total wealth is higher at the end of the sample period than at the start. This lack of deccumulation at the end of life is inconsistent with a basic life cycle model where households accumulate wealth during working life and draw down their wealth in retirement.

Similar patterns in total wealth are widely studied in the US (such as resuls in De Nardi et al., 2018, who document the savings profiles of elderly US couples and singles) and typically exhibit more deccumulation. Medical costs, longevity risk, bequests, and housing decisions have been discerned as important factors explaining these asset holdings.

One striking feature of the UK data is the presence of time effects, which have been little studied in the context of the US.[6] The x-axis plots the average age within birth cohort - consequently, within cohort ageing is equivalent to plotting a time dimension. The steep growth in total wealth followed by a levelling out occurs for the same calendar years in each birth cohort. For the youngest two cohorts who age into the sample in later calendar years only the flat portion of the profile after the initial increase is observed. As I document below, the rapid rise and peak in household total wealth broadly follows the aggregate trend in house prices around the 2008 financial crisis.

As a cohort ages, it is increasingly comprised of rich people due to mortality differences between the rich and poor.[7] To mitigate this composition effect and highlight cross sectional differences in the level and portfolio composition of wealth, I pursue three complementary approaches. First, I present results for total wealth grouped by permanent income quantiles. This controls for the lifetime income levels of the households. To calculate permanent income I follow the approach in De Nardi et al. (2018) and exploit the approximately monotonic relationship between lifetime resources and pension income in the UK. Each household is then ranked by their position in the permanent income distribution and the measure is invariant to household demographics (I describe this in more detail in Appendix A). I generate three permanent income groups: the top 25% of households, the second quartile, and the bottom 50% of households. I merge together the bottom two quartiles as conditional on their initial home ownership status the two groups are extremely similar. However, there are substantial differences in initial home ownership rates in the two bottom quartiles.

Second, to understand changes in their portfolio I present results for the different forms of wealth, housing and non-housing wealth, by PI, and by the initial home owner-

[6]As noted in Schulhofer-Wohl (2018) many studies attempt to cleanse time effects from moments in the data

[7]Attanasio and Emmerson (2003) document this composition difference in the UK

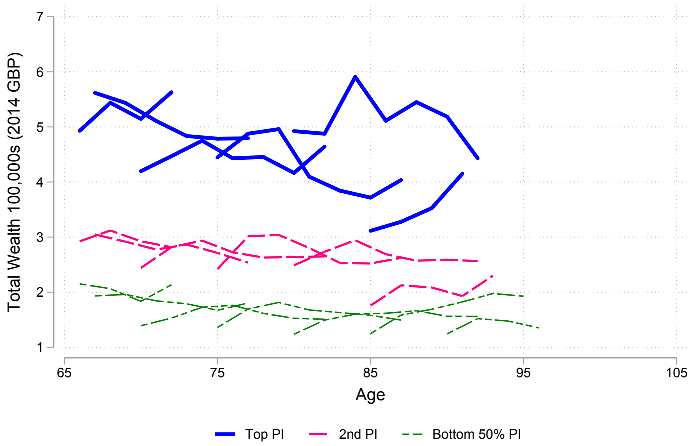
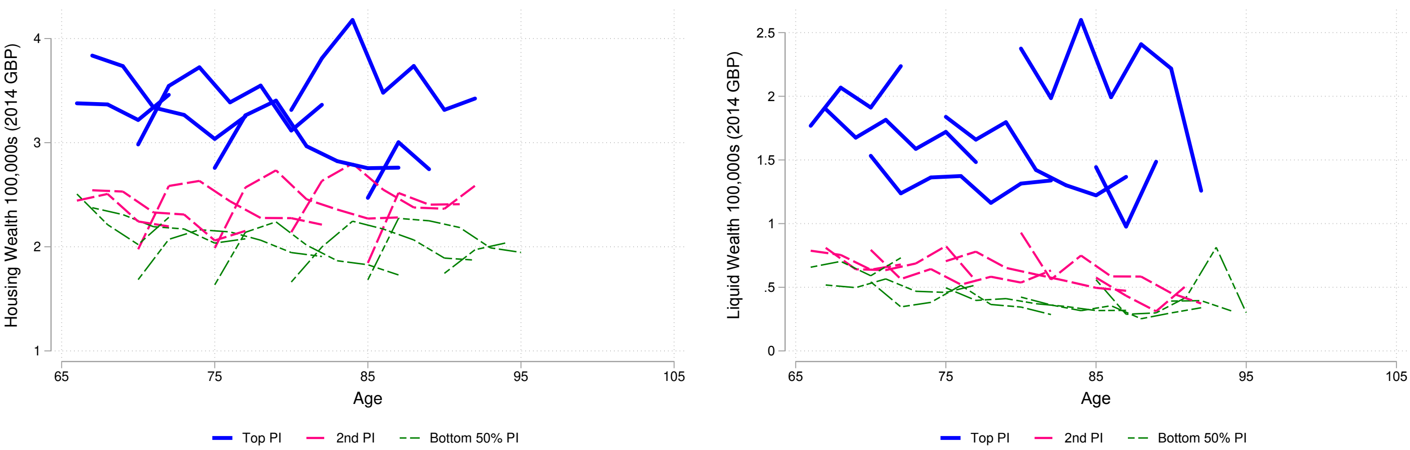


Figure 2: Mean Total Wealth by Cohort

ship status of households. This not only controls by income levels and housing tenure, but also shows how households save in different savings vehicles. Initial home ownership is defined in the first wave a household is sampled and this definition keeps the household composition constant in the analysis. Third, in Appendix B I present results for a balanced panel consisting of those households who enter the sample in the first wave and survive until the final wave. This eliminates composition bias, but by imposing stricter selection requirements imposes a selection bias. Nevertheless, the results in Appendix B indicate that the stylized facts in this section are not driven by changing household composition.

In figure 2, I reproduce the mean total wealth for birth cohorts also separated by their permanent income. Comparing figures 1 and 2 suggest that the means in figure 1 mask considerable heterogeneity, with a strong permanent income gradient. The top quartile of households have more than twice the assets of the bottom half of the distribution. While those in the 2nd quartile are around £200,000 poorer on average than their top quartile counterparts, they are also around £100,000 richer than retirees in the bottom half of the lifetime resources distribution.[8] Although there are signs of wealth deccumulation by households, it remains minimal. Furthermore, within permanent income group, the evidence of cross cohort deccumulation (or pervasive cohort effects) is much smaller. In figure 2, mean total wealth rises by approximately £50,000 in the first three waves and gradually declines through the remainder of the sample. This initial increase occurs across PI groups for all birth cohorts in the sample in 2002/03, however, conditional on PI there is a larger decrease in wealth after the increase for those with higher PI levels. Consequently, between the start and the end of the sample, total wealth remains almost

[8]Excluding the 1915 birth cohort, for whom the difference is in the region of £50,000. There is also considerable heterogeneity in the size of these gaps by Permanent Income with the gap exceeding £100,000 for a number of cohort age combinations



(a) Mean Housing Wealth

(b) Mean Liquid Wealth

Figure 3: Wealth by Cohort & PI (Initial Owners)

flat for all cohorts.[9] This limited deccumulation of resources across and within cohorts suggests that even those who survive until older ages will bequeath much of their initial wealth held at age 70. Using comparable US data from the HRS, Poterba et al. (2017) similarly document a high degree of persistence in early retirement wealth and wealth at death.

2.3 Different Forms of Wealth

Figures 1 and 2 show that the savings of households in retirement differ by household lifetime resources. To understand the importance of household portfolios, I continue to document savings heterogeneity by a) the type of wealth owned by households and b) the home ownership status of households. In Figure 3 I plot the mean wealth of initial owners by birth cohort and permanent income.

The left panel shows the mean housing wealth of households (their primary residence) and the right panel shows the corresponding mean liquid wealth for the same groupings. For all cohorts and PI groups, housing wealth displays evidence of the aggregate trend in the total wealth profiles, However, liquid wealth does not exhibit the same degree of cyclicality. As with the total wealth profiles in figure 2, there is a permanent income gradient (here while also conditioning on initial home ownership status) for both housing and liquid wealth. Peak mean owner occupied housing wealth is above £350,000 for the top permanent income group while on average it is approximately £260,000 for the second quartile. The differences between PI groups are compressed when compared with total wealth (although the base is smaller) with the average gap between the second quartile and the bottom half of the distribution dropping to £40,000.

[9]This suggests that composition bias drives some of the flattening of savings profiles and the cross cohort gradient in figure 1. I discuss this in more detail in Appendix B.

The gap between the liquid wealth of the top quartile and the second permanent income quartile is of similar magnitude to the absolute gap in housing wealth because housing wealth is a smaller proportion of the portfolio of richer households. However, the difference between the liquid wealth of the second quartile and the bottom 50% is much smaller. In levels, liquid wealth shows some evidence of deccumulation which is concentrated at older ages. The largest change in the top two permanent income groups are £110,000 and £55,000 respectively, but for most cohorts the drop is below £25,000. For the largest reductions, this is equivalent to a 30-35% reduction in the liquid wealth stock (rising to 50% for the largest drop), but has a small effect on the total wealth base. In contrast, there is even less deccumulation of housing wealth. At most, mean household housing wealth decreases by £60,000 (the top PI group and second youngest birth cohort who age into the sample during house price depreciation), but the majority of cohorts retain similar levels of housing wealth or even grow in real terms between the beginning and the end of the sample.

Returns or appreciation in asset prices driven by aggregate trends affect housing, but similar patterns are not present in liquid wealth. Furthermore, housing provides a consumption flow and functions as a store of wealth as well as being subject to large adjustment costs. Explicitly modelling these assets is important for understanding household savings and household demand for self insurance. However, Figure 3a is still insufficient to disentangle the active and passive saving in housing wealth. Later in this section I show direct evidence of housing transitions and the change in the value of housing wealth to provide evidence on the active saving component of deccumulation.

Finally, I turn to initial renters and their liquid wealth. After retirement, initial renters tend to belong to lower PI percentiles. For this reason I pool all renters together. At the mean, initial renters are poorer than their home owning counterparts. They hold around 25% of the liquid wealth of the corresponding bottom PI groups. However, unlike homeowners who have on average £200,000 in housing wealth and £50,000 in liquid wealth, initial renters are cash and income poor. The liquid wealth for initial renters is approximately stable, in contrast with Nakajima and Telyukova (2018a) who show that the assets of elderly US households who transition from owner occupation to renting decline.

The key fact established in this section is that, even stratifying by wealth type and important financial characteristics, neither housing wealth or liquid wealth exhibit large declines. Furthermore, households retain capital gains in housing which exposes housing to aggregate fluctuations in house prices which effect different birth cohorts at different ages. Similar results using ELSA data are found in Blundell et al. (2016) and Crawford (2018) who projects that the median household will spend down less than £10,000 of their financial wealth in retirement. In the next part of this section I further explore the housing transitions of older households.

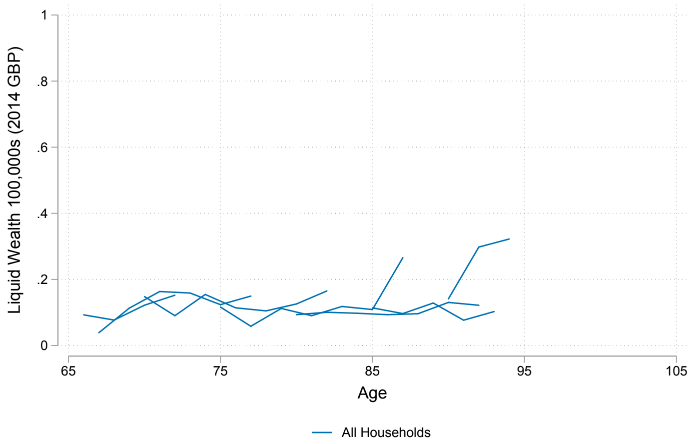
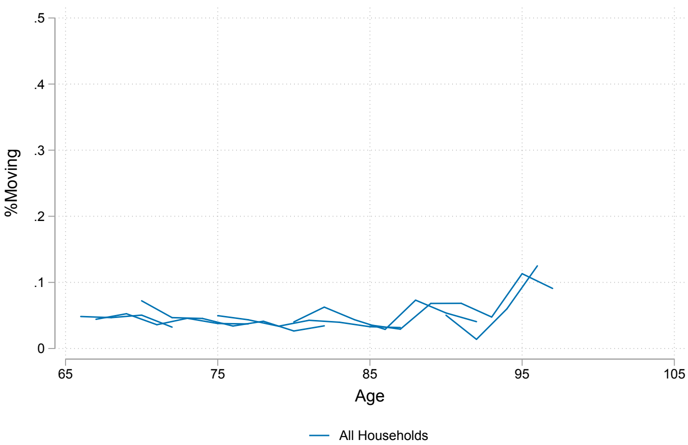
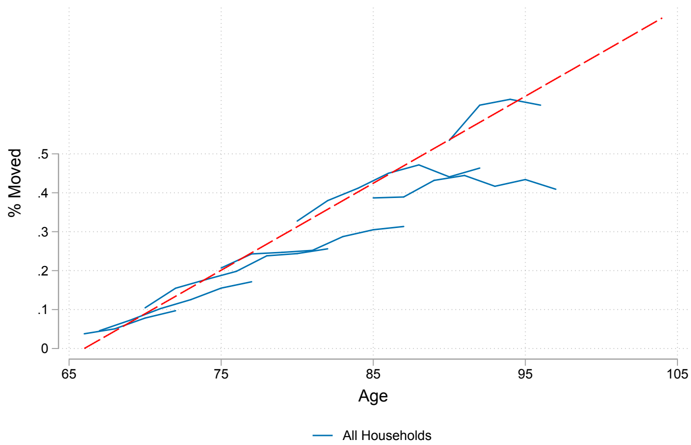


Figure 4: Mean Liquid Wealth by Cohort (Initial Renters)



(a) Moves in the last 2 years



(b) Moves since Age 65

Figure 5: Frequency of moves

2.4 The Role of Housing Transitions in Retirement

To understand the economic importance of household mobility and the active portfolio rebalancing of older households, I focus on the frequency and size of decisions to adjust housing wealth.[10]

Figure 5a shows the frequency with which initial homeowners move properties in two year periods (the frequency of the ELSA data). There is limited age and cohort variation with an average of 4.5% of households moving each wave. Instead of looking at the between wave transitions, Figure 5b plots the probability of any move since age 65. The line for each cohort rises almost linearly at the same average frequency of move because households over 65 move infrequently and on average only once. There is little evidence, in contrast with Angelini et al. (2014), that retired households front-load their movement

[10] An alternative exercise deflating housing wealth by house price change is presented in appendix C

	Downsizers		
	All	Remaining Owners	All Upsizers
Mean Housing Change[a]	-136	-104	55.4
Mean Relative Change[b]	0.48	0.72	1.34
Fraction of Movers (%)	76.8	50.9	23.2
N	219	145	66

Source: Author's own calculation from ELSA. [a] £1000s in 2014 prices, [b] Relative change is defined as the ratio of the new price to the old price at time of sale.

Table 1: Average Housing Wealth Change by Move Type

decisions and almost 50% of households have moved by age 90.

The home moving decision is one of the key financial decisions households make during retirement. Table 1 provides statistics on the mean level and relative change in housing wealth for three different categories: all downsizers, those who downsize excluding household's who transition to renting, and those who upsize. Separating households by those who downsize and those who upsize controls for differences in the type of move. Within downsizers, who are over 75% of moves, I also separate out transitions to renters to control for the largest differences in the fraction withdrawn. Conditional on downsizing, the average household releases 52% of the current value of their house or over £135,000.

Among downsizers the largest relative changes are those who completely downsize, Downsizers who remain owner occupiers release over £100,000 of equity, or approximately 40% of the average wealth level, and 30% of their housing wealth. Finally, household's who upsize are the smallest group, but represent over 20% of move. In levels they make the smallest change to the mean level of their housing wealth. Nevertheless, the £55,000 change they make is still an economically significant increase and on average they increase their housing wealth by one third. These are large changes in the portfolio composition of households who move house.

2.5 Subjective Bequest Probabilities

ELSA includes a number of survey questions that directly elicit the subjective expectations of respondents. I make use of a standard survey instrument that asks the probability of leaving a bequest larger than £150,000 with answers on a 101 point scale between 0 and 100. Household responses covary strongly with wealth and in Appendix D I provide an example question, further discussion of subjective probability questions in ELSA, an alternative validation approach, and within birth cohort age profiles.

This subsection establishes two empirical facts. First, that subjective bequest probabilities contain informational content over and above demographic or economic variables. This demonstrates the advantage of including these measures as moments when estimating the model. Second, that different households report systematically different expectations about leaving bequests even after controlling for an extensive set of observable characteristics. I interpret this as indirect evidence supporting the hypothesis that bequest preferences are heterogeneous.

Subjective bequest probabilities contain information about a household's expected future path of savings over and above their current observable characteristics. To formalize this intuition, I estimate a series of quantile regressions for the partial correlation of future wealth and current subjective probabilities (controlling for additional observables $X_{i,t}$). The conditional quantile function $Q(\cdot|\cdot)$, for a given quantile τ, is given by:

$$Q_{Wealth_{i,t+1}}(\tau|\cdot) = \beta(\tau)Pr(Bequest \geq £150,00)_{i,t} + \delta(\tau)X_{i,t} \quad (1)$$

Figure 6 displays the results of these estimated partial correlations, $\beta(\tau)$, graphically for two alternative specifications of the conditional quantile function, in the first I additionally control for current period wealth; polynomials in age and permanent income; household demographics; the health of each individual in the household; the sample wave and homeownership status. In the second specification I control only for sample wave and current period wealth. The value of the coefficient at each point of the x-axis is the partial correlation (at a given conditional quantile of total wealth) of a 1 percentage point increase in the probability of leaving a large bequest.

The results from the quantile regression show that individual level variation in the subjective probability of leaving a large bequest is a statistically and economically significant predictor of future wealth holdings for all but the top of the wealth distribution. Under both specifications there is a decreasing pattern. In the main specification, at the conditional 5th percentile of future wealth a percentage point increase in the probability is associated with a £425 increase in tomorrow's wealth, while at the median this has fallen to approximately £100. Part of this decline is driven by difference in observables across the wealth distribution. However, the absence of the effect for the richest households is also an artefact of the survey design: these households hold assets well in excess of the £150,000 threshold and report that they are likely to leave a large bequest (reducing variation in the independent variable). Comparing the alternative specification, the estimated effect approximately halves in size when a full set of controls is included. Interpreting this systematic fall in the estimated effect across the distribution of total wealth highlights that while observable characteristics (or the state variables in a household problem) may explain a large fraction of the link between subjective beliefs and

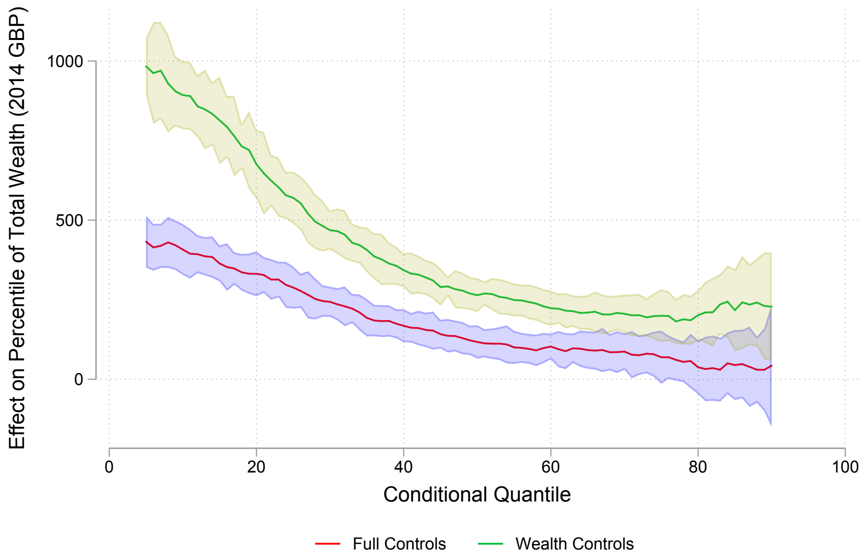


Figure 6: Information Content of Subjective Bequest Probabilities

Estimated partial correlations. Full controls include: current period wealth; polynomials in age and permanent income; household demographics; the health of each individual in the household; the sample wave and homeownership status

wealth there is a significant proportion that is unexplained. Exploiting this additional source of variation is useful when estimating a large structural model of retirement savings decisions.

2.5.1 Preference Index

There is considerable evidence that households differ in their preferences for leaving an inheritance. This is important because it may affect their savings decisions over the life-cycle, the extent to which they realize capital gains from house price changes by downsizing, and how they value resources that are not spent during their lifetime.

To better measure preference heterogeneity in the population (and how it is correlated with observable characteristics), I construct a single index of a household's likelihood of leaving a large bequest. I exploit the panel component of the ELSA data and combine multiple self reported probabilities (measured in different waves of the survey) into a single time invariant index that captures persistent and systematic differences across households.

Formally, I estimate a regression where the continuous measure of the self reported probability is the dependent variable. The object of interest is a household specific fixed effect which proxies the permanent differences in bequest preferences.[11] To the extent that all relevant state variables in the household problem are controlled for, fixed effects do

[11] In constructing this index I control for a number of contemporaneous household characteristics. See Appendix D for a full description.

	OLS	Observables	Household Fixed Effect	Residual
Fraction of Total Variation	0.497	0.426	0.307	0.267

Table 2: Decomposing Variation in Subjective Probabilities

not proxy systematically different expectations or the average realization of uncertainty. Instead, the fixed effect absorbs variation in the idiosyncratic preference for bequests and other time invariant features. Table 2 reports the share of variance in the subjective probability of leaving a bequest greater than £150,000 attributable to: this rich set of covariates, their bequest preference index (a transformation of the intraclass correlation) and a residual. In addition, I report the share of the variance attributed to the same set of covariates in a linear regression (the R-Squared) for comparison.

These results reinforce the link between wealth accumulation and self reported bequest probabilities displayed in Figure 6. First, observable household characteristics explain a large proportion of the individual variation in reported bequest probabilities, and, second, a significant fraction of the variation is attributed to systematic and persistent difference across households. As discussed above, these persistent differences may reflect variation in preferences for bequests. For this reason I model heterogeneity in household preference and exploit the bequest preference index in estimating the distribution of latent preference types discussed in more detail in Section 5.

3 Tax Reform as a source of Quasi-Experimental Variation

The UK tax system provides substantial variation in incentives for retired households due to features of estate and housing transaction taxes. When households cross thresholds in these tax systems their incentives can change substantially.

To help identify the structural model described in the next section I leverage variation over time in tax policy and the cross-sectional differences in household incentives produced by these thresholds. Changes to estate taxation and residential property transaction taxes provide a source of quasi-experimental variation that change the returns to leaving a bequest, the returns to holding different assets, and the cost of transforming housing wealth into liquid wealth at different points in the wealth distribution over time. In addition to the effect of exogenous policy changes, the large appreciation in house prices provides a second source of variation in the form of 'bracket creep' effects when price appreciation moves households into higher tax brackets. This section begins by describing the important reform to inheritance taxation before also describing the changes to transaction taxes. Finally, I show the reduced form effect of transaction tax reforms on the decisions of retired households using a regression discontinuity research design.

3.1 Inheritance Tax in the Sample Period

Despite its name, UK Inheritance Tax is levied on the estate of an individual who dies and not on the recipient of a bequest. Where an individual leaves the entirety of their estate to a spouse or civil partner (in the case that there are privately owned assets) there is no inheritance tax levied on the estate.

During the sample period, Inheritance Tax is charged at a constant rate of 40% of the estate above an exemption threshold and the Inheritance Tax exemption threshold is indexed to RPI. In 2010, this threshold was £325,000. A major reform was implemented on the 9th of October 2007. From this date, the tax exemption threshold increased by any unused proportion of a deceased spouse or civil partner's nil-rate band (even if the first partner died before 9 October 2007). Suppose the husband in the household died in 2003 and left £50,000 to their heirs and the wife died in 2010. The effective exemption threshold for the wife would be £600,000 because she is entitled to the full amount of her own exemption threshold (£325,000) and the unused proportion of her husband's nil-rate band (£325,000 less the £50,000 already bequeathed).

This effectively doubled the exemption threshold for the majority of older households.[12] Figure 2, which shows the mean wealth by birth cohort and PI, shows that the mean wealth holdings in the top 50% of the lifetime resource distribution are near or above the original exemption rate.

3.2 Housing Transaction Taxes in the Sample Period

The Stamp Duty Land Tax (SDLT) was introduced in the UK in 2003, replacing the pre-existing Stamp Duty, and constitutes a transaction tax levied on all residential properties in the UK. During the sample period, the tax takes the form of a percentage rate charged on the whole purchase price if the price is above a particular threshold (because SDLT varies the average tax rate this creates discontinuous jumps, or *notches*, in the tax incentives). In 2005 the threshold for the lowest rate, 1%, doubled and increased again in 2006. In 2011, new higher rates were introduced at 5% and 7% for all properties above £1 million and £2 million respectively. In addition to these changes, in 2008 the UK government introduced the 'Stamp Duty Holiday' a temporary (15 month) increase to the

[12]For the UK, Crawford and Mei (2018) report that nearly all wealth is left to a surviving partner when one exists.

	Threshold by Rate				
Effective from	1%	3%	4%	5%	7%
28 March 2000	£60,000	£250,000	£500,000	*Not in use*	*Not in use*
17 March 2005	£120,000	£250,000	£500,000	*Not in use*	*Not in use*
23 March 2006	£125,000	£250,000	£500,000	*Not in use*	*Not in use*
03 September 2008[a]	£175,000	£250,000	£500,000	*Not in use*	*Not in use*
01 January 2010	£125,000	£250,000	£500,000	*Not in use*	*Not in use*
06 April 2011	£125,000	£250,000	£500,000	£1,000,000	£2,000,000

All thresholds and rates refer to transactions of residential property. During this time period there are additional exemptions for disadvantaged areas. [a] denotes the "Stamp Duty Holiday" where the 0% rate threshold was temporarily extended

Table 3: Rates and Thresholds for Stamp Duty Land Tax

lower threshold from £125,000 to £175,000 expiring on December 31st 2009. This change is studied in both Besley et al. (2014) and Best and Kleven (2018). Table 3 summarizes the changes over the duration of my sample.[13]

How do transaction taxes affect retired households? Households who have large amounts of wealth tied up in their home face these transaction costs if they choose to downsize and withdraw equity (or re-optimize because of reduced demand for housing services). Relative to a world without the transaction tax this creates significant disincentives. Consider a household owning a £400,000 house and wishing to downsize to a £300,000 house. Absent transaction costs (and any fixed costs of adjustment or changes due to collateral) the home owner would release £100,000 of equity. Under the SDLT policy the transaction tax levied on the new purchase is £9,000 which has an implied tax rate of 9% on the equity withdrawal. Besley et al. (2014) suggest that the incidence falling on sellers is 40%[14] and in this example the total cost paid is equivalent to a 10.2% tax on the £100,000 released (40% of £12,000 and 60% of £9,000).[15]

3.3 The Impact of SDLT on Home Moving Decisions

In estimating the structural model outlined in the next section, this paper directly incorporates variation in tax schedules over time. In the case of reforms to UK transaction taxes, this generates additional variation over time in the incentives households face when

[13]In addition between the 1st of January 2010 and the 24th of March 2012 first time buyers enjoyed an additional exemption for residential properties costing less than £250,000

[14]Kopczuk and Munroe (2015) present alternative estimates of transaction tax incidence using New Jersey Mansion taxes and find that it is entirely incident on the seller. In contrast, Slemrod et al. (2017) use notches from Washington, DC and estimate equal incidence on buyers and sellers.

[15]For a a household with a house worth £250,000 wishing to downsize to a house worth £200,000, and now release 20% of the equity in their home, the effective tax rate on the equity released is 13.2% (40% of £7,500 and 60% of £6,000 divided by the £50,000 base)

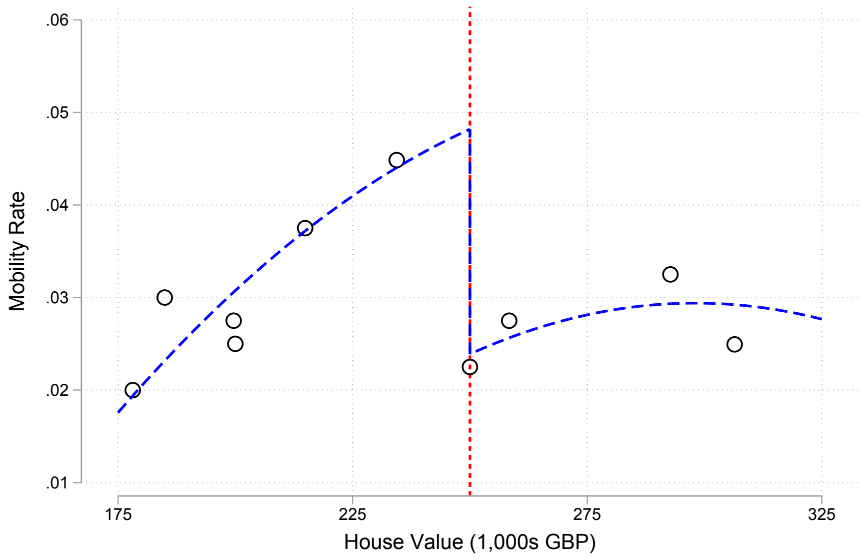


Figure 7: Mobility Rate and House Values

Circles are mobility rates for deciles of house value distribution within the sample window. The blue dashed shows the predicted fit of a regression of moving on a treatment for exceeding the £250,000 threshold and a quadratic in home value using a 30% window around the threshold. Further details in Table 4.

choosing whether or not to sell their house. How strongly older households decisions vary with the changes to these incentives is an empirical question.

I show the response to the effects of transaction taxes in reduced form evidence by analysing the mobility decisions of older households around stamp duty thresholds using a regression discontinuity research design.[16] A reduction in home mobility is a reduction in the extensive margin of home equity adjustment. The empirical specification draws on Hilber and Lyytikäinen (2017) who analyse the moving decisions of working age UK households and my results suggest that the effect of transaction taxes is of the same order of magnitude for old and young households.

I focus on a *notch* in the tax system at the £250,000 threshold because it remains constant throughout the sample period. For sale values that exceed this threshold, there is an increase in the average tax rate paid on the transaction from 1 to 3% and a discontinuous increase in the SDLT burden of £5,000. The outcome variable of interest, $Move_{i,t}$, is a dummy variable denoting a household's mobility between waves t and $t+1$ with treatment defined as a house value greater than or equal to £250,000:

[16]A recent literature has shed light on the effect of housing transaction taxes and their impact on transaction volumes (Best and Kleven, 2018), sale prices (Besley et al., 2014; Kopczuk and Munroe, 2015; Slemrod et al., 2017) and mobility decisions (Hilber and Lyytikäinen, 2017). However, a potential concern is that these findings are driven by younger households who have a higher baseline mobility rate - if that were true there would be no additional identifying power from the SDLT reforms when studying older households.

$$Move_{i,t} = \beta_0 + \beta_1 Treat_{i,t} + f(HouseValue_{i,t}) + \delta X_{i,t} + u_{i,t} \quad (2)$$

The vector of control variables, $X_{i,t}$, includes a polynomial in household age, a polynomial in permanent income, household demographics, and wave and region indicators. I present results approximating the flexible function of house value $f(\cdot)$ in the conditional expectation function under three separate specifications: linear and quadratic with common slopes and a non-parametric local linear estimator where the slope differs across the discontinuity. I limit the analysis to a maximum 30% interval around the discontinuity in the tax schedule to avoid contamination from the effects of the 'Stamp Duty Holiday' (see Table 3).

The key identifying assumption is that, conditional on the covariates, $u_{i,t}$ is uncorrelated with the treatment indicator $Treat_{i,t}$. In regression discontinuity frameworks, this is satisfied if other covariates vary smoothly and the forcing variable ($HouseValue_{i,t}$) cannot be manipulated. Two features of the data reduce the concern of manipulation: first, home moves are measured in the following wave so that the reported home value is predetermined and, second, self reported home valuation is not the actual sale price used to calculate the SDLT burden. Following Kolesár and Rothe (2018) I report standard errors clustered at the household level and provide alternative confidence intervals with guaranteed coverage properties in appendix E.[17]

Figure 7 plots the results graphically and shows evidence of a decrease in mobility for those households who exceed the £250,000 threshold. Table 4 presents results from the regression analysis, varying the order of the polynomial in house value and the band around the stamp duty threshold included in the regression. The first row shows the results for a linear specification with a common slope on either side of the discontinuity. Consistent with the graphical evidence, the negative effect of an increase in the transaction tax burden on home moves is largest for narrow windows around the threshold. However, it is negative and statistically significant across all of the reported bandwidths. The second row displays results for a quadratic specification. For the smallest band around the cut-off value the result is of a similar magnitude to the linear specification, but estimated with less precision. Increasing the size of the band around the cut-off has a larger effect on the precision of the estimate than in the linear specification and has only a modest effect on the point estimate which is stable across different windows around the discontinuity in the SDLT schedule.

Finally, the third row displays a specification using a non-parametric local linear estimator. For all bands around the discontinuity the non-parametric method yields similar point estimates to the parametric approach; however, for small bands around the

[17] Appendix E additionally provides results for higher order polynomials.

	Band around cuttoff				
Order of polynomial	10%	15%	20%	25%	30%
Common Slope					
Linear	-0.0445**	-0.0475***	-0.0207*	-0.0200*	-0.0250**
	(0.0181)	(0.0160)	(0.0114)	(0.0116)	(0.0110)
	-729.5	*-879.4*	*-2118*	*-2112*	*-2873*
Quadratic	-0.0365	-0.0450**	-0.0270**	-0.0218*	-0.0265**
	(0.0241)	(0.0193)	(0.0133)	(0.0130)	(0.0112)
	-727.9	*-877.5*	*-2118*	*-2110*	*-2873*
Non-parametric					
Local Linear	-0.0278	-0.0341	-0.0356*	-0.0303**	-0.0287**
	(0.0334)	(0.0247)	(0.0189)	(0.0155)	(0.0141)
N	1224	1559	3023	3233	3979

All regressions additionally control for wave fixed effects, a polynomial in age, household demographics, a polynomial in permanent income and region dummies. Following Kolesár and Rothe (2018), Standard Errors are clustered by household. The Akike Information Criterion is shown in italics * $p < 0.10$, ** $p < 0.5$, *** $p < 0.01$

Table 4: The Effect of Transaction Taxes on Household Mobility

cut-off these results are imprecisely estimated. For larger bands around the discontinuity in the SDLT schedule the results are precisely estimated and the negative effect of an increase in the transaction tax burden is statistically significant. The treatment effect of exposure to higher transaction taxes is negative in all specifications and the magnitude of the effect is robust to alternative estimation windows and methods for approximating the conditional expectation function.

The estimates of exposure to higher transaction taxes, which range from a 2 to 4 percentage point reduction in mobility, suggest that the effect of an increase in transaction taxes for older households is also economically significant. Despite their lower baseline mobility, these results imply older households have similar reductions to working age households (Hilber and Lyytikäinen, 2017) in relative terms.

4 A Model of Household Savings After Retirement

In this section, I introduce a model of the savings decision of retired households that is able to generate the key empirical results in Section 2. The model features realistic risks in retirement and includes a rich model of housing decisions that matches the institutional features of the UK. Households face idiosyncratic and exogenous risk in health status, mortality, long term care expenditures, and (for couples) the size of the household. In addition, households are exposed to aggregate risk in the form of a common and stochastic process for house prices. The model advances the retirement savings literature in two main dimensions. First, I allow for each household to have heterogeneous preferences over bequests and, second, I allow for households to adjust their stock of housing on the intensive margin as well as the extensive margin of homeownership.

A household begins retirement as either a single or couple. For couples, if their spouse dies the surviving member continues as a single. Single retirees cannot remarry. Household size affects the income available to households, their utility from consumption as well as health transitions, mortality and medical expense risk.

Households may be either homeowners or renters (with housing wealth equal to zero). Each period, a household chooses their consumption, home equity, and the stock of financial assets for the next period. Financial assets are risk free, perfectly liquid and yield constant interest r. There is no borrowing.[18] The housing stock depreciates at rate δ and has a price p_h which households take as given. In addition, renters (who may choose to purchase a house) must choose a level of housing services purchased at rental price r^h.

At the beginning of each period, each household observes their current age, permanent income, who is alive in the household, cash on hand, housing wealth, health, medical expense shock and the level of the aggregate house price. Decisions are made after shocks are observed and new shocks arrive at the end of the period after decisions have been made.

When describing the model, I suppress the index i for an individual household - in the interest of clarity I make one exception: the coefficients of their heterogeneous bequest motive.

4.1 Demographics

A household is either a single man, single woman, or a couple. The state variable f is the household structure describing their demographics.

[18]In the current version of the model I rule out collateralized and uncollateralized borrowing. The reasons for this are threefold. First, the majority of older households have paid off their mortgage or have positive liquid wealth balances. Second, after retirement many households fail to meet the income requirements of traditional forward mortgages and in the data very few retired households take out new mortgages to upsize. Third, although reverse mortgage products do exist (as considered in Nakajima and Telyukova, 2017; Cocco and Lopes, 2018) they are rarely used in the UK context. I provide further discussion of the UK and US reverse mortgage markets in appendix H. Finally, the UK market is tightly controlled on negative equity where the total value of the mortgage is still required to be paid in full.

$$f = \begin{cases} \text{Single Man} \\ \text{Single Woman} \\ \text{Couple} \end{cases} \tag{3}$$

4.2 Preferences

Preferences are time separable, with a constant discount factor β. Households maximize expected utility, the per-period utility function is given by:

$$u(s_j, c_j, h_j) = \frac{s_j(\frac{1}{\alpha_{s_j}} c_j^{\sigma} h_j^{1-\sigma})^{1-\gamma} - 1}{1-\gamma} \tag{4}$$

where c_j is the consumption of non-durable goods at age j and h_j is the level of housing consumption at age j. The term s is a deterministic function of family status f and is the size parameter equal to the number of adults in the household and α_s is the consumption equivalence scale for total consumption. In this specification, γ is the coefficient of relative risk aversion and σ is the weight of non-durable consumption relative to housing services.[19]

Utility from bequests for a household i, $\phi^i(b)$ is net of taxes and takes the form of a warm glow bequest motive as in De Nardi (2004) or Andreoni (1989). The functional form for $\phi^i(b)$ is given by:

$$\phi^i(b) = \frac{\phi_1^i(\phi_2^i + b)^{(1-\gamma)} - 1}{1-\gamma} \tag{5}$$

where ϕ_1^i controls the relative weight of bequests and total consumption for household i, while ϕ_2^i controls the curvature. Therefore ϕ_2^i controls the extent to which bequests are a luxury good. For positive ϕ_2^i marginal utility of small bequests is bounded, while the marginal utility of large bequests declines more slowly than consumption. One interpretation of the household specific preferences[20] is that ceteris paribus ϕ_1^i represents heterogeneity in altruism (or varies with the weight on the utility of future generations), while ϕ_2^i represents the human and financial wealth of the next generation. This specification is also consistent with other interpretations of the bequest motive such as pure egoism or strategic bequest motives (Bernheim et al., 1985).

[19] I impose a within period Cobb-Douglas aggregator for total consumption as many studies, such as Davis and Ortalo-Magné (2011), find that the expenditure shares on housing and consumption are constant

[20] This interpretation is consistent with Abel and Warshawsky (1988) formulation of so called 'Joy of Giving' bequest motives as a reduced form of altruism

4.3 Income, Health Status and Mortality

Income Households earn a return r on their financial assets a. Non-asset pension income y is deterministic and depends on age j, current family structure f and permanent income I:

$$y = y(j, f, I) \tag{6}$$

In addition to Estate Tax and Stamp Duty levied on housing transactions which are described in detail above, taxes are levied on pension income and income from financial assets.

Health Status Health status can take one of three values for each living household member

$$m = \in \{good, bad, ADL, dead\} \tag{7}$$

and transitions according to an age, family structure and permanent income dependent Markov process. Following Ameriks et al. (2018) I use difficulties with Activities of Daily Living (ADLs) to define the worst health state. For couples, m denotes a pair with a health status for each member - for notational convenience I continue to use m to denote this nine valued health status for the couple.

Mortality Individuals within households face exogenous mortality risk which depends on age, family structure, health status and permanent income.

4.4 Medical Spending

In the literature focusing on US retirees, out of pocket medical expenditure risk is an important driver of precautionary savings. In the UK the NHS provides comprehensive coverage for acute and chronic medical expenses. However, long term care risks pose considerable out of pocket risk- with lifetime care costs for 10% of individuals exceeding £100,000.[21]

I define mx_j as the flow of all out-of-pocket medical expenses incurred between j and $j-1$. Medical expenses are exogenous[22] and depend upon the current health status of the

[21] The UK figure is drawn from the Dilnot Report. This is lower than the figures for US lifetime medical spending of retirees reported in Jones et al. (2018), but there are two major differences: comparable US numbers include all medical spending (including Medicaid expenditure and hospital stays) and are reported at the household level, not for individuals

[22] This is consistent with Ameriks et al. (2018) who find limited income elasticity of endogenous medical spending for individuals with ADL needs using flexible health state dependent utility of spending and an estimated structural model.

household, the last period health status of the household, household permanent income, family structure, age, and an idiosyncratic component, $\epsilon_{mx,j}$:

$$\ln mx_j(\cdot) = \mu_{mx}(m_{j-1}, m_j, I, f_{j-1}, f_j, j + \sigma_{mx}(m_{j-1}, m_j, I, f_{j-1}, f_j, j) \times \epsilon_{mx,j} \tag{8}$$

$$\epsilon_{mx,j} \sim N(0,1) \tag{9}$$

4.5 Housing

It is costly to move home. I model these transaction costs with three features that capture the different types of costs faced by different households: the formal transaction tax (SDLT), a proportional transaction cost, and an age varying fixed cost of adjustment. These costs reflect real transaction or moving costs as well as any psychic costs (expressed in their financial value) associated with the housing search and moving between homes.

The total value of a house, h, is $p_h h$. If a household wishes to purchase a new house (including renters who hold $h = 0$ housing) they must pay the transaction cost with the total cost of adjusting housing $Q(\cdot,\cdot,\cdot)$ taking the following form:

$$Q(h_{t+1}, h_t, p_{h,t}, j) = \begin{cases} 0, & \text{if } h_{t+1} = h_t \\ p_{h,t}h_{t+1} - p_{h,t}h_t(1-\pi) + F_j & \\ +(1-\kappa)\cdot\tau_h(p_{h,t}h_{t+1}) + \kappa\cdot\tau_h(p_{h,t}h_t), & \text{if } h_{t+1} \neq h_t \end{cases} \tag{10}$$

A household that does not adjust their housing stock has an adjustment cost of 0. If they adjust their stock of housing, the total cost consists of three parts. First, the change in housing evaluated at today's price and net of a proportional transaction cost π. The proportional component of the transaction cost allows the costs to vary between houses of different values or sizes.[23] Second, the age dependent fixed costs of moving, F_j. These account for age variation in these costs such as those driven by declining physical ability in old age. Finally, the transaction tax (SDLT), $\tau_h(\cdot)$, which has incidence on the seller $\kappa \in [0,1]$. Accounting for the incidence which falls on buyers and sellers captures a salient feature of the UK tax landscape and incorporates the effect of potential sale price manipulation around SDLT thresholds in a reduced form way.

To parametrize the incidence of transaction taxes I use estimates from Besley et al. (2014) and model the evolution of the tax system over time - this is key to identifying the rich cost structure in the model. The age dependent fixed costs of moving is an age invariant fixed cost and quadratic in age:

[23] Real costs may be proportional because the complexity of realtor fees, legal agreements or surveying varies with the property value. Likewise hassle or psychic costs may vary because larger houses are associated with moving (or disposing of) more possessions or require different search intensities due to differential market thickness.

$$F_j = F_0 + F_1 j + F_2 \frac{j^2}{100} \tag{11}$$

In addition to costs when they move, homeowners must pay the maintenance cost δ every period which is proportional to the total value of their house. Renters (who may choose to purchase) rent housing services this period at a fraction r^h of the sale price.[24] Consequently, renters are exposed to housing market volatility and the model can generate precautionary savings for renters, as well as a precautionary owning motive for housing rich and income poor households.[25]

4.6 House Prices

House prices are stochastic and their log evolves as follows:

$$\ln(p_{h,t+1}) = \mu_h + \rho_h \ln(p_{h,t}) + \epsilon_{h,t+1}, \quad \epsilon_{h,t+1} \sim N(0, \sigma_h) \tag{12}$$

This is a standard AR(1) process with drift μ_h which reflects the trend growth in house prices. This formulation, including the nested random walk case with $\rho_h = 1$, is common in the literature[26] and fits the data at both individual and aggregate levels well (see Nagaraja et al., 2011; Berger et al., 2018, respectively). I model aggregate house price movements rather than the exposure of households to idiosyncratic shocks. Thus, the price level is common to all households at calendar time t.

4.7 Recursive Formulation

Let a_t denote the liquid wealth balance of households at time period t and let r denote the return on these balances. Total post tax income is $\tau_y(r\, a_t + y_t(\cdot), \tau)$ with vector τ summarizing the tax system. I follow Deaton (1991) and redefine the problem in terms of cash-on-hand:

$$x_t = a_t - \delta p_{h,t} h_t + \tau_y(r\, a_t + y_t(\cdot), \tau) + tr_t(\cdot) - m x_t, \tag{13}$$

[24] This rental price includes the rental premium and any additional utility from home ownership. A higher value of r^h implies that it is costlier for renters to rent a home providing equivalent levels of housing consumption.

[25] This is consistent with the empirical evidence in Sinai and Souleles (2005) suggesting that some owner occupiers use housing to hedge against volatility in rental markets.

[26] See, for example, Mitman (2016) and Berger et al. (2018) as well as Campbell and Cocco (2007) and Attanasio et al. (2012) in the UK context

The law of motion for cash on hand next period is given by

$$\begin{aligned}x_{t+1} &= x_t - r^h \widetilde{h}_t p_{h,t} - c_t - \delta p_{h,t+1} h_{t+1} - Q(h_{t+1}, h_t, p_{h,t}, j) - m x_{t+1} \\ &+ y\big(r\,(x_t - c_t - r^h \widetilde{h}_t p_{h,t} - Q(h_{t+1}, h_t, p_{h,t}, j)) + y_{t+1}(\cdot), \tau\big) + tr_{t+1}(\cdot)\end{aligned} \tag{14}$$

Here $\widetilde{h}_t$, the rental choice is, 0 for all households who own a house in period t ($h_t > 0$). The first line is the amount of savings brought forward into the period, net of housing maintenance costs, and the second line is income after taxes and transfers.

The tax function accounts for means tested transfers excluding the state coverage of Long Term Care expenses. Following Hubbard et al. (1994, 1995), and De Nardi et al. (2010) I assume that the government provides means-tested transfers, $tr_t(\cdot)$, that bridge the gap between a minimum consumption floor and the household's resources when households are exposed to long term care costs. Define the resources available next period after tax, but *before* government transfers with

$$\begin{aligned}\widetilde{x_{t+1}} &= x_t - r^h \widetilde{h}_t p_{h,t} - c_t - m x_{t+1} - Q(h_{t+1}, h_t, p_{h,t}, j) - \delta p_{h,t+1} h_{t+1} \\ &\quad + \tau_y\big(r\,(x_t - c_t - r^h \widetilde{h}_t p_{h,t} - Q(h_{t+1}, h_t, p_{h,t}, j)) + y_{t+1}(\cdot), \tau\big)\end{aligned} \tag{15}$$

Consistently with the state coverage of long term care expenses which depends on total resources, housing, health status and family status, government transfers next period are

$$\begin{aligned}tr_{t+1}(\widetilde{x}_{t+1}, f_{t+1}, h_{t+1}, m_{t+1}, p_{h,t+1}) = &\max\big\{0, c_{min}(f_{t+1}, h_{t+1}, m_{t+1}) - \\ &(\widetilde{x}_{t+1} - a_{D,t+1}(f_{t+1}, \widetilde{x}_{t+1}, m_{t+1}) - h_{D,t+1}(f_{t+1}, h_{t+1} p_{h,t+1}, m_{t+1}))\big\},\end{aligned} \tag{16}$$

Where $a_{D,t+1}(\cdot)$ and $h_{D,t+1}(\cdot)$ are an asset and housing disregard respectively. In the UK this means testing occurs at the individual level and implies that housing owned by couples and 50% of their assets are excluded from means testing at the household level when only one member of the household enters a long term care facility.[27] This is a key feature of the economic environment for retirees which introduces large distortions into their self insurance decision.

The law of motion for cash on hand next period can thus be rewritten as

$$x_{t+1} = \widetilde{x}_{t+1} + tr_{t+1}(\widetilde{x}_{t+1}, f_{t+1}, h_{t+1}, m_{t+1}, p_{h,t+1}). \tag{17}$$

To ensure that savings are always non-negative, I require total expenditures do not exceed

[27] A household which cannot afford to reach the minimum level of consumption even after liquidating their assets is forced to sell their house and expend all of their assets. They begin the next period as a renter and receive transfers which provide them the consumption floor.

total resources:

$$c_t + Q(h_{t+1}, h_t, p_{h,t}, j) + r^h \widetilde{h}_t \leq x_t, \quad \forall t. \tag{18}$$

I define liquid savings as cash on hand net of total expenditure:

$$a_{t+1} = x_t - c_t - Q(h_{t+1}, h_t, p_{h,t}, j) - r^h \widetilde{h}_t \tag{19}$$

Finally, I assume bequests are only possible when the final surviving member of the household has died. Bequests are exposed to long term care costs and constrained to be non negative. When calculating the current value of the estate, houses are liquidated at current prices and the total value of the estate is taxed. This implies the following formulation for the after tax value of their consolidated wealth:

$$b_t = \tau_b(max\{Q(0, h_{t+1}, p_{h,t}) + a_{t+1} - mx_{t+1}, 0\}) \tag{20}$$

Where estates face the adjustment cost of selling, but with no other purchase.

I now provide the recursive formulation of the household problem. As is conventional, I use a prime to denote next period variables. The state variables of a household are given by $\Omega = (i, j, f, I, m, h, x, p_h)$. These variables are: the idiosyncratic bequest motive (index i), age (j), family structure (f)[28], permanent income (I), health status (m), housing (h), cash on hand (x), and the aggregate house price level (p_h). Throughout I use $h = 0$ to denote renters. First, the recursive problem for homeowners is:

$$\begin{aligned} V^i_j(f, I, m, h, x, p_h) = max_{\{c,h',a'\}} \Big\{ & u(s, c, h) + \\ & \beta \cdot surv(j, I, m, f) E[V^i_{j+1}(f', I, m', h', x', p'_h) \,\big|\, \Omega, h', a'] \\ & + \beta(1 - surv(j, I, m, f)) E[\phi^i(b) \,\Big|\, \Omega, h', a'] \Big\} \end{aligned} \tag{21}$$

subject to equations (3)-(12) and(15)-(18) and bequests are constrained by (20). Households choose this period consumption c, savings in financial assets (before long term care costs) a' and the new housing stock h'. Household's take expectations over individual mortality, the size of the family structure tomorrow f', household health m', the transitory component of medical expenses ϵ_{mx}, and the level of house prices, p'_h. Due to medical expense uncertainty, households also take an expectation over realized cash on hand tomorrow x' and the possibility that they are compelled to sell their house to finance long term care costs.

Second, the recursive problem for the renter ($h = 0$) is:

[28] Note that household size, s, is a deterministic function of family structure

$$
\begin{aligned}
V_j^i(f, I, m, h=0, x, p_h) = max_{\{c,a',\tilde{h},h'\}}\Big\{ & u(s, c, \tilde{h}) + \\
& \beta \cdot surv(j, I, m, f) E[V_{j+1}^i(f', I, m', h', x', p_h') \,|\, \Omega, h', a'] \\
& + \beta(1 - surv(j, I, m, f)) E[\phi^i(b) \,\Big|\, \Omega, h', a'] \Big\}
\end{aligned}
\tag{22}
$$

subject to equations (3)-(12) and(15)-(18) and that bequests are constrained by equation (20).

The problem for the renter differs from the homeowners problem in equation (21) in two simple ways. First, the value of their existing housing stock is zero and, second, they must purchase a level of housing services $\tilde{h}$ at associated rental price r^h. Together, these two differences imply a renter specific budget constraint.

5 Estimation

I adopt a two-step estimation strategy. In the first step I estimate (or calibrate using existing evidence) those parameters that can be cleanly identified outside of the model. In the second step I estimate the remaining model parameters with the method of simulated moments (MSM) taking the first step parameters as given. I find the parameter values that minimize the distance between the simulated life cycle profiles and the profiles in the data where the distance criteria is measured by the GMM criterion function.

Heterogeneity in individual preferences for bequests is estimated in this two step procedure, as part of the first step I *classify* households into latent groups and in the second step I estimate the preference parameters for these groups. Crucially, this two step approach retains tractability in the estimation. This section proceeds as follows: first, I elaborate on this *classification* step. Second, I discuss the remaining first stage estimation. Third, I detail the moment conditions I choose to match and how I construct the moments in the simulated data. Finally, I provide a discussion of the model's identification which serves an explanation for how these moment conditions were selected. The results of the estimation procedure are discussed in Section 6.

5.1 Preference Heterogeneity

Equation 5 specifies the form of preference heterogeneity, allowing both the relative weight and curvature of the bequest motive to vary across households. In practice, I discretize preference heterogeneity by assuming that households can belong to one of a finite number of types (or classes) which differ in their preferences over bequests.

I do not observe each household's latent type - instead , for each household, I estimate type membership outside the model. Subsequently, I treat these types as given when estimating the preference parameters for each group with the remaining preference parameters in the second stage. I follow Bonhomme et al. (2018), who discretize the types of possible firms in a first stage, in adopting a two stage estimator and use a k-means clustering approach to determine type membership.[29] This approach treats the bequest preference parameters as non-linear group fixed effect that is assumed to be time and policy invariant.

Letting z_i denote a vector of household characteristics, the k-means clustering problem used in the classification step (for a given number of clusters K) is defined as:

$$\min_{\mathscr{K},\{\bar{z}_k\}_{k=1}^K} \sum_{k=1}^{K} N_k \sum_{k(i)=k} \| z_i - \bar{z}_k \|^2 \quad = \min_{\mathscr{K},\{\bar{z}_k\}_{k=1}^K} SSE, \quad \text{with} \bar{z}_k = \frac{1}{N_k} \sum_{k(i)=k} z_i \tag{23}$$

Where the classification is given by:

$$\mathscr{K} = \{k(i)\}_{i=1}^{n} \tag{24}$$

I fix the number of types, K, at five and treat this as known throughout the analysis.[30] Given the vector of household characteristics, the classification step minimises the within cluster sum of squared errors (equivalent to selecting clusters to minimise the population sum of squared errors). Informed by the existing empirical literature and economic theory, cluster assignment is an unrestricted function of three household characteristics: their estimated permanent income rank, their total wealth at their initial observation, and their value of the bequest preference index. These variables allow for a flexible, yet parsimonious, grouping of households. Each of these measures is individually (and jointly) correlated with potential unobserved differences in the desire of households to leave an inheritance because they are outcomes of choices made by households. Retirement wealth is determined by early life choices (Venti and Wise, 1998) and this may reflect differential saving rates or portfolio investments made by households with different desires to leave an

[29] Lentz et al. (2019) further allow for an iterated classification procedure in a dynamic sorting model of workers and firms. As discussed in Bonhomme et al. (2017) (which establishes asymptotic properties of two step grouped fixed effect estimators as approximations to underlying continuous distributions in non-linear panel data models) these methods are particularly attractive because they maintain tractability by using a data driven approach to reduce the state space (alleviating the curse of dimensionality). The use of unsupervised learning techniques to cluster households is gaining traction in economics as a data driven method for establishing latent household types- additional applications include: identifying the life cycle employment paths of entrepreneurs (Humphries, 2018), the work disincentives and investment productivity of mothers (Mullins, 2018), the decomposition of wage inequality across workers and firms (Lentz et al., 2019), and the associative matching between workers and firms Dauth et al. (2018).

[30] Heuristic methods for k-means clustering identify this as the optimal number of clusters. These heuristics are described in more detail in Appendix F.

Group	Number of Households	Share	Mean Characteristics: Permanent Income (Percentile Rank)	Mean Characteristics: Total Wealth (2014 GBP)
Type 1	847	18.23%	66.9	157,647
Type 2	1,584	34.09%	21.8	67,913
Type 3	573	12.33%	82.8	998,855
Type 4	980	21.09%	72.6	312,900
Type 5	663	14.27%	26	323,902

Table 5: Distribution of Latent Household Types

inheritance. As I focus on the retirement period I abstract from these decisions, but allow the types to depend on the observed level of household wealth that may be informative about differences in their preferences. Put differently, allowing for an arbitrary correlation between household wealth when they enter the sample and their preferences allows for the possibility that part of these differences are explained by choices made in early life that I do not explicitly model. Allowing type membership to vary with a household's lifetime income allows those who are lifetime poor (rich) and maintain large levels of wealth in retirement to be distinguished from those who do not as well as the potential that past work effort is determined by the desire to leave a bequest. Finally, while the bequest preference index may be a noisy measure of household preferences it is informative about systematic expected differences in future bequests across households.

Table 5 gives the distribution of households over these discrete types.[31] Additionally, I present summary statistics for permanent income and wealth by household type. This provides a concise characterization of the estimated types. The marginal distributions of household characteristics are shown in appendix F to provide a comprehensive characterization.

Type 1 is comprised of households with above average lifetime incomes, but comparatively low levels of wealth. In contrast, Type 2 households are on average lower lifetime income with low levels of wealth in retirement. Initial renters are classified into Type 1 and 2 with high lifetime income renters falling into the first type. Type 4 and 5 are distributed in a similar pattern with Type 4 households high income and high wealth. Type 5 households are relatively high wealth households drawn from the lower part of the lifetime income distribution. The remaining Type 3 households are comprised of the richest households in lifetime income and retirement wealth. Household types are ranked in order of their bequest preference index: Type 1 and 2 have values that are on average

[31]While any labelling of households is ad hoc, I label types numerically such that the average value of the bequest preference index is increasing across types.

below the mean (and vice versa for Types 4 and 5) with the largest systematic differences in household subjective probabilities of leaving a bequest occurring in Types 1 and 5.

5.2 First Stage Estimates

In the first stage I calibrate the remaining parameters that control the utility function, housing market and budget constraint using values from the literature and estimate parameters that are cleanly identified outside the model. These are: the deterministic profile for household income as a function of the state variables (equation 6) and income tax function; the estimated health status transition probabilities and mortality (including transitions in family structure); and the time series for aggregate house prices (equation 12). Table 6 summarizes the value and source of the first stage estimates. I report all values as annual.

The Utility Function I parametrize that the consumption equivalence scale, as a function of household size, using the OECD scale. The remaining parameters in the per-period utility function and bequest utility are estimated in the second stage.

The Housing Market The annual depreciation cost offset by maintenance, δ, is set at 2% and the rental cost is set at 4.05% of the sale price (Cocco and Lopes, 2018; Etheridge, 2017, respectively). The rental cost captures the implied gross rental yield for private landlords as well as the implicit utility premium from home ownership. I estimate the time series profile for aggregate house prices using the HM Land Registry UK house price index series.[32] House prices are highly persistent, have a significant upwards trend, and large innovations at an annual frequency. The incidence of the transaction cost that falls on the seller is taken from the estimates in Besley et al. (2014).

The Budget Constraint I calibrate the annual rate of return on the risk free asset, r, as 3% following Bozio et al. (2017). I estimate non-asset pension income directly from the data in ELSA and describe this procedure in more detail in Appendix A.

The income tax function is a modified version of a common log-linear functional form[33] where after tax income is given by:

$$\tilde{y} = \bar{y} + \lambda_y y^{1-\tau_y}$$

where λ_y controls the level of taxation, τ_y controls the progressivity and $\bar{y}$ captures features of state assistance for older households which correspond to an income floor. I estimate this separately for couples and singles using ELSA data combined with tax and

[32]The UK has a number of house price series see Chandler and Disney (2014) for a review.
[33]The earliest example dates to Feldstein (1969)

Parameter	Description	Value	Source
		Utility Function	
α_s	Consumption Equivalence Scale	1.5	OECD Modified Scale
		Housing Market	
δ	Housing Maintenance Costs	0.02	Cocco and Lopes (2018)
r_h	Rental Cost	0.0405	Etheridge (2017)
ρ_h	House Price AR(1) persistence	0.977	HM Land Registry
μ_h	House Price Drift	0.019	HM Land Registry
σ_h	House Price S.D. Innovations	0.095	HM Land Registry
κ	Incidence of SDLT on Seller	0.4	Besley et al. (2014)
		Budget Constraint	
r	Risk Free Return	0.03	Bozio et al. (2017)
$y(\cdot)$	Deterministic Income Profile		ELSA
τ_y	Income Tax Function		TAXBEN
c_{min}	LTC consumption floor (Singles)	£4,956	Lockwood (2018)
c_{min}	LTC consumption floor (Couples)	£7,434	Lockwood (2018)
		Mortality and Demographic Transitions	
$surv(\cdot)$	Survival Probabilities		ELSA
$Pr(m^g_{j+1}\|\cdot)$	Health status		ELSA
		LTC Costs	
$\mu_{mx}(\cdot)$	Mean		HRS
$\sigma_{mx}(\cdot)$	Conditional variance		HRS

All values are annual and expressed in 2014 prices.

Table 6: 1st Stage Parameter Estimates

PI Percentile	Men: Good Health Life Expectancy	Men: Good Health ADL Years	Men: Bad Health Life Expectancy	Men: Bad Health ADL Years	Women: Good Health Life Expectancy	Women: Good Health ADL Years	Women: Bad Health Life Expectancy	Women: Bad Health ADL Years
Singles								
10th	13.65	2.02	11.23	2.85	18.21	2.57	16.38	3.82
50th	16.91	2.32	14.91	2.92	20.02	2.65	19.14	3.82
90th	19.57	1.58	17.83	1.87	20.93	1.91	20.03	2.66
Couples								
10th	13.31	2.15	10.95	3.02	19.18	3.92	17.99	5.60
50th	16.79	2.36	15.10	3.21	21.19	4.07	20.65	5.48
90th	19.29	1.57	17.40	2.19	21.89	2.65	20.88	3.56

Conditional on surviving to age 66. ADL difficulties defined as 2 or more. For couples the. calculation assumes both spouses have the same health at age 66

Table 7: Life Expectancy & Expected Duration of ADL difficulties

benefit entitlements calculated using TAXBEN.[34] Means tested coverage of social care costs is not included in the data used to estimate the tax function. The consumption floor is set to replicate the utility value of receiving public assistance for long term care needs and includes any disutility from receiving state care. For couples this value is equivalized.

Mortality and Demographic Transitions I estimate survival probabilities and health status transition probabilities directly from the ELSA data using a multinomial logit approach and allow transitions to depend on age, family size, health status and permanent income. ELSA has data on six different ADL measures for each individual and I define the ADL state as those who have difficulties with at least two of these measures. I use ADL measures as this captures a range of needs associated with institutional long term care use and care in the community. Summary statistics are reported in table 7. The ELSA ADL data and the specifics of these measures are discussed in more detail in Appendix I.

Long Term Care Costs Micro-data on the out of pocket costs faced by households in the UK is scarce, however, for some smaller costs Banks et al. (2016) document that figures reported in the Health and Retirement Study (HRS) line up closely with those reported in ELSA.[35] I use the HRS to estimate the cost of care in the community and long term care costs for UK households. Specifically, I construct an equivalent health status measure and estimate the parameters of the medical spending process described

[34] Appendix K provides additional details.
[35] These data are only available for wave 8 of ELSA.

in equation 9. After estimating this process for the US, I impose that the mean and variance of medical spending is zero in all health states other than the ADL state to better replicate the institutional environment of the UK.

5.3 Moment Conditions

In the second stage I estimate the remaining parameters taking the first stage estimates as given. The remaining parameters are:

$$\theta = (\{\phi_1^k, \phi_2^k\}_{k=1}^5, \beta, \gamma, \pi, F_0, F_1, F_2) \tag{25}$$

The following moment conditions comprise my estimator:

1. For initial homeowners, I match mean liquid wealth and housing wealth by age, permanent income, and cohort because liquid and housing wealth imply different ability to self insure over short and long run horizons and because the mortality and LTC expenditure risks households face vary with their age and permanent income. For renters I match mean liquid wealth by age and cohort because renters are predominantly drawn from low lifetime incomes.

2. To exploit the additional information about future wealth trajectories contained in self reported bequest probabilities, I match mean subjective bequest probabilities by age, permanent income, and cohort for initial homeowners. For renters I match mean subjective bequest probabilities by age and cohort.

3. Moving is costly, but liberates liquidity from housing. To identify the extent of these costs and help pin down household's demand for liquidity versus housing services I also match the fraction of moves by age and cohort for initial homeowners.[36]

Using within group means as moment conditions requires that the model is able to fit well the full distribution of wealth holdings in the population because I condition the moments on permanent income and a household's total wealth rank is closely correlated with their lifetime permanent income. I provide more details of the model's identification and the motivation for selecting these moments in section 5.4. Finally, I top code wealth moments in the data and in the simulations at the 95th percentile. This mitigates the impact of the very wealthy and other potential sources of measurement error. In practice I use 7 five year birth cohorts and 3 PI groups. The data versions of these moments are discussed in Section 2 and I perform identical operations to calculate the simulation equivalents. To calculate model moments for subjective bequest probabilities I compute the model implied objective probabilities for each individual.

[36] In the data very few renters choose to purchase homes, but many move between different rental accommodation. The model has no conceptual equivalent of rental to rental moves

The MSM approach is standard.[37] I simulate 50,000 sample households where their initial state variables (including sample wave of entry) are drawn from the joint distribution of state variables in the ELSA data. These simulated households are simulated for the duration that the equivalent ELSA household remains in the sample and receive the same realization of shocks that their ELSA donor receives. Consequently, households are sampled for a window that includes the same reforms to Inheritance Tax and Transaction Taxes (SDLT) that they experience in the data (at most 5 different regimes). Due to the frequency of these reforms, I do not explicitly target pre and post periods - instead, the behavioural response to the tax system are embedded in the moments I target: the home moving decisions, wealth deccumulation, and bequest expectations of households by cohort and wave. I use a diagonal weighting matrix which takes the diagonal of the asymptotically optimal weighting matrix because the full asymptotically optimal weighting matrix is known to behave poorly in small samples (Altonji and Segal, 1996).

5.4 Identification

In this class of retirement savings models it is difficult to separately identify bequest and precautionary motives using only data on the levels of household wealth (see De Nardi et al., 2016b, for a discussion).[38] Instead, I combine data on wealth composition, subjective bequest probabilities and exogenous policy reforms (discussed in detail in section 3) to identify parameters of the utility function, the additional costs of moving home and heterogeneous bequest motives. These policy reforms shift the returns and risks associated with holding different assets as well as the returns to adjusting home equity.[39] In complex non-linear models, all moments potentially influence all model parameters, however, I provide intuition for why particular moments are more informative about certain parts of the model.

Parameters in the period utility function In the joint estimation, I estimate three parameters of the utility function: the intertemporal discount factor, β, the coefficient of relative risk aversion, γ, and the non-housing consumption share, σ. Both the intertemporal discount factor (β) and the coefficient of relative risk aversion (γ) affect the slopes of consumption and wealth profiles. To separately identify them I exploit variation in the risks household face at different ages and levels of the permanent income distribution: those with low PI face lower longevity and higher LTC costs while alive. In contrast, those

[37] See for example Gourinchas and Parker (2002); De Nardi et al. (2010). The model outlined above has no closed form solution and instead I use numerical methods which are described in Appendix G

[38] When targeting moments at the average, a small change in the risk aversion parameter (and consequently the precautionary savings motive) compensates the change in fit from eliminating the bequest motive.

[39] The assumption that the preference parameters of the structural model are not affected by the policy changes or house prices is a form of the exclusion restriction.

with higher permanent income survive for longer and experience lower LTC costs. The differences in the level of liquid wealth (and the consequently the portfolio share) across the PI and age distribution identifies the risk aversion of households and the discount factor.

Renters are particularly responsive to the consumption share of housing because it determines their expenditure share on rent. This parameter drives variation in their marginal utility of expenditure as house prices change throughout the sample.[40] Matching the liquid wealth of renters identifies σ through variation in the house prices they face.

The Cost of Moving Households in the model move only when the benefits of adjusting their housing stock are larger than the costs. Households who hold similar housing stocks have potentially large differences in their financial incentives due to the design of the tax system. Tax policy and aggregate house prices generate variation in the returns to holding housing assets and, importantly, the cost of adjusting them over time and at different points in the distribution. However, the remaining costs of adjustment at each age, π and F_j, is policy invariant (an exclusion restriction) and is identified by the frequency of home moving by birth cohort and age.

Consider two otherwise identical households who are born in different birth cohorts. At the same age they face different house prices and different tax incentives for adjusting their housing stock. Differences in the home moving rate between ages and across cohorts (who face exogenously different costs and returns) as well as across the wealth distribution can be used to identify the parameters of π and F_j analogously to a difference in difference research design.[41]

Bequest Motives Intuitively, households with lower survival probabilities are more responsive to their bequest motives. Furthermore, the opportunity cost of saving for a bequest differs across assets. Matching the savings behaviour (in different assets) of households at different ages (and PI levels) exploits age (and PI) variation in their survival probability and saving motives, however, in practice it is difficult to separately identify the demand for housing from the demand for bequests.

The reform to estate taxation shifts the return to saving for a bequest independently from the return to saving for future lifetime consumption (including the flow consumption

[40]The substitutability of housing and non-housing consumption also determines how homeowners are differentially insured by the flow consumption of their housing - a form of housing services annuity. The higher the degree of substitutability between housing and non-housing consumption, the fewer liquid assets a household needs to self insure. However, renters provide an alternative to identify this substitution.

[41]In practice, the full dynamic model controls for differences across households such as differences in portfolio, health, PI or differences in bequest motives and contamination from multiple reforms that would otherwise confound this approach. Furthermore, it conditions on the full sequence of future mortality, demography, and long term care risks.

from housing): the extent to which households adjust their savings decisions in response to this tax reform helps pin down the weight on bequests. To leverage information on the full path of future wealth deccumulation for all households I match subjective bequest probabilities which provides a separate source of identification for bequest motives over and above their observed current choices.[42] I match measures of household subjective bequest probabilities where conditioning on age, PI, and homeownership captures variation in the life expectancy, risks, and portfolio structure that also influence the bequests that households expect to leave.[43]

Heterogeneity in Bequest Motives Systematic differences in expected bequests across household types reflect systematic differences in their expected wealth paths. Likewise, systematic differences in household responses to policy changes reflect systematic differences in their incentives. The structural model provides a parametric interpretation for these differences. The model environment is rich enough to incorporate many other sources of observable heterogeneity across households including the effects of aggregate shocks, the tax environment, their endogenous portfolio choices, realisations of idiosyncratic shocks and any differences in initial conditions. This is crucial to identify structural differences in bequest motives rather than other characteristics that lead households to save (or expect to save) differently.[44] Finally, it is important to stress that the differences across households in each of the five types may be rationalized solely by differences in their observables (for instance expected longevity and liquidity of their portfolio) and the estimation approach in this paper imposes no *a priori* restrictions on the differences in bequest motives or their relative magnitudes.

5.5 Econometric Concerns

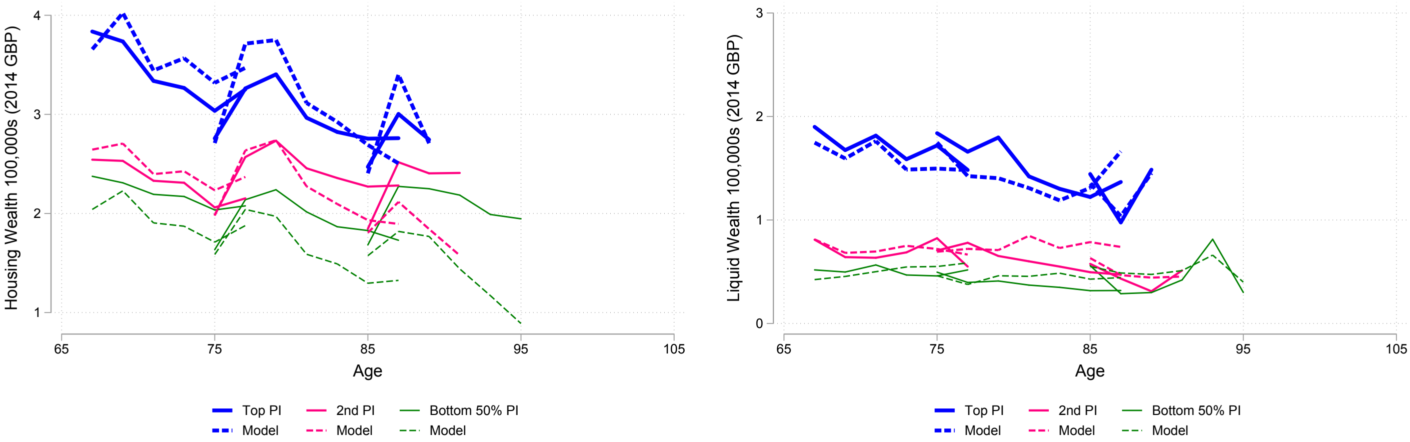
When simulating the model there are two important sources of non-stationarity: cohort effects and time effects. I now describe the approach to mitigate the effects of non-stationarity concerns.

Different cohorts have been exposed to differential income growth, asset prices and asset growth. Consequently their wealth holdings at the same age can differ substantially

[42]Similarly, van der Klaauw and Wolpin (2008) argue that subjective household expectations contain household level information on optimal future behaviour conditional on current state variables.

[43]The different components of identification also exploit variation at different parts of the wealth distribution. It is only households who either exceed the exemption threshold in 2007 or expect to on death that are effected by the reform to estate taxation (the "treated" households). When preferences are not (necessarily) homogeneous and correlated with wealth, this is insufficient variation to recover the full distribution of bequest preferences. As shown in section 2, the subjective bequest probabilities are more informative for the bottom 50% of the wealth distribution.

[44]Household types are estimated *ex ante* which allows the model to replicate the composition of types in each of the moments (by cohort, PI, age and ownership). Furthermore, each of the groupings that define moments closely map to each of the types.



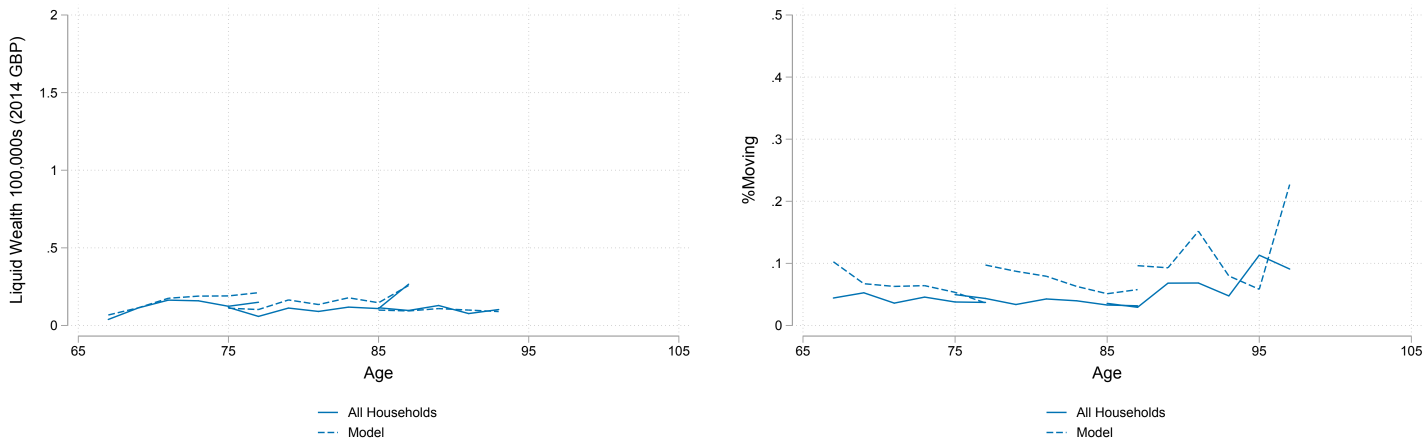
(a) Mean Housing Wealth

(b) Mean Liquid Wealth

Figure 8: Model Fit - Wealth Profiles (Initial Owners)

- in other words cross sectional moments may attribute differences between cohorts to differences in the savings rates of households and imply substantially different estimated preference parameters. As outlined above, aggregate house prices vary substantially across time and households in the data are exposed to different policy regimes at different points in time. By sampling household initial conditions, controlling flexibly for household permanent income, and simulating the sequence of observed aggregate shocks and policy reforms faced in their retirement I replicate differences across cohorts and time periods. I then construct moment conditions by cohort to eliminate the source of bias in parameter estimates. Formally, this paper makes two assumptions to address the age-time-cohort problem: that cohorts vary in their composition and initial characteristics (but not the other features of their economic environment) and, second, that relevant time effects are captured by the policy reforms and changes to the aggregate house prices. This is a structural approach to the age-time-cohort problem that explicitly accounts for differences across households and leverages policy reforms for identification - for a related semi-structural approach that purges data of age and cohort effects see Schulhofer-Wohl (2018).

A related problem is that household mortality is negatively correlated with lifetime income which means that surviving members of a cohort have higher wealth. To address this "mortality bias" (and an analogous problem of sample attrition) in the simulations each household is given the sequence of mortality and attrition shocks that are observed in the data household from which their initial conditions are drawn. The selection in the simulated unbalanced panel mirrors that in the data following the approach suggested in De Nardi et al. (2010).



(a) Mean Liquid Wealth (Initial Renters)

(b) Moves in the last 2 years

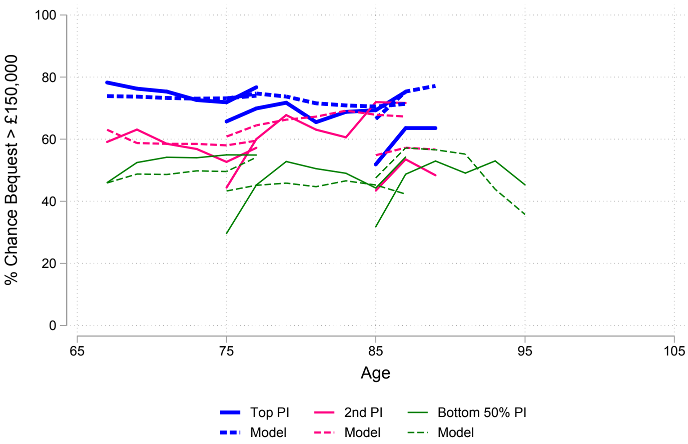
Figure 9: Model Fit - Home Moving Rates and Renters

6 Estimation Results

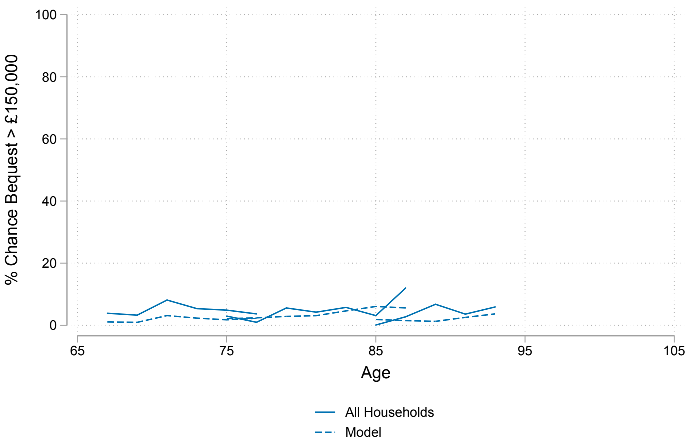
Results from the second stage estimation and their standard errors are provided in Table 6. Figures 8 - 10 display the corresponding data and simulated moments. For clarity I display only an alternating subset of the birth cohorts in each graph. I validate the model against moments that were excluded from the estimator and present the additional birth cohorts in appendix K. The model is able to capture key features of the data well across birth cohorts and permanent income levels. It correctly predicts the sharp increase in housing wealth and gradual decline throughout the sample. It also matches the relative magnitudes of housing and liquid wealth. Furthermore, it is able to match the permanent income gradient in wealth and the differences in wealth levels between owners and renters. The liquid wealth levels of initial renters in the model are very close to their data counterparts. The model underpredicts the housing wealth of lower income owners while modestly overpredicting their liquid wealth holdings. This is because it understates the persistence of the increase in housing wealth for the lower parts of the permanent income distribution.

The model endogenously generates the illiquidity of housing, producing a moving rate that approximately matches the infrequent decision to move home observed in the data. Despite the higher moving rate, on average households move only once during their retirement.

Finally, Figure 10 plots the data and simulated profiles for the subjective bequest probabilities. The simulated profiles match the permanent income and homeownership gradient while also matching differences across cohorts and the within cohort gradient. If anything, on average the model slightly overpredicts the probability of leaving a bequest



(a) Initial Owners



(b) Initial Renters

Figure 10: Model Fit - Subjective Bequest Probabilities

in the future.[45]

The first panel of Table 6 reports the estimated parameters which are assumed to be common across households. The value of the time discount factor, β, on an annual basis is close to 1 which is higher than many life cycle estimates. However, the retired households I model in this framework face substantial mortality risk in each period which implies a much lower effective discount factor.

The coefficient of relative risk aversion, γ, is in line with typical life cycle estimates. Together with estimated weight on non-housing consumption, σ, it implies an intertemporal elasticity of substitution for consumption of 0.36 which falls within the range of mean intertemporal elasticity of substitution in a recent meta-analysis of 169 published articles (Havránek, 2015, which also corrects for publication bias). Although estimated values for retired households are typically lower than working age households, the weight on non-housing consumption is lower than values in excess of 0.75 used in the literature on housing decisions (see, for example, Berger et al., 2018; Nakajima and Telyukova, 2017, 2018a). The value estimated in this paper implies the housing expenditure share for renters is 0.364 which almost exactly reproduces the mean housing expenditure share for retired renters of 0.341 derived from expenditure data.[46]

The second row of Table 6 report the coefficients for the proportional transaction cost and the age polynomial for the fixed cost. Taken together, these coefficients imply

[45]Note that this feature of the simulated data helps explain why the fit of the model does not increase when moving costs are increased. While this would improve the model fit for the moving rate and some of the wealth moments for owners, the induced increase in non-liquid housing wealth would increase the probability of leaving a bequest and increase the error between these simulated and data moments.

[46]This is calculated from the Living Costs and Food Survey (the national UK expenditure survey) using over 65 households in England during the same sample period. I use the sum of non-durable expenditures and housing expenditures to calculate total consumption. Using total expenditure instead gives a share of 0.314

Common Parameters				
		Preferences		
β		γ		σ
Time Discount Factor		CRRA		Consumption Weight
0.999		3.82		0.636
(0.007)		(0.0475)		(0.0083)
		Transaction Costs		
π		F_0	F_1	F_2
Proportional		Fixed (Age Polynomial)		
0.0926		12,176	27.1	33.7
(0.0032)		(214)	(1.73)	(1.35)

Bequest Parameters by Type					
Type 1		*Type 2*		*Type 3*	
Φ_1^1	Φ_2^1	Φ_1^2	Φ_2^2	Φ_1^3	Φ_2^3
Weight	Shifter	Weight	Shifter	Weight	Shifter
0.173	299,727	0.0118	100,708	0.0255	12,997
(18.23)	(2.54E+08)	(19.85)	(1.77E+07)	(0.0037)	(2,928)
Type 4				*Type 5*	
Φ_1^4	Φ_2^4			Φ_1^5	Φ_2^5
Weight	Shifter			Weight	Shifter
0.315	7,355			0.223	4,746
(0.0286)	(366)			(0.0284)	(451)

Standard Errors are in parenthesis. These are calculated using the standard formula for the asymptotic variance and correct for simulation error.

Table 8: Estimated Parameters

that housing assets have substantial adjustment costs and are broadly in line with values estimated in other lifecycle settings. Typically, proportional transaction costs on housing π are calibrated or estimated between 5% to 6% (e.g. Bajari et al., 2013), however, Cocco (2013) argues that the total costs often reach between 8% and 10%. The fixed cost estimates imply little age variation in the fixed costs and reflect additional financial costs such as realtor fees, solicitors fees, property surveys or the hiring of movers that are not modelled explicitly as well as hassle costs expressed in their financial value.

I estimate housing adjustment costs without also estimating a multiplicative utility premium for homeowners[47] which generates incentives to remain in both owner occupied housing and a larger home by distorting the marginal rate of substitution between housing and non-housing consumption. Instead, the estimated transaction costs produce these incentives. While the these costs would be smaller in a model with a homeownership utility premium the size of the trade-offs facing households would remain the same - it is the magnitude of these trade-offs rather than their composition that is key for the quantitative results in the paper.

The lower panel displays the type specific estimated bequest parameters. Consider first the heterogeneity in the weight of the bequest motive (ϕ_1). Consistent with Venti and Wise (1998), these results suggest that there is an association between initial retirement wealth and the strength of a household's bequest motive. Conditional on PI those with lower levels of retirement wealth (i.e Type 1 instead of Type 4 and Type 2 instead of Type 5) have weaker estimated bequest motives.[48] For Types 3- 5, bequests are modest luxuries. The next section provides additional discussion of the estimated bequest motives.

6.1 Validation against Quasi-Experimental Evidence

Examining moments of the data that were not explicitly targeted in estimation provides a test of the model's goodness of fit. In this subsection, I focus on the quasi-experimental effect of housing transaction taxes on home mobility estimated using a regression discontinuity design in section 3. To compare the model and the data I estimate an identical equation in the model and the data. I report these results in Table 9

To compare the model and the data I rescale the treatment effect by average mobility at the threshold because, as discussed above, the model produces higher level of mobility in the elderly population than in the data. Consequently, Table 9 displays the relative

[47]This is a feature in a number of papers including Cocco and Lopes (2018); Nakajima and Telyukova (2018a, 2017); Bajari et al. (2013). An estimated rental cost which has equivalent implications is also used in Berger et al. (2018); Etheridge (2017)

[48]For Type 1 and Type 2 households the standard errors on both bequest parameter estimates suggest that they are not identified. The next section shows that for these households the combined effect of these parameters is to generate zero effective bequest motive and, consequently, the point estimate of each individual parameter is uninformative. Conditional on no bequest motive these parameters are not separately identified. The absence of the bequest motive is the result of the estimation and it is not imposed ex-ante.

	Band around cut-off				
Order of polynomial	10%	15%	20%	25%	30%
Data					
Linear	-0.912**	-0.973***	-0.4251*	-0.411*	-0.512**
	(0.372)	(0.329)	(0.234)	(0.237)	(0.225)
Quadratic	-0.748	-0.923**	-0.553**	-0.446*	-0.512**
	(0.494)	(0.396)	(0.272)	(0.266)	(0.230)
Model					
Linear	-0.522	-0.394	-0.347	-0.402	-0.410
Quadratic	-0.556	-0.404	-0.312	-0.399	-0.410

All regressions additionally control for wave fixed effects, a polynomial in age, household demographics, a polynomial in permanent income and region dummies. Following Kolesár and Rothe (2018), Standard Errors are clustered by household. * $p < 0.10$, ** $p < 0.5$, *** $p < 0.01$

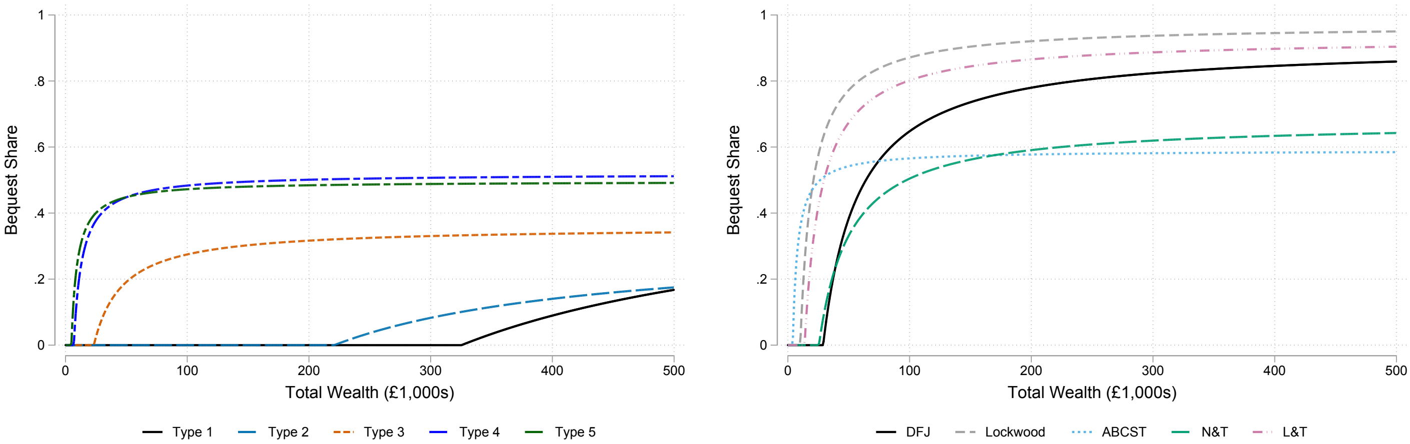
Table 9: The Relative Effect of Transaction Taxes on Household Mobility: Model and Data

change in mobility as a household crosses the £250,000 (treatment effects without normalization are reported in appendix K). Comparing the upper panel with the lower panel shows that across the linear and quadratic specifications, the model generates a reduction in mobility of 40% which is economically and statistically comparable to the responses in the data.

One of the key trade-offs in this model is the households' willingness to transform housing wealth into liquid assets. In particular, understanding the implications of changes of house prices and the demand for public insurance hinges on the magnitude of this trade-off. Housing transaction volumes are known to be pro-cyclical (See Ortalo-Magné and Rady, 2004) and the size of the extensive and intensive margin responses to changes in housing wealth are a crucial part of the model implications discussed in the next section. Using quasi-experimental evidence to validate model responses to changes in the transaction cost and changes in the implicit cost of home equity withdrawal demonstrate that these responses are quantitatively important and realistic.

7 Model Implications

The previous section discusses values of the estimated parameters, however, in a large model it is often difficult to interpret the size of these parameters. This section attempts to address this issue by examining the bequest motives and quantifying the mechanisms that drive the savings of the elderly.



(a) Bequest Allocation (Estimates)

(b) Bequest Allocation (Literature)

Figure 11: Bequest Allocation

Types 1-4 in panel (a) refer to preference types estimated in section 6 and allocations are calculated with estimated preference parameters reported above. In panel (b) the same statistics are calculated using results from De Nardi et al. (2010) (DFJ), Lockwood (2018), Ameriks et al. (2018) (ABCST), Nakajima and Telyukova (2018a) (N&T), and Lee and Tan (2017) (L&T). Further details of the calculation provided in Appendix J.

7.1 Interpreting the Size of the Bequest Motive

It is widely accepted that estimated parameters for the weight and curvature of the bequest function are difficult to interpret and, when the weight and curvature vary, lead to ambiguous ranking of the role of bequest motives across studies. Instead, following De Nardi et al. (2010), it has become standard to express these numbers in terms of a static allocation problem. Suppose a single individual knew they were going to die next period and faced no further uncertainty, then how much would they consume today and how much would be left as a bequest? When bequests are luxuries, the level at which they become operable can be loosely interpreted as the annuity value of consumption below which households have zero marginal propensity to bequeath. Figure 11 reports the bequest share in this thought experiment for different values of total wealth.[49]

The left panel shows bequest allocations for each of the estimated types. The right panel calculates the implied bequest share for a variety of related studies which estimate bequest motives in retirement. Beginning with the estimated parameters, Type 1 (who have a high weight, but the highest curvature) and Type 2 have effectively 0 estimated bequest motives. Indeed, they would need to achieve an annuity value of consumption above £300,000 and £200,000 respectively before the bequest motive is active. This closely corresponds to the latent type in Kopczuk and Lupton (2007) who are assumed to have no bequest motive although the fraction of households without a bequest motive is larger due to additional features (such as housing and long term care risk) which

[49]Full details of this calculation and how studies are made comparable are given in appendix J

rationalize the savings decisions of older households.[50]

Turning to Type 4 who have the largest weight. This type has the strongest bequest motive, both in terms of the allocated share, which approaches 52%, and that it is operative for much of the wealth distribution. The estimated weight for Type 5 households are slightly weaker implying small differences in the degree of luxuriousness and allocations. However, in total the estimates imply very similar allocations among those making positive bequests.

In contrast, Type 3 has more modest bequest motives with asymptotic marginal propensity to bequeath of 35%. Conditional on their high level of retirement wealth, the model is able to explain the continued wealth holdings of the richest households through observable differences in the state variables of these households rather than preferences. It is important to stress that there is considerable overlap in the support of household wealth between types which means that the heterogeneity in bequest motives is not only capturing an underlying luxury good.

Comparing these results with the results in the right hand panel reveals three important differences from existing estimates in the literature. First, the bequest shares implied by my estimates are more conservative. The closest estimates in the literature are Nakajima and Telyukova (2018a), who model the homeownership decision, and Ameriks et al. (2018) who model the financial wealth of a wealthier population and match strategic survey responses. Taken together, this suggests that other estimates may capture either the illiquid nature of housing or its consumption flow in their estimates of the bequest motive. Second, the estimates for a heterogeneous bequest motive suggest a degree of variation across households that is as large as the variation in homogeneous bequests produced by different estimates.

Third, despite allowing the degree to which bequest motives are luxuries to vary across households the estimated bequest shares show less curvature within type relative to the literature.[51] It is possible differences in the portfolio of households or heterogeneity in the strength of the bequest motive (that are correlated with wealth) are no longer proxied by the degree to which bequests are a luxury. An alternative explanation for the lack of curvature is an issue of common support. For example, while Types 1 and 2 contains many renters, the households in Type 4 and 5 are typically richer. Likewise very few households in Type 1 are rich enough to make a positive bequest allocation. Without variation across the entire support of the wealth distribution it is hard to precisely identify the extent to which bequests are a luxury among households.

[50]Interpreting these allocations through the lens of the annuity value of consumption implies extrapolating to large values beyond the support of the type specific distribution.

[51]While the presence of dispersion in bequest motives echoes findings in Kopczuk and Lupton (2007), the functional form here is more flexible

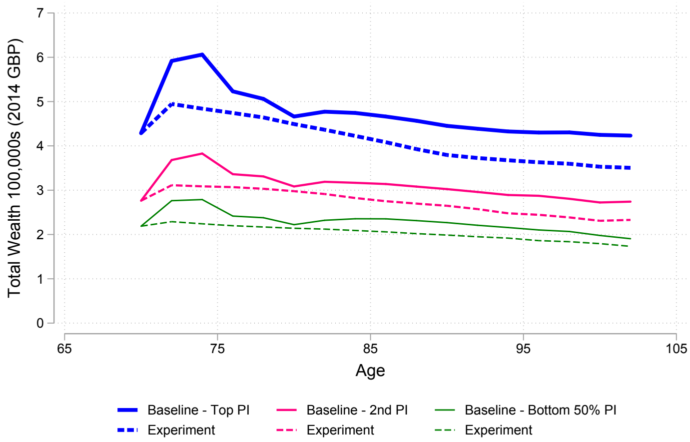


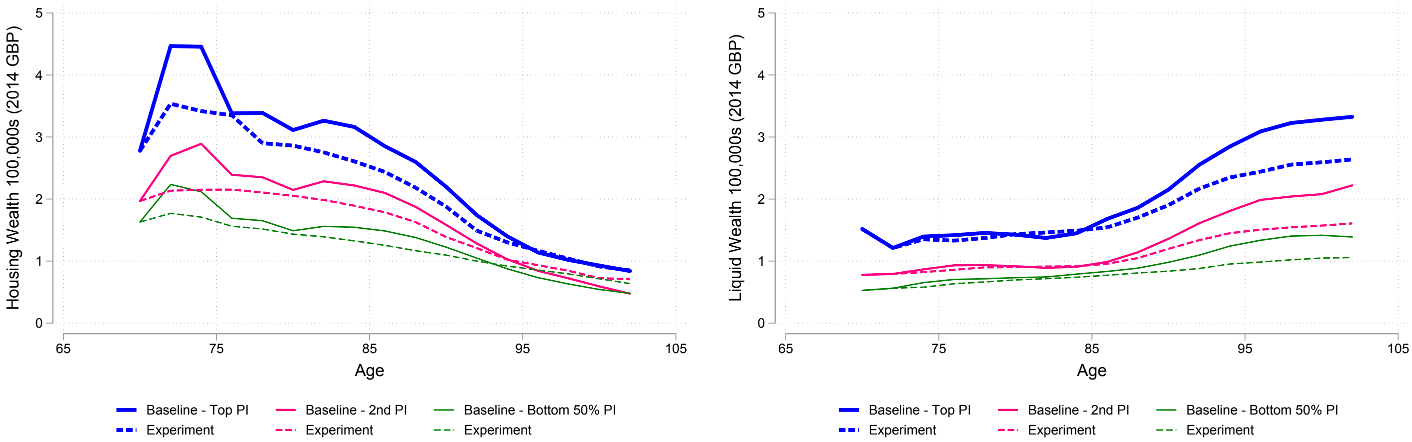
Figure 12: Experiment 1- Total Wealth

7.2 Decomposing the Role of Housing

To determine the quantitative importance of housing in retirees savings, I use the estimated parameters and change one feature of the model at a time. For each of these different environments, I compute the new household policy functions, simulate the model and compare the resulting asset accumulation profiles to the asset profiles generated by the baseline model. I display asset profiles for households who are age 68 in the first wave of ELSA. Throughout, I focus on the wealth of initial homeowners because the wealth of renters is negligible. Appendix L provides additional decomposition exercises.

First, I fix house prices at their 2002 level, but hold household expectations constant. Figure 12 plots the simulate profiles of total wealth for initial owners. Compared to the wealth profiles in the baseline simulated economy, total household wealth decrease at all ages. The effect is largest at younger ages where the baseline profiles include the rapid house price appreciation of the early 2000s, but also has long lasting effects at older ages where the cumulative effect of downsizing behaviour is largest- on average total wealth at age 96 falls by 15%. Figure 13 breaks the total wealth into its two components.

Housing wealth decreases when house prices are held constant. The left panel shows housing wealth. There is a reduction in the level of housing wealth held by households due to the mechanical effect of eliminating house prices as well as the behavioural response as simulated households re optimize, however these two effects almost cancel out by late into their retirement. The right panel shows the corresponding effect on their liquid wealth. Households continue to maintain large levels of wealth as buffers against future shocks and substitute from consumption to saving to offset the wealth effect of decreased house prices. This explains why liquid wealth is almost constant through the start of the sample. Averaged across the households' remaining life span liquid, wealth balances decrease due to the effect at older ages (7.5%) while housing wealth declines by a larger fraction (12.5%). Relative to the baseline, when households don't experience periods of



(a) Mean Housing Wealth

(b) Mean Liquid Wealth

Figure 13: Experiment 1- Portfolio

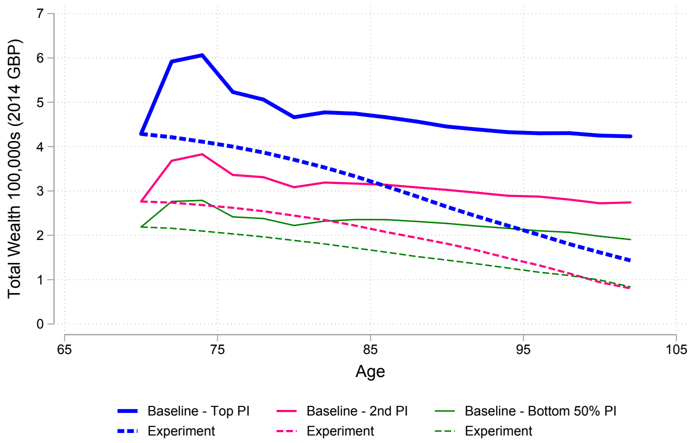


Figure 14: Experiment 2-Total Wealth

house price appreciation, they reduce the frequency with which they move home (by 25%) because there is less equity in their home to cash out. This transmits into a reduction in consumption by around 5% over their remaining lifetime, but additionally a reduction in bequests of over 10%.

Next, I eliminate the remaining features of housing that make it different from liquid wealth: the difference in returns, the consumption flow, the illiquidity and different exposure to long term care costs. This is equivalent to a single asset model and the total wealth profile of households shown in Figure 14.

Eliminating house price fluctuation has a significant effect on the savings behaviour of retirees, but eliminating the remaining features of housing assets has an even larger effect. In contrast to the baseline, households deccumulate the majority of their wealth throughout retirement. Averaging over the periods a household is alive, total wealth decreases by 28% while the size of the average bequest left decreases by almost 40% and the effect on those who survive past 95 is even larger. The results of this experiment show that the portfolio composition and the differences between asset classes have a first order effect on the levels and age profiles of household savings as well as the bequests they leave. Understanding and accounting for differences in asset classes is important in evaluating policy proposals that affect the elderly.

7.3 Responses to Unanticipated Shocks

The previous experiments decompose savings behaviour, highlighting housing wealth and how illiquid assets affect the trajectory of wealth in retirement. To further decompose these important mechanisms I turn to an additional set of experiments which simulate household responses to an unanticipated increase in either their after tax income or an increase in the aggregate house price they face.

The income shock is equivalent to a tax rebate (See e.g. Parker et al., 2013; Kaplan and Violante, 2014; Misra and Surico, 2014) targeted at age 70 households and generates a one-time 10% increase in their after tax income. The house price shock also occurs at age 70 and raises the level of house prices by 10%. However, after age 70 the future house prices follow the AR(1) process describe in equation 12 and thus the effect of the unanticipated shock is persistent.

To understand how households respond to changes in their portfolio and total wealth, I report two measures: Marginal Propensity to Consume (MPC) for annual non-housing consumption as well as the Marginal Propensity to Bequeath (MPB). The MPC is measured in the period the shock arrives and captures the contemporaneous non-housing consumption response to these changes. The MPB is measured at death and provides a summary statistic of how this wealth is used over their remaining life cycle. This includes financing other expenses such as housing adjustment costs and Long Term Care expenses.[52] Table 10 reports the average Marginal Propensity to Consume (MPC) as well as the Marginal Propensity to Bequeath (MPB).

Turning first to the MPCs. At the arrival of the shock, the contemporaneous MPC out of a transitory income shock is larger than the housing wealth shock and both estimates are within the range of estimates in the respective literatures.[53] They imply that for an additional £1 of wealth at age 70, an age 70 household consumes an additional 15 pence when they experience an income shock and 3 pence when they experience an increase in house prices. Furthermore, the MPB out of the two shocks are very different. Almost twice as much of the one time income shock is transmitted to bequests[54] than the house

[52] The average MPBs reported below integrate over uncertainty in their remaining lifetime including mortality risk, house price changes and medical expense risk.

[53] For example, Aladangady (2017) finds an MPC out of housing wealth of 0.047 on the dollar.

[54] The order of magnitude is consistent with estimates of the MPB out of social security income reported in Lee and Tan (2017) and substantially larger than the MPB estimated in Altonji and Villanueva (2003)

Shock	Marginal Propensity to Consume	Bequeath
Income	0.151	0.71
House Price	0.029	0.38

Simulated responses for a single birth cohort to a one-time 10% increase in income and a one-time 10% increase in house prices. In both simulations the shock arrives at age 70 and the annual MPC is measured contemporaneously.

Table 10: Household Responses to Unanticipated Shocks

price shock.

Households respond differently to the two shocks over time - particularly those who are liquidity constrained (or likely to be during their remaining lifetime). In response to the income shock, low wealth households with large housing portfolio shares are less likely to downsize. These households no longer liquidate housing wealth and no longer pay the cost of adjustment because the income shock alleviates liquidity constraints in some states of the world. This effectively increases their lifetime saving.

In contrast, an unanticipated increase in housing wealth driven by price appreciation actually reduces the savings of these same households over their remaining lifespan. These households increase the frequency with which they move home to access this otherwise trapped home equity because the financial return to downsizing has grown (the utility effect of changing housing consumption is constant). On average there is a similar change in their available liquid resources (cash on hand) under both experiments, but in the case of the house price shock this is driven by an increase in the intensive and extensive margins of downsizing. The key driver of the difference in MPBs is the response of the constrained households and how they trade off housing for liquidity.[55]

It is important to emphasize that these results do not suggest that houses are less likely to be bequeathed than financial wealth nor that homeowners are less likely to leave a bequest.

Finally, I explore this differs across household preference types. To isolate the effect of preferences, I resolve and simulate the model shutting down the correlation between types and initial conditions. This means mortality, health and medical expense uncertainty is held constant across the types as well the wealth, permanent income and portfolio composition. Table 11 reports the results of this experiment for the income shock. Results for the house price shock and reintroducing the correlation between initial conditions and

[55] A second mechanical effect also explains differences in household response. house prices are *persistent* not *permanent*: the mechanical effect of the house price shock at age 70 on average dies out of the households remaining life. This means that even if they do not adjust their behaviour in response to the house price shock, its transmission to bequests will be smaller.

Shock		Marginal Propensity to Consume	Bequeath
Income	Type 1	0.295	0.526
	Type 2	0.294	0.526
	Type 3	0.274	0.566
	Type 4	0.076	0.785
	Type 5	0.043	0.838

Simulated responses for a single birth cohort to a one-time 10% increase in income. The shock arrives at age 70 and the MPC is measured contemporaneously. Preference parameters for each type are taken from the estimation results above. To separate the role of preferences the correlation between preference type and initial conditions is set to 0.

Table 11: Household Responses to Unanticipated Shocks by Preference Type

preferences are presented in Appendix M.

Focussing on the variation in MPCs across preference type (to either shock): there is is a correlation with preference type and realized bequests. Recall that Types 1 and 2 have essentially no estimated bequest motive while Types 4 and 5 have the strongest. In addition to heterogeneity in household constraints, differences in preferences generate substantial difference in household responses. Finally, it is important to summarize the evidence of the strength of the bequest motive and it's heterogeneity. That Types 1 and 2 still bequeath a positive share (on average) from these unanticipated shocks suggests that a significant proportion of bequests occur in the absence of bequest motives. This is consistent with the effect of eliminating bequest motive in the previous experiments. However, bequest motives have an important effect on portfolio choice and generate substantially different pass through of income shocks to bequests. This is inconsistent with the view that bequests are entirely accidental. Instead, it supports the argument that many bequests are *incidental*: households with bequest motives value the large bequests that arise incidentally from self-insuring late-life risks by holding stocks of liquid wealth and maintaining large housing wealth positions.

8 Policy Experiments: Valuing the Means Testing of Long Term Care Programs

Many countries provide means tested benefits for households who have large long term care expenditures, but limited private resources. Perhaps the most prominent of these programs is Medicaid in the US, which shares a number of institutional features with its UK counterpart. In the UK and the US, means testing occurs at the individual level.

The asset component of means testing includes the value of a primary residence if they are single and move into a residential facility, but excludes their home when they are in a couple.[56] Similarly, for those in a couple only half of their assets must be used to finance the long term care needs of an individual before state assistance is provided. In practice this provides insurance for a spouse against the risk associated with their partner and also creates differences in the extent of social insurance for Long Term Care needs across the wealth and income distribution as well as between couples and singles.

In this section, I simulate changes to the generosity and design of this means testing. I compare the resulting increases (or decreases) to the resulting gains (losses) in consumer welfare. To measure the costs associated with these reforms I compute the present discounted value of payment changes (including implicit changes covered by disregarded assets) and assume it costs the government £1 to provide £1 of payments.[57] I compare the compensating variation under the alternative policy environment with the actuarial value of the alternative policy. I consider three reforms (in the current version of the paper these reforms are not revenue neutral): first, I increase the value of transfers for those receiving the ADL consumption floor, second, I eliminate only the financial wealth disregard that applies to couples, and, third, I eliminate the financial wealth and housing asset disregards that apply to couples. In the baseline these disregards apply at 100% of the housing and 50% of the financial wealth of couples where only one member has ADL needs.[58]

The compensating variation to each reform is the immediate cash on hand payment that would leave the retiree as well off as before the reform. This is an ex-ante measure that is forward looking - it incorporates mechanical effects and the behavioural responses to the reform. Specifically, this is computed at age 68 and defined as $\chi_{68} = \chi^i_{68}(f_{68}, I, m_{68}, h_{68}, x_{68}, p_h)$ where:

$$\chi_{68} = V^i_{68}(f_{68}, I, m_{68}, h_{68}, x_{68}, p_h|Base) = V^i_{68}(f_{68}, I, m_{68}, h_{68}, x_{68}+\chi_{68}, p_h|Reform) \quad (26)$$

Where $V^i_{68}(\cdot)$ is the age 68 value function computed for a given set of state variables. When reporting results by group I average across all members and define groups by initial status.

To understand the insurance provided by the consumption floor I first analyse a 10% increase in this floor. This corresponds to an increase in the consumption floor from

[56]Strictly, in both cases houses are countable assets (in the language of Medicaid) while "homes" are excluded. Although there is some variation between US states, a house continues to qualify as a "home" if either a spouse (community spouses in the language of Medicaid) or dependent relative continues to live there or a nursing home stay is deemed temporary with intent to return.

[57]This benchmark assumes the government does not use other methods to make transfers more or less attractive to potential claimants.

[58]In the model the 50% rule applies each period to avoid keeping track of an additional state variable rather than as an effective lifetime cap. This potentially understates the value of the financial disregard. However, for most households the effect is negligible.

	Increase in PDV of payments			Compensating	Ratio
	Total	Transfers	Disregard	Variation	CV/PDV
Initial Renters	389	371	18	-565	1.46
Initial Owners	157	109	48	-540	3.44
Initial Owners					
Top PI quartile	56	22	34	-170	3.3
2nd PI quartile	137	94	43	-793	5.80
Bottom 50% PI	244	182	62	-639	2.62
Single Men	92	92	n/a	-173	1.89
Single Women	428	42	n/a	-97	2.30
Couples	369	288	82	-1044	2.83
Health					
Good	126	94	33	-310	2.45
Bad	227	187	41	-899	3.95
ADL	568	493	76	-1360	2.39

Note: Columns (1)-(3): £increase in the present discounted value of government transfers as of age 68. Column (4): £value of transfer needed to compensate people for the expansion of the consumption floor. Column (5): Ratio of columns (4 and 3)

Table 12: The Costs and Benefits of Increasing the ADL consumption floor by 10%

£4,956 (£7,434) to £5,452 (£8,177) per year for singles (couples). Table 12 reports the results from this exercise.

The discounted present value of total payments is reported in the first column and columns (2) and (3) separate this into direct transfers and implicit payments through disregards. Payments increases for initial owners and initial renters. The total increase in present discounted value of payments is relatively small because the onset of ADL conditions is typically some time after age 68 and a low probability event and, although there is some change to implicit payments through disregards, the fiscal burden is primarily driven by an increase in transfer receipt. To understand how this is driven by the income and wealth gradient among households, I decompose the sample by permanent income for those who are initial owners. On average, initial owners receive a smaller increase in transfers which also decrease in the level of their lifetime income. Separating the population by their family status indicates that the majority of these payments are made to those in couples or who are single women at age 68.

The fourth column presents the compensating variation and the final column presents the ratio of compensating variation to the change in total payments. Despite differences in the present discounted value of payments, the compensating variation between renters and owners is similar. However, the final column reveals that although the poorest households receive the largest increase in payments they also have a lower private value per £1 that is spent. Across all households the ratio of the compensating variation and payments is greater than 1- demonstrating that the consumption floor provides valuable insurance to retired households. Both the compensating variation and the ratio increase in income, but are not monotonic. High income households have higher lifetime levels of consumption. Consequently, large nursing home expenses precipitate a larger drop in consumption. Second, although they are less likely to have ADL needs at the beginning of the sample, they face higher life expectancy and are more likely to have high long term care costs when they survive long into retirement.[59]

However, for those at the very top of the distribution the value falls. The total value of these households' portfolio is almost twice as high as the next PI group which makes them less likely to qualify for the consumption floor and reduces the ratio of compensating variation to payments. Furthermore, they are more likely to be in a couple and have assets covered by the couple specific disregard. Despite the large benefits for richer households, it is worth emphasising that this does not account for the financing of this expansion: under a progressive tax system these households who have higher incomes are likely to bear a greater share of the costs.

Table 13 presents results from eliminating only the disregards for the financial assets of couples while maintaining the housing disregard. By construction, this reform has no effect on singles. The changes in the total value of government transfers are much larger than the reform to the consumption floor. While the reduction in payments is driven by a reduction in the disregarded assets, for many households it is offset by a substantial increase in payments. In contrast to the expansion of the consumption floor, the effects are monotonic in lifetime income. As before, those with the highest consumption experience the largest drops when exposed to large long term care costs. However, this reform substantially increases their exposure to the risk of high medical expenses associated with their spouse - increasing the probability that ex post they rely on their housing wealth to finance future consumption. It is worth remarking on two important effects for households who experience "smaller" and "larger" long term care costs. For these "smaller" shocks, households may not find it optimal to adjust their housing stock and instead exhibit excess sensitivity in their non-housing consumption - as discussed in Chetty and Szeidl (2007) and Kaplan and Violante (2014), this magnifies the welfare costs of these shocks. In the baseline, the disregard on financial assets provides insurance against these fluctuations. Under "larger" shocks, households absorb these shocks into non-housing consumption and also housing consumption because they downsize to liquidate housing wealth. This ex-post reliance means that they pay large adjustment costs to liquidate wealth and provide a buffer for their future. This exacerbates the wealth effect from losing their financial wealth, lowering the utility received from future bequests, but also in turn exposes newly

[59] De Nardi et al. (2016a) present a similar argument when evaluating Medicaid expansion for singles.

	Increase in PDV of payments			Compensating	Ratio
	Total	Transfers	Disregard	Variation	CV/PDV
Initial Renters	-342	576	-918	595	1.74
Initial Owners	-852	159	-1012	5678	6.66
Initial Owners					
Top PI quartile	-921	49	-970	9225	10.02
2nd PI quartile	-1012	157	-1169	6308	6.23
Bottom 50% PI	-730	216	-946	3107	4.23
Single Men	n/a	n/a	n/a	n/a	n/a
Single Women	n/a	n/a	n/a	n/a	n/a
Couples	-1474	528	-2002	9040	6.13
Health					
Good	-491	88	-579	4169	8.488
Bad	-620	346	-966	4441	7.16
ADL	-1938	863	-2801	5108	2.64

Note: Columns (1)-(3): £increase in the present discounted value of government transfers as of age 68. Column (4): £value of transfer needed to compensate people for the elimination of the disregards. Column (5): Ratio of columns (4 and 3)

Table 13: The Costs and Benefits of Eliminating the Financial Asset Disregard for Couples

	Increase in PDV of payments			Compensating	Ratio
	Total	Transfers	Disregard	Variation	CV/PDV
Initial Renters	-347	2985	-3332	663	1.91
Initial Owners	-1750	470	-2220	7681	4.34
Initial Owners					
Top PI quartile	-1924	74	-1998	12200	6.34
2nd PI quartile	-2043	452	-2495	8526	4.18
Bottom 50% PI	-1496	701	-2197	4514	3.02
Single Men	n/a	n/a	n/a	n/a	n/a
Single Women	n/a	n/a	n/a	n/a	n/a
Couples	-2857	2190	-5047	12214	4.27
Health					
Good	-972	297	-1269	5281	5.43
Bad	-1048	1580	-2628	5789	5.52
ADL	-3786	3657	-7443	9353	2.47

Note: Columns (1)-(3): £increase in the present discounted value of government transfers as of age 68. Column (4): £value of transfer needed to compensate people for the elimination of the disregards. Column (5): Ratio of columns (4 and 3)

Table 14: The Costs and Benefits of Eliminating Disregards for Couples

liquidated wealth to long term care costs. When it is costly to adjust housing and households place a large value on the consumption from housing this also raises the value of liquid buffers that allow them to avoid adjusting their housing stock. This intuition helps explain why the valuation of each £1 is high.

Finally, Table 14 presents results from eliminating both disregards for couples. For initial renters who benefit primarily from the financial component the valuations are similar. For owners the total value of government payments is substantially larger as the new policy environment affects a larger fraction of their portfolio. As outlined above, under the baseline policy many couples find saving to self insure relatively cheap. Liquid wealth is only partly exposed to these costs, but can be used to insure any future long term care risks for the spouse as well as provide self insurance against longevity risk. In the event that a household is fortunate and does not face high long term care expenses it may always be left as a bequest. At the same time they can enjoy the utility of a large house and consumption today without requiring high levels of liquidity for self insurance. This policy additionally eliminates the housing disregard and increases the exposure of households to long term care risk. Household valuations, column (4), increase substantially when compared to the experiment that eliminates financial disregard. However, the per £1 valuation falls because the policy is almost twice as expensive for each initial owner.

In contrast to higher wealth households and home owners, for initial renters the ratio of their private valuation to £1 spent by the government is approximately constant across experiments. While households place a high value on the state provided insurance for long term care needs (see above), the design of means testing which imposes a 100% effective tax rate on their household wealth substantially mutes these benefits for the richer households. In particular, these results suggest that households place a high value on policies that insure their liquid wealth and help them avoid liquidity constraints, but have a lower per £1 valuation for policies that insure their housing wealth.

9 Conclusion

In this paper, I develop and estimate a structural model of retirement savings decisions with realistic risks, housing, and heterogeneity in bequest preferences. Combining data on wealth composition and exogenous policy changes facilitates the separate identification of different motives for holding wealth. Estimation reveals that households exhibit large differences in the weight they place on leaving wealth for future generations and this is closely correlated with the wealth they accumulate across their lifetime. Accounting for differences in preferences and the liquidity composition of households' portfolios reduces the estimated level of risk aversion and the role of the precautionary savings channel in explaining the retirement savings puzzle.

Simulating a number of counter-factual economic environments isolates the role of different model features in driving retirement savings. Housing explains a substantial fraction of the level of wealth holdings in retirement. Understanding the portfolio composition of households and how they trade-off liquidity and housing is key. Model validation shows that these mechanisms reproduce reduced form estimates identified from quasi-experimental variation. This trade-off drives differences in the response to unanticipated income and housing wealth shocks. Demand for extracting liquidity from their home is increased when house prices increase, but reduced by an unanticipated liquid wealth shocks. This has opposite effects for marginal downsizers and creates a lower aggregate marginal propensity to bequeath from house price shocks. The estimated response to shocks differ substantially from the estimates in Altonji and Villanueva (2003), suggesting that a large proportion of retirement wealth is eventually bequeathed. As suggested in Gan et al. (2015), this may mitigate some of the concerns of financing an ageing population because older generations share their good fortune with future generations.

Finally, I address the role of means testing in the tax and transfer system with a particular focus on how means testing treats different asset classes. I concentrate on publicly provided Long Term Care insurance which features substantial means testing and an exemption for housing that varies across married and single individuals in the UK and the US. I calculate to which households the welfare benefits of this policy accrue and find that households value the insurance provided by the government, but also exemption policies that eliminate the 100% marginal tax rate implicit in many means testing designs. Furthermore, differences in asset classes mean that differences in the design of means testing program may reinforce or discourage self insurance behaviour. When households like to live in their home, this amplifies precautionary savings motives and the demand for liquidity so that, for every pound it costs the government, increasing the disregard for liquid assets provides more value than increasing the disregard for housing.

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A Computing Household Level Permanent Income

Following De Nardi et al. (2018) I infer household level measures of permanent income that is invariant to the household structure. Individual non-labor income is the sum of state pension income, private pension income, annuity income, war pensions, widows pensions and any other declared non-labor income. It excludes both employment and self-employment income. Other than state pensions it does not include benefit income (in the model benefit income is computed as part of the tax function). For singles household income is the same as individual income and for couples it is the sum across husband and wife.

I assume log household income for household i at age j follows:

$$
\begin{aligned}
\ln y_{i,j} = \beta_0 + \mathbf{1}[f_{i,j} = \textit{single man}] \cdot (\beta_{sman} + \beta_{age\times sman} \cdot j) \\
+\mathbf{1}[f_{i,j} = \textit{single woman}] \cdot (\beta_{swoman} + \beta_{age\times swoman} \cdot j) \\
+\beta_{age} \cdot j + \beta_{age^2} \cdot j^2 + \beta_{age^3} \cdot j^3 \\
+\beta_{PI} \cdot I_i + \beta_{PI^2} \cdot I_i^2 + \beta_{PI^3} \cdot I_i^3 + \beta_{PI^4} \cdot I_i^4 + \beta_{PI^5} \cdot I_i^5 + e_{i,j}
\end{aligned}
\tag{2}
$$

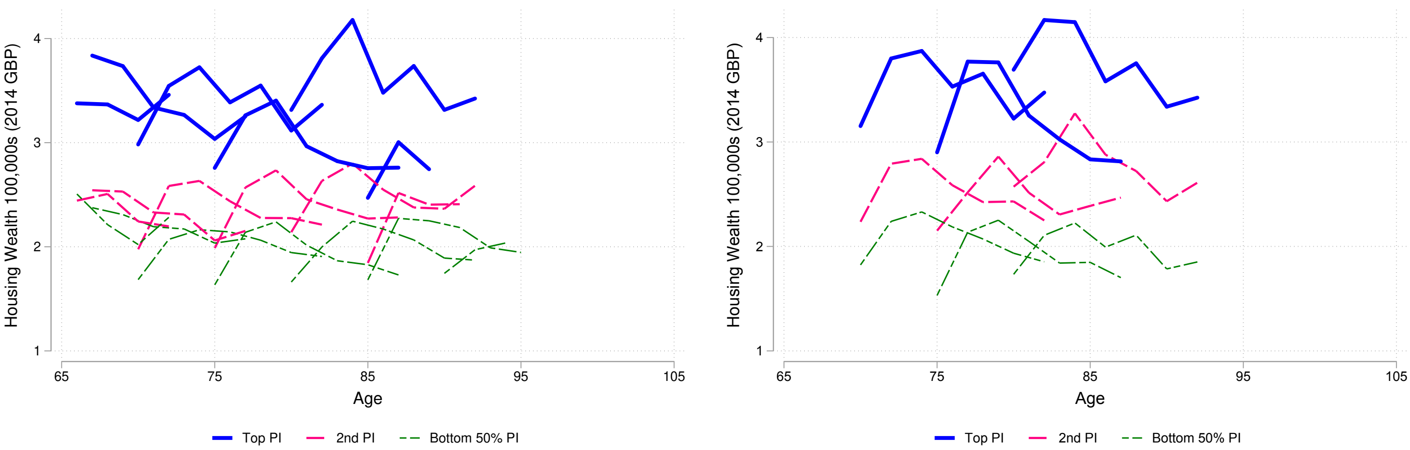
where as in the main text $f_{i,j}$ represents family status for household i at age j and I_i their time invariant permanent income. In practice I estimate the following fixed effect regression to obtain consistent estimates of the coefficients on age, family structure and their interaction:

$$
\begin{aligned}
\ln y_{i,j} = \beta_0 + \mathbf{1}[f_{i,j} = \textit{single man}] \cdot (\beta_{sman} + \beta_{age\times sman} \cdot j) \\
+\mathbf{1}[f_{i,j} = \textit{single woman}] \cdot (\beta_{swoman} + \beta_{age\times swoman} \cdot j) \\
+\beta_{age} \cdot j + \beta_{age^2} \cdot j^2 + \beta_{age^3} \cdot j^3 + \gamma_i + e_{i,j}
\end{aligned}
\tag{3}
$$

For each household the estimated vector of coefficients is used to compute the mean residual (or the estimate of their fixed effect) $\hat{\gamma_i}$. $\hat{I_i}$ is computed as the percentile rank of $\hat{\gamma_i}$. The final step is to perform the following regression:

$$
\hat{\gamma_i} + \hat{e_{i,j}} = \beta_{0,PI} + \beta_{PI} \cdot \hat{I_i} + \beta_{PI^2} \cdot \hat{I_i}^2 + \beta_{PI^3} \cdot \hat{I_i}^3 + \beta_{PI^4} \cdot \hat{I_i}^4 + \beta_{PI^5} \cdot \hat{I_i}^5 + u_{i,j} \tag{4}
$$

Which recovers the mapping from the permanent income index to the log of household income. For further exposition I refer the reader to De Nardi et al. (2018).



(a) Mean Housing Wealth (Unbalanced)

(b) Mean Housing Wealth (Balanced)

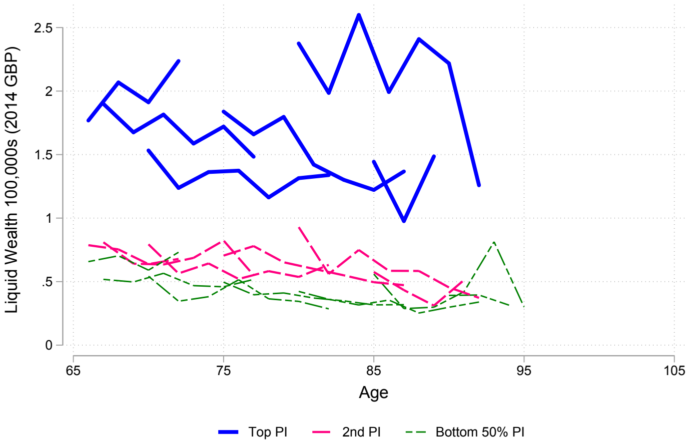
Figure A.1: Housing Wealth by Cohort & PI (Initial Owners)

B Attrition and Composition Bias

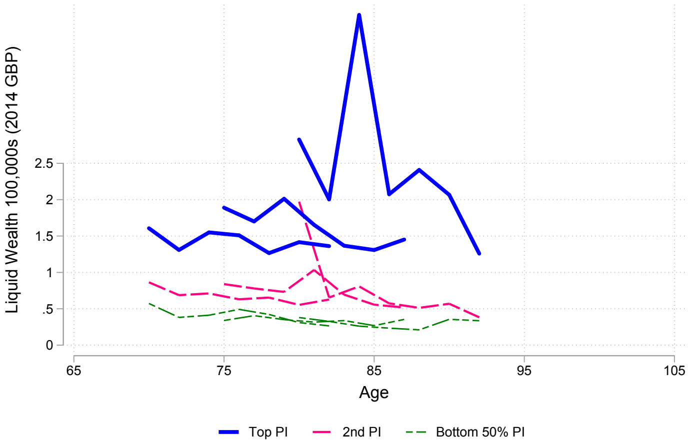
In this appendix I present results comparing the main sample with an alternative subsample - households who enter in the first wave of ELSA and remain in the sample until the final wave of my sample. These are the unbalanced and balanced panels respectively. By considering the same sample of households this eliminates composition bias as the year on year changes in asset levels are the changes experienced by those households and not changes in the composition of the sample. However, this imposes stricter selection criteria - those who remain in the sample for its full length are, on average, richer than those who exit the sample. Consequently, this selected sample is initially richer than the unbalanced panel and the results are not representative of the elderly population. This is true within both birth cohort and PI grouping.

Figure A.1 presents the housing wealth of these two samples while figure A.2b presents the liquid wealth of these households. The left hand panels reproduces results for the unbalanced samples from figures 3a and 3b.

Comparing the unbalanced panel to the balanced panel in figure A.1 there are two important differences. First, the youngest and oldest cohorts are omitted from the balanced panel as they do not satisfy sample selection in the first wave or survive until the final wave. Second, within PI groups and birth cohorts, the balanced panel has more wealth than the unbalanced panel. There is little evidence of more deccumulation in the housing wealth of the balanced panel than the unbalanced panel for any of the PI groups. For some groups, relative to the start of the sample, there is a small amount of overall deccumulation of housing wealth, however, conditioning on PI and birth cohort does almost completely removes the attrition bias. The housing wealth profiles in both the unbalanced and balanced panels are qualitatively and quantitatively similar, confirming



(a) Mean Liquid Wealth (Unbalanced)



(b) Mean Liquid Wealth (Balanced)

Figure A.2: Liquid Wealth by Cohort & PI (Initial Owners)

two of the key findings above.

First, the overall feature of these profiles is that deccumulation in housing wealth is slow. Second, the housing wealth of households rises and falls in line with aggregate trends. These key facts are present in both the unbalanced and balanced sample, which shows that they are not driven by compositional changes in the unbalanced sample.

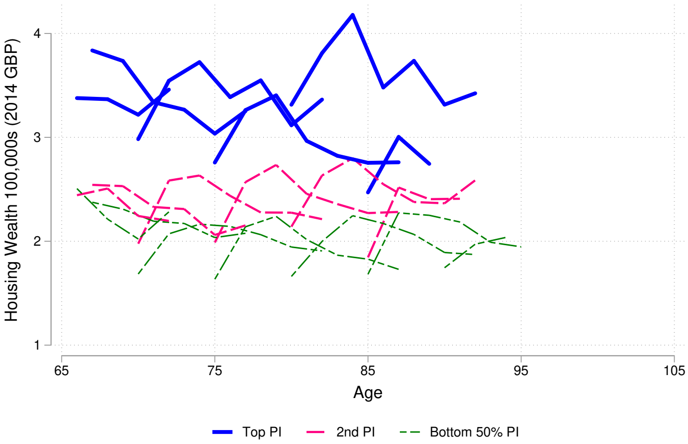
Similarly, when comparing the liquid wealth of the balanced and unbalanced panels (figure A.2) the top two PI groups in the balanced panel are richer than their unbalanced panel counterparts. The liquid wealth of the bottom group is similar in both the balanced and unbalanced panel. There is evidence of more deccumulation in the balanced panel. The top two PI groupings in the balanced panel deccumulate more liquid wealth than in the unbalanced panel. Despite more deccumulation of liquid wealth by the top two PI groups in the balanced panel, the pattern of slow liquid wealth deccumulation in retirement is present in both the unbalanced and balanced samples.

The key findings in this section, that households deccumulate wealth slowly and have wealth profiles that are driven by aggregate trends, are not caused by compositional bias. These results are consistent with similar exercises for the US in De Nardi et al. (2010, 2018) and for the UK and US in Blundell et al. (2016).

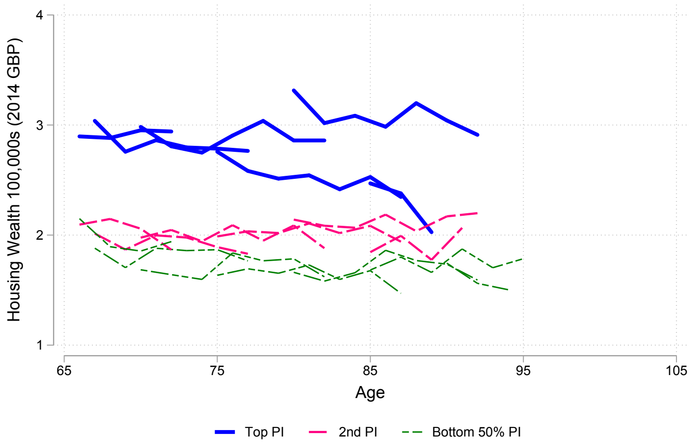
C House Price Deflated Wealth Profiles

For this population standard forward mortgages are not widely available and in this sample period reverse mortgages are very rare, therefore, many households withdraw housing wealth by downsizing.[1] As discussed in the section 2, volatility in house prices

[1] I provide further discussion of the UK and US reverse mortgage markets in appendix H and discuss collateralized and uncollateralized borrowing in section 4 where I describe the model.



(a) Mean Housing Wealth



(b) Mean Housing Wealth (HPI Deflated)

Figure A.3: Housing Wealth by Cohort & PI (Initial Owners)

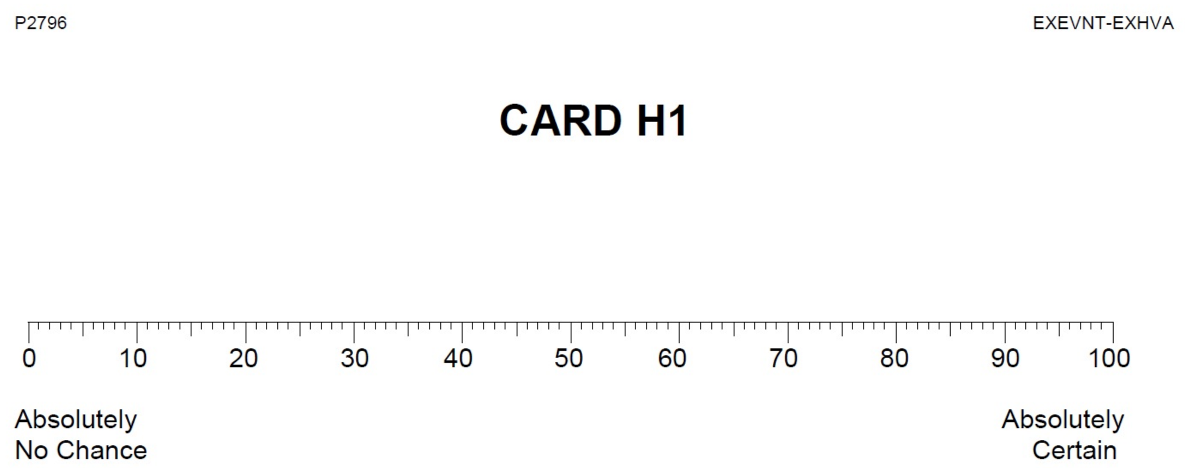
causes figure 2 to conflate active and passing saving.

Households care about their realized wealth, however, this masks the amount of deccumulation that occurs for individual households. As an attempt to disentangle the active and passive saving decisions of households I construct counter-factual housing wealth profiles that hold constant aggregate trends.

In panel A.3a I reproduce the housing wealth profile of the initial owners. While figure A.3b shows the housing wealth profile (separated by birth cohort and permanent income) for the same households, but deflating the value of their housing by a Housing Price Index.[2]

Absent price changes, on average households slowly deccumulate housing wealth. Comparing the two panels of figure A.3 shows that the change in asset prices obscures the decision by households to on average lower their housing wealth. Although there is some heterogeneity across cohorts and PI, mean housing wealth (the left panel) exhibits only small changes between the start of the sample period an the end. The deflated profiles show that the effects of passive saving explain the initial increase in housing wealth and the maintained high levels despite the active dis-saving decision of households at the mean (an infrequent decision).

[2]I use the UK HPI provided by HM Land Registry which uses transaction data (include cash purchases) to construct house prices. A similar exercise, without differentiating by permanent income or initial home ownership status, is presented in Blundell et al. (2016). Household downsizing decisions in year t are made with the actual wealth they have at t. By deflating the profiles, I implicitly assume that a household who release 25% of their true value at time t would also release 25% of their deflated value - this allows for the mechanical effect of the counter-factual price, but no behavioural effect. This is a strong (and unreasonable) assumption, but it highlights the first order effect of house price growth on the housing wealth profile.



Source: English Longitudinal Study of Ageing

Figure A.4: Interviewer Show Card

D Subjective Bequest Probabilities: Further Details

As in the HRS, ELSA respondents are asked to provide their subjective probabilities for a number of events. In addition to the questions about the distribution of bequests they may leave, households in ELSA are asked about their subjective survival probabilities; that they will have to enter a nursing home or pay for long term care and the probability that they have sufficient financial resources to meet their needs in retirement. ELSA subjects are given the following prompt before being asked any of these questions

> 'Now I have some questions about how likely you think various events might be. When I ask a question I'd like you to give me a number from 0 to 100, where 0 means that you think there is absolutely no chance an event will happen, and 100 means that you think the event is absolutely certain to happen.'

and provided with the show card in figure A.4. Furthermore, they are asked a practise question of weather events in order to familiarize them with the concept. I provide an example of the subjective bequest expectation below.

> 'Including property and other valuables that you might own, what are the chances that you will leave an inheritance totalling £150,000 or more?'

Despite the battery of subjective probability questions it is still possible that respondents may not understand the question or that the reported probability is uninformative and does not reflect the individual's actual subjective expectation. The ideal test of the assumption that they are informative would be to use realized and counter-factual bequests for each household. However, this is impossible as I do not observe bequests under the counter-factual.

The results in the main text demonstrate that subjective probabilities correlate with household wealth. In order to further validate the information content of the subjective probability measures I perform two validation exercises. First, I make use of an approach in Hurd and Smith (2002) to validate similar HRS questions which follows from a recursive decomposition. Second, I test the significance of lagged subjective probabilities to predict future wealth (de)accumulation.

For an age j individual i the subjective probability $y_{i,j}$ satisfies:

$$y_{i,j} = Pr(bequest \geq £150,00) = \tag{5}$$

$$E_j\Big[\sum_{t=j}^{T}[Pr(wealth_{i,j+1} \geq £150\text{k}) \cdot \prod_{h=j}^{t} surv_h \cdot (1 - surv_{t+1})\Big] \tag{6}$$

$$y_{i,j} = \mathbf{1}\{wealth_{i,j+1} \geq £150\text{k}\} \times (1 - surv_{i,j+1}) + surv_{i,j+1} \times E_t[y_{i,j+1}] \tag{7}$$

In this recursive decomposition the first component is the probability I die before the next period and have at least £150,00 in total wealth. The second component is the probability I survive to tomorrow multiplied by my expectation of tomorrow's subjective probability. Letting D_t denote the set of households who die between t and $t+1$, for small time intervals the average over the population at time t satisfies:

$$\bar{y}_{i,t} \approx \sum_{i \in D_t} \mathbf{1}\{wealth_{i,t+1} \geq £150\text{k}\} + \sum_{i \notin D_t} y_{i,t+1} \tag{8}$$

The right hand side of this equation can be directly calculated in ELSA up to wave 5 as death data is not available after this date. Finally, the gap between these two objects is given by:

$$Error_t = \bar{y}_{i,t} - \big(\sum_{i \in D_t} \mathbf{1}\{wealth_{i,t+1} \geq £150\text{k}\} + \sum_{i \notin D_t} y_{i,t+1}\big) \tag{9}$$

Table A.4 reports the wave specific error (measured in percentage points). The average error in household predictions is small when pooling across eaves and is largest when house prices undergo the largest changes in the sample. This demonstrates that self reported probabilities are consistent with the observed aggregate wealth decisions of households.

Wave	Error
1	-11.04
2	-5.57
3	-1.37
4	-2.22
All	-5.41

Table A.4: Average Forecast Error

D.1 Constructing the Preference Index

I control for total wealth by allowing for within wave quintile specific effects and control separately for home ownership and the share of total wealth in housing. These quantile specific effects impose limited restrictions on the underlying function and allow me to recover the effect of total wealth holdings and portfolio composition. I control for contemporaneous characteristics of the household with time t period controls for age, household income, gender, marital status, health for all household members, subjective survival probabilities, and vital statistics of their parents as well as wave fixed effects.[3] Finally, the object of interest is a household specific fixed effect. Household fixed effects are additionally rezidualized on time invariant permanent income and birth cohort dummies.

E Additional Reduced Form Results

E.1 Additional RDD results

Table A.4 presents additional results from the regression discontinuity estimation of the effect of transaction taxes on the mobility of older household described in section 3.

Panel A shows the robustness of the common slope estimates to a higher order polynomial. First, using both the cubic and quartic estimators the estimated treatment effect remains negative for all bandwidths and is significant for larger bandwidths around the discontinuity in the SDLT schedule. The results are consistent with the lower order polynomial and local linear estimates presented in the main text. Gelman and Imbens (2017) caution over using higher-order global polynomials as they may lead to noisy estimates, sensitivity to the degree of the polynomial and poor coverage of confidence intervals. While the results here demonstrate some of these problems, nevertheless the

[3]Including wave specific effects is important in this analysis because the survey question is defined in reference to a nominal threshold that is fixed for all waves and consequently progressively less informative in real terms.

Panel A: Higher Order Polynomials

	Band around cuttoff				
Order of polynomial	10%	15%	20%	25%	30%
Common Slope					
Cubic	-0.0548*	-0.0377	-0.0575***	-0.0533***	-0.0287**
	(0.0332)	(0.0289)	(0.0180)	(0.0176)	(0.0140)
	-730.9	*-877.8*	*-2124*	*-2118*	*-2871*
Quartic	-0.0383	-0.0305	-0.0519**	-0.0549***	-0.0293**
	(0.0398)	(0.0294)	(0.0207)	(0.0180)	(0.0148)
	-727.7	*-882.1*	*-2127*	*-2116*	*-2869*
N	1224	1559	3023	3233	3979

Panel B: Bounded Second Derivative Inference

Smoothness (K)	0.001	0.01	0.02	0.1	0.1
Local Linear	-0.0290	-0.0290	-0.0290	-0.0290	-0.0290
BSD CI	[-0.0571,-0.000892]	[-0.0571,-0.000875]	[-0.0572,-0.000826]	[-0.0587,0.000694]	[-0.0539,-0.00405]
Implied Bandwidth	30%	30%	30%	30%	30%
Significance Level	5%	5%	5%	5%	10%
Eff. Sample Size	943	943	943	943	943

All regressions additionally control for wave fixed effects, a polynomial in age, household demographics, a polynomial in permanent income and region dummies. Following Kolesár and Rothe (2018), Standard Errors in panel A are clustered by household. The Akike Information Criterion is shown in italics. In panel B the implied bandwidth is the one that minimizes the length of the resulting CI for a given choice of K. * $p < 0.10$, ** $p < 0.5$, *** $p < 0.01$

Table A.4: The Effect of Transaction Taxes on Household Mobility resulting point estimates are similar to those obtained with lower order polynomials and non-parametric methods (particularly over the largest estimation window). The estimated treatment effects are not driven by the choice of approximation to the conditional expectation function.

A key issue in many of the applications of regression discontinuity analysis is the underlying discrete support of the forcing variable - this is also a concern in this context. In Table 4, tests of statistical significance use standard errors clustered at the household level. As recommended by Kolesár and Rothe (2018) they are not clustered at the values in the support of the forcing variable (Lee and Card, 2008, motivates adjusting standard errors in this manner). However, the confidence intervals in Table 4 undercover the true average treatment effect when model misspecification bias is large (typically when large bandwidths are used or the discrete support leads to insufficient observations in a small neighbourhood of the threshold). Panel B uses an alternative method in Kolesár and Rothe (2018) to construct confidence intervals that corrects for misspecification bias and has guaranteed coverage properties.

Implementing this alternative method requires that the researcher chooses a smoothness constant K (which is equivalent to a bound on the second derivative of the conditional expectation function) with a value of $K = 0$ indicating that the conditional expectation function is known to be linear. In each column the bias corrected point estimate is estimated using a local linear estimator and with the bandwidth chosen optimally for a fixed smoothness constant (and smoothness class).

Column 1-5 report confidence intervals constructed with $K \in \{0.001, 0.01, 0.02, 0.1\}$ which represent a range of smoothness parameters ranging from an 'optimistic' to a 'pessimistic' choice (the central values are chosen to sandwich a lower bound estimate for K of 0.012). The resulting confident intervals are reasonably tight and correspond to the clustered standard errors reported in Table 4 and results remain statistically different from 0 at the 5% significance level for all but the most pessimistic value of the smoothness value. Furthermore, even for this extreme case a 90% confidence interval excludes 0.[4]

F Additional Clustering Details

F.1 Marginal Distribution of Household Characteristics

The marginal distributions of the household characteristics z_i by household type are displayed in figures A.5 to A.7 with mean values denoted by the dashed vertical line. These marginal distributions give a succinct description of how the *k-means* clustering algorithm partitions household's based on their characteristics.

[4]Although this is not analogous to a one-sided test it is also the case that the null hypothesis of a weakly positive treatment effect is rejected at the 5% significance level.

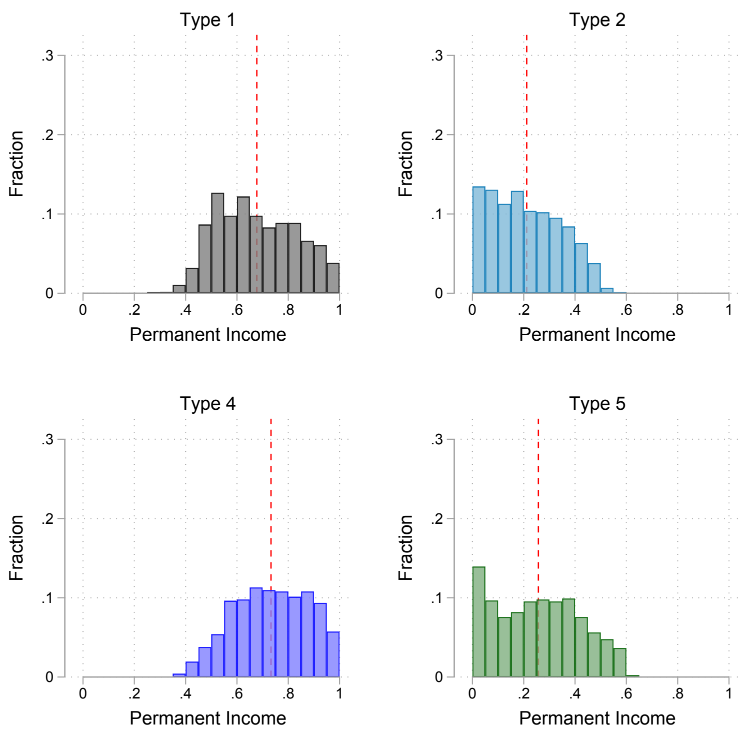


Figure A.5: Permanent Income Across Groups

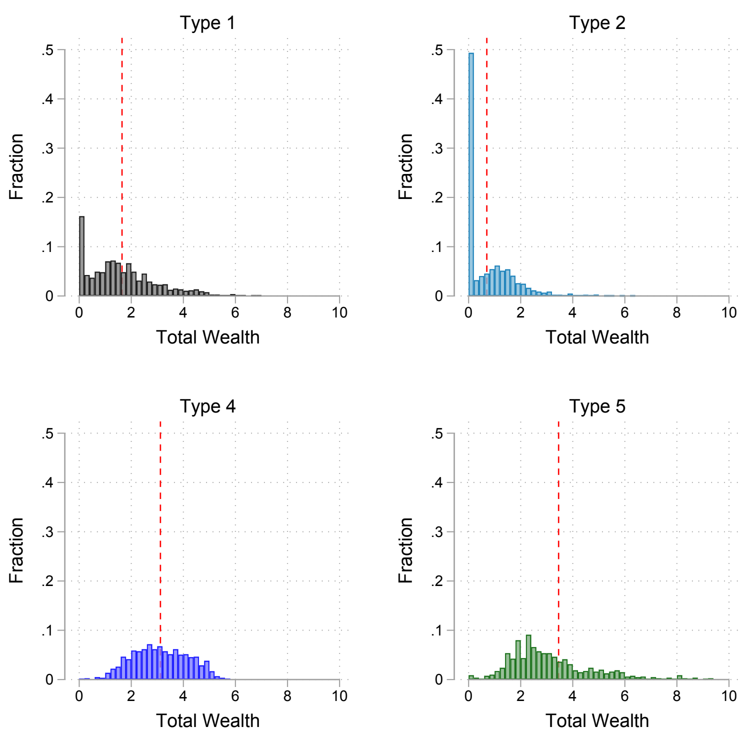


Figure A.6: Total Wealth Across Groups

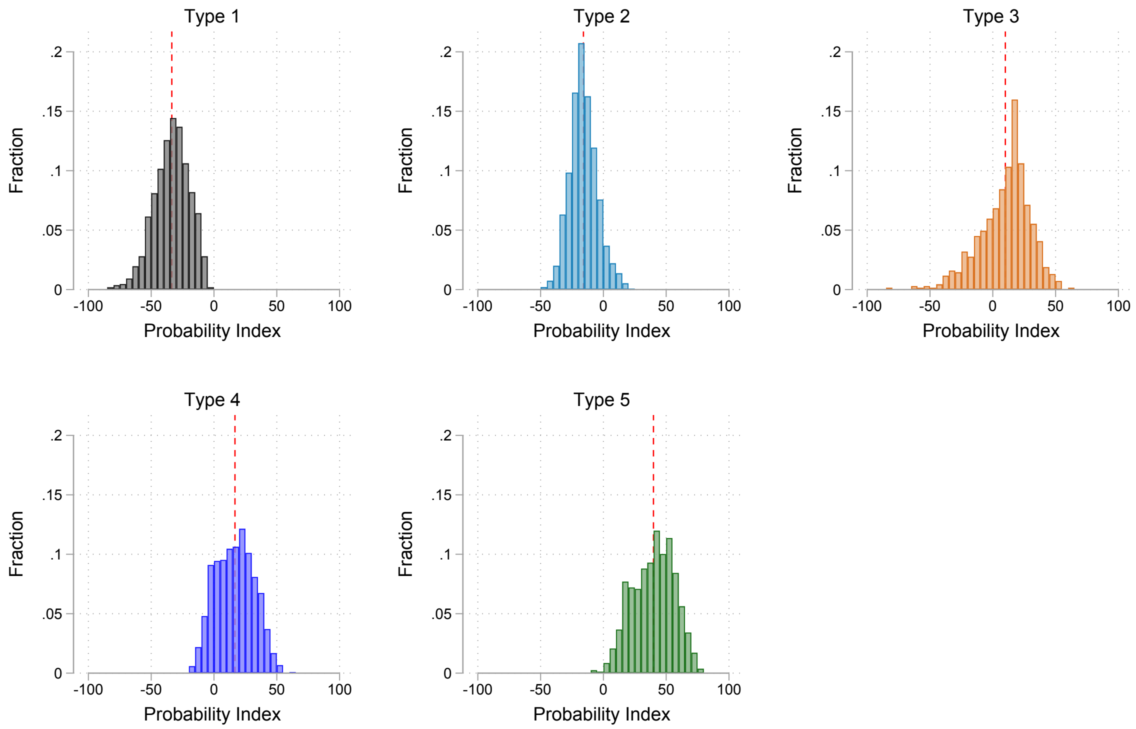


Figure A.7: Bequest Probability Index Across Groups

Figure A.5 plots the marginal distribution of permanent income by clusters. Both Type 1 and Type 4 are primarily drawn from the upper half of the PI distribution. Type 3 is also concentrated in the upper half of the PI distribution and is drawn from primarily the richest households. In contrast, Types 2 and 4 have the majority of households are drawn from the bottom half of the PI distribution. Despite their different clusters, Type 1 and 4 have similar marginal distributions of permanent income and the same is true for the marginal distributions for Types 2 and 5.

Types 1 and 2 (figure A.6) have the lowest level of assets, with the majority of renters contained in Type 2. Types 4 and 5 hold more wealth, with Type 3 having the highest average wealth (and a long tail which is omitted from figure A.6 for ease of comparison). Despite similar PI distributions Types 1 and 4 differ in their average wealth holdings by almost £150,000. Similarly, Types 2 and 5 (who also had similar PI distributions) differ by £250,000. Despite largely being drawn from opposing halves of the PI distribution, the marginal distribution of wealth held by Types 4 and 5 is similar. Finally, figure A.7 plots the marginal distribution of the bequest probability index - I adopt a naming convention that means the household groups are labelled by their bequest probability index. On average Type 1 and Type 2 households systematically report lower probabilities of leaving an inheritance than observationally similar households while those in Type 4 and Type 5 report systematically higher probabilities. Type 3 households also report systematically higher probabilities of leaving an inheritance than observationally similar households due to the negative skew in the distribution, however Type 3 contains a large mass of both households reporting systematically higher and lower probabilities. Although the clustering algorithm assigns each household to a fixed group, the support of z_i for each Type is not exclusive and there is considerable variation in household characteristics within types.

F.2 The Number of Clusters in the K-Means Clustering

The approach to estimating household level latent preference types in this paper draws on the two step procedure in Bonhomme et al. (2018). When using the k-means clustering approach, the researcher is left with two degrees of freedom: a) which variables to use to cluster the households (denoted by the vector z) and b) the number of clusters.[5] The choice of variables to cluster on is motivated by the economic problem agents face and is discussed in more detail in Section, this appendix details the choice of the number of clusters.

In order to select the number of clusters used in the analysis, I follow standard data-based methods used in the machine learning literature (See Hastie et al., 2009, for an overview of both clustering methods and data-based heuristics used in k-means clustering). First, restating the clustering problem indexed by a given number of clusters K:

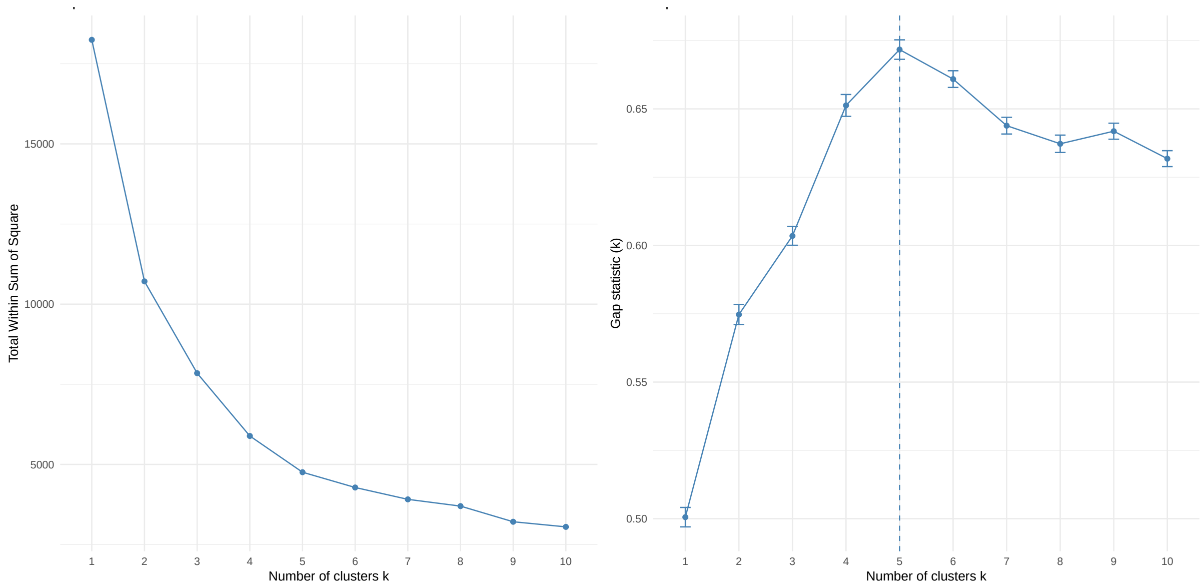
$$\min_{\mathscr{K}_K, \{\bar{z}_k\}_{k=1}^K} \sum_{k=1}^{K} N_k \sum_{k(i)=k} || z_i - \bar{z}_k ||^2 = \min_{\mathscr{K}_K, \{\bar{z}_k\}_{k=1}^K} SSE_K \tag{10}$$
$$\bar{z}_k = \frac{1}{N_k} \sum_{k(i)=k} z_i$$

Where the classification (for a given number of clusters K) is given by:

$$\mathscr{K}_K = \{k(i)\}_{i=1}^n \tag{11}$$

In order to select the optimal number of clusters, separate solutions are obtained to the problem in equation for number of clusters $K \in \{1, ..., K_{max}\}$. It is well documented that the measure of within cluster dissimilarity (the Sum of Squared Errors) is decreasing in the number of clusters k which precludes the use of cross-validation techniques. Instead, a number of heuristics which use the following intuition are proposed: suppose there is a true number of clusters in the data K^{true}. Then for $K < K^{true}$ the algorithm assigns a subset of the true groups to each cluster, consequently, increasing the number of clusters

[5]It is also necessary to specify the initialization of the clusters, however, I use a multi-start algorithm where the initial assignment of clusters across households is drawn from 10,000 random seeds



(a) Elbow Method

(b) Gap Statistic

Figure A.8: Optimal Number of Clusters

allows the algorithm to assign groups in a subset to a new cluster. To the extent that these subgroups are strict, increasing the number of clusters when $K < K^{true}$ is associated with a large decrease in the measure of within cluster dissimilarity. In contrast, when $K > K^{true}$ one of the clusters partitions a true group into two clusters and the decrease in the measure of within cluster dissimilarity must be smaller. This logic forms the basis of using within cluster dissimilarity measures to select the optimal number of clusters - the optimal number of clusters is located at the kink in the marginal decrease in the Sum of Squared Errors.[6]

Figure A.8 displays results for two commonly used heuristic methods for identifying this kink point. Figure A.8a plots the Sum of Squared Errors (SSE_K) against the number of clusters. The 'Elbow statistic' identifies the kink point from this graph by visual inspection. Using this metric suggests a kink point at $K = 5$.

Figure A.8b instead plots the Gap statistic Tibshirani et al. (2001) which is an automated way of identifying the kink point. The gap statistic is defined as:

$$Gap_n(K) = E_n^*[log(SSE_K)] - log(SSE_K) \tag{12}$$

Where E_n^* denotes a bootstrapped expectation drawn from a uniform sampling over the data.[7]. Let B denote the number of bootstrap replications and $sd_B(K)$ denote the standard deviation of the $log(SSE_K)$ replications. Then

[6] Alternatively, where the marginal increase in the Explained Sum of Squares begins to asymptote

[7] In practice, I use 50 bootstrapped replications to calculate the expected $log(SSE_K)$

$$\hat{K}^{true} = \arg\min_{K}\{K : Gap_n(K) \geq Gap_n(K+1) - s_{K+1}\} \tag{13}$$

$$s_K = sd_B(K)\sqrt{(1+1/B)} \tag{14}$$

In words, the Gap statistic identifies the optimal number of clusters as the smallest K such that the increase in the Gap statistic is less the the simulation error (displayed in the error bars in figure A.8b). The optimal number clusters as determined by the Gap statistic is $K = 5$.

One potential concern in using a two-step approach to estimating latent heterogeneity is that the sample size in each cluster may be small which may deliver imprecise estimates in the second stage without enough variation to credibly identify differences across the population. Instead, the optimal number of clusters determined by the heuristic methods generates groups with large sample sizes.

F.3 Alternative Clustering Procedure

The estimation procedure in this paper estimates preference parameters taking the results of the assignment procedure as given. Although the k-means algorithm is a popular technique to partition the data into clusters and is widely used in economic applications of group fixed effects, a number of alternative methods for partitioning data into clusters are used in other applications - these alternative methods often return different partitions of the underlying data. It is not feasible to estimate the model for a variety of assignment procedures and, instead, I present a comparison of the partitions under an alternative k-medoids assignment procedure (holding fixed the number of clusters).

Formally, k-medoids clustering is defined as:

$$\min_{\mathscr{K}_K, \{\bar{z}_k\}_{k=1}^K} \sum_{k=1}^{K} N_k \sum_{k(i)=k} \mid\mid z_i - \bar{z}_k \mid\mid \tag{15}$$

$$\bar{z}_k = \text{median}_{k(i)=k}(z_i)$$

While the k-means procedure minimizes the sum of squared Euclidean distances, the k-medoids procedure instead minimizes a sum of pairwise distances. Consequently, it is more robust to large outliers and measurement error (that produces large distances).

A comparison between the estimated clusters under a k-means and a k-medoids procedure are displayed in Table A.8.

		k-medoids					
		Type 1	Type 2	Type 3	Type 4	Type 5	Share
k-means	Type 1	97.76	0	0.35	1.89	0	18.23%
	Type 2	10.48	89.27	0	0	0.25	34.09%
	Type 3	0	0	93.72	6.28	0	12.33%
	Type 4	1.73	0.1	0	95.71	2.45	21.09%
	Type 5	0	0.6	0.15	1.06	98.19	14.27%
Share		21.73%	30.54%	11.64%	21.45%	14.52%	

Table A.8: Comparison of Latent Household Types with Alternative Clustering Procedure

G Numerical Procedure

The dynamic programming problem described in Section 4 does not admit a closed form analytic solution.

I solve the model using backwards induction. At each age I compute the optimal savings, housing and consumption decision for all possible combinations of the state variables. I use the policy functions to compute the value function and iterate backwards. Given the optimal household decisions for a given set of parameter values and household initial conditions I simulate forward households through the different policy regimes drawing values of ξ and ζ from their distribution using Monte Carlo methods. I then construct moment conditions from this simulated data in the exact same way as in the data - this forms the basis of my estimation procedure.

This appendix discusses the implementation of each of these procedures in more detail.

G.1 Discretization

The model has four discrete state variables: age, health status, family structure and idiosyncratic bequest motive. There are four additional state variables that must be discretized: permanent income, housing, cash on hand, and the aggregate house price level as well as the additional transitory medical expense shock. Permanent income is placed on an unequally spaced grid with 6 elements, where the grid points are concentrated towards the extremes of the distribution.

Housing, which is both a state and a choice variable, is discretized[8] using a single point to denote current renters and 14 additional points for homeowners - the first 12

[8]The presence of numerous notches in the transaction tax mean that the budget set is non-convex. The flow utility of housing depends on the initial state variable rather than the choice of next period housing (excepting renters) Together these features necessitate the practical choice to discretize both the state variable and housing choice.

points of this grid are placed at the median of the 12 quantiles of the 2002 housing wealth distribution of my ELSA sample (conditional on being below £1,250,000 which covers over 99% of the sample) with two additional points placed at £1,250,000 and £2,500,000. Cash on hand is placed on a grid with 42 points placed on an exponential scale. I use a small number of cash on hand points for the available resource because the solution method (described below) involves calculating an exact solution to the Euler Equation at each point. The log of the aggregate house price level is placed on a grid with 6 elements using the method of Tauchen (1986). Finally, the transitory component of medical expenses is placed on a grid with 3 elements using the method of Tauchen (1986).[9]

Consumption and next period liquid wealth are not placed on a grid. Instead, individuals can choose any feasible level of consumption and next period liquid wealth. In total, the value function and policy functions are calculated for 23,619,600 combinations of state variables for each age and policy regime.

G.2 Computing the Solution to the Household's Problem

In order to tractably solve this problem while maintaining a high level of accuracy I model the choice of housing as a discrete choice and follow the modified version of the endogenous grid-point method (EGM) algorithm for discrete continuous dynamic choice models in Iskhakov et al. (2017)[10]. The EGM algorithm was first introduced in economics by Carroll (2006) who demonstrated improvements in both speed and accuracy in a buffer stock savings model.

However, the model presented here introduces non-convexities through the consumption floor and housing choice (which I discretize) as well as the kinks in the transaction tax and tax on estates. In this paper, cash on hand is not deterministic and I adapt their method by controlling for household savings (the deterministic component of cash on hand) as the end of period state variable. Holding fixed the housing choice combining the Euler equation for consumption with the predetermined level of saving delivers the optimal consumption policy, savings and the cash on hand state variable given the housing stock. A variation of the same EGM approach is discussed in **?** for a retirement framework without a housing choice, but featuring public care aversion.

However, housing is a choice variable. The housing stock today effects the marginal utility of consumption today and the level of housing tomorrow effects expected marginal utility of consumption tomorrow and total available resources tomorrow. In practice, at each set of state variables today I compute the implied consumption and savings decision using the household Euler equation for every choice of housing tomorrow. This is referred

[9]Results with 3 or 5 points for the transitory shock are indistinguishable

[10]Fella (2014) also considers a version of the EGM algorithm for non-smooth non-convex problems

to as the EGM step which returns the housing choice conditional policy functions[11] for a given set of state variables Ω:

$$c^*(\Omega|h') \tag{16}$$

$$a'^*(\Omega|h') \tag{17}$$

Which can then be combined to give the housing choice conditional value function:

$$\begin{aligned} V(\Omega|h') = u(s, c^*(\Omega|h'), h, m) + \\ \beta \cdot surv(j, I, m) E[V(\Omega') \,|\, \Omega, h', a'^*(\Omega|h')] \\ + \beta(1 - surv(j, I, m)) E[\phi^i(b) \,|\, \Omega, h', a'^*(\Omega|h')] \end{aligned} \tag{18}$$

Given the optimal rules conditional on the choice of housing tomorrow, I compute the conditional value function for every possible choice of housing tomorrow and take the maximum across all house choices. The value function is then given by:

$$V(\Omega) = \max_{h' \in \mathscr{H}} \{V(\Omega|h')\} \tag{19}$$

G.2.1 Calculating the Housing Choice Conditional Optimal Policy and Value Function

The Euler equation for the homeowner gives:

$$\begin{aligned} & u_c(s, c, h', m) \geq \\ & \beta \cdot surv(j, I, m) E[\frac{\partial}{\partial \tilde{a}'} V^i_{j+1}(f', I, m', h', x', \zeta', p'_h) \Big| \Omega, c', h'] \\ & + \beta(1 - surv(j, I, m)) E[\frac{\partial b}{\partial \tilde{a}'} \frac{\partial}{\partial b} \phi^i(b) \Big| \Omega, c', h'] \end{aligned} \tag{20}$$

Away from the borrowing constraint the Euler equation holds with equality and the EGM approach is to calculate the right hand side of this expression (for a given savings choice) and calculate the implied optimal consumption by inverting the marginal utility of consumption. Given consumption and savings, cash on hand today is found by rearranging the budget constraint.

Conditional on tomorrow's housing choice I follow this procedure and I document

[11] The rental expenditure for current renters follows from the within period marginal rate of substitution.

the calculation of the expected future marginal utility of saving. For saving below the consumption floor, the marginal utility of saving is 0 and I follow Hubbard et al. (1995) in replacing the consumption floor with an indicator function in the Euler equation.

$$\begin{aligned}\frac{\partial}{\partial \tilde{a}'}V^i_{j+1}(f',I,m',h',x',\zeta',p'_h) =& \frac{\partial x'}{\partial \tilde{a}'}\frac{\partial}{\partial x'}V^i_{j+1}(f',I,m',h',x',\zeta',p'_h)\\ =&(1+r\tau'_y(ra'+y))\frac{\partial}{\partial x'}V^i_{j+1}(s',I,m',h',x',\zeta',p'_h)\\ =&(1+r\tau'_y(ra'+y))u_c(s',c^\star(\Omega'),h^\star(\Omega'),m')\cdot \mathbf{1}[c_{min}(s',h')<\tilde{x}'+\delta h']\end{aligned} \tag{21}$$

This is then inserted into the right hand side of equation 20. Similarly, the effect of increasing saving on the marginal utility of bequests is given by the following upper envelope of the choice-specific value functions:

$$\begin{aligned}\frac{\partial b}{\partial \tilde{a}'}\frac{\partial}{\partial b}\phi^i(b) =& \frac{\partial b}{\partial \tilde{a}'}\phi^i_b(b) = \frac{\partial b}{\partial a'}\phi^i_b(b)\\ =&\mathbf{1}[Q(0,h',p'_h)+a'>0]\cdot\phi^i_b(Q(0,h',p'_h)+a')\end{aligned} \tag{22}$$

Substituting the results in equations 21 and 22 and inverting equation 20 gives:

$$\begin{aligned}c^\star(\Omega|h') = u_c(s,h',m)^{-1}(&\\ &\beta\cdot surv(j,I,m)E[(1+r\tau'_y(ra'+y))u_c(s',c^\star(\Omega'),h^\star(\Omega'),m')\cdot\mathbf{1}[c_{min}(s',h')<\tilde{x}'+\delta h']\,|\,\Omega,\tilde{a}',h'\\ &+\beta(1-surv(j,I,m))E[\mathbf{1}[Q(0,h',p'_h)+a'>0]\cdot\phi^i_b(Q(0,h',p'_h)+a')\,|\,\Omega,\tilde{a}',h'])\end{aligned} \tag{23}$$

Where the expected value on the right hand side is left in terms of a' conditional on the chosen level of savings $\tilde{a}'$.

When the continuation value, the sum of the discounted expected value function and expected utility from bequests, is globally concave then the the FOC outlined above will be necessary and sufficient. However, when this continuation value is not concave the FOC is necessary, but not sufficient. The continuation value of the model studied in this paper is not globally concave due to the presence of the consumption floor and the discrete housing decision which introduce kinks in the value function.[12] Consequently, the optimal policies delivered by the EGM step do not necessarily correspond to the optimal

[12]Typically kinks which occur due to next period non-concavities are referred to as *primary* kinks while kinks that perpetuate backwards from future period non-concavities are referred to as *secondary* kinks. The presence of further uncertainty in future periods helps to smooth out some of the secondary kinks, but the approach used here accounts for both types of kinks.

policies of the model.

In order to ensure that the globally optimum consumption value is selected from the multiple solutions to the Euler Equation I construct the (housing choice specific) upper envelope over segments of the (housing choice specific) value function in regions of the endogenous cash on hand grid where multiple solutions are detected. This procedure follows the method described in Iskhakov et al. (2017).

The DC-EGM method specifies a grid for the post-decision savings state and returns the housing choice-specific optimal policies and value functions on an endogenous grid. Consequently, an extra step is needed before it is possible to compare them in the upper envelope calculation in 19. I refer to this step as *regularization* and interpolate each of the housing choice-specific value functions and policy functions onto a pre-specified exogenous cash on hand grid that is common across housing choices. In the *regularization* step, when interpolating the value function for households who choose to locate at the borrowing constraint for the next period I use the analytic solution for their value function (given the computed expected value function associated with the borrowing constraint) next period.

G.3 Simulation

I simulate 50,000 simulated households who have initial conditions observed in the data. Household's are simulated through the path of observed shocks (health, mortality and aggregate house prices) together with the entire profile of unobserved shocks. This procedure perfectly replicates any compositional changes in the sample as they age and die.

Given household states the optimal choices in the simulation are calculated starting from the age of first observation and moving forward. As in the solution of the dynamic programming problem the optimal policy is found by first conditioning on next period housing choice and then by maximising over these conditional value functions. In doing so, the problem must now be evaluated at points which are outside the grid chosen in the solution. This is achieved by discretizing the choice of available consumption (into 100 possible choices for the percentage value of current resources) and using linear interpolation.

In the simulation, I assume that households face a maximum of five different tax regimes during the sample period (depending on their entry into the sample and duration). The transition across these tax regimes is treated as a zero probability event with the exception of the tax regime which corresponds to the so called "Stamp Duty Holiday". This means the model is solved separately for each of these tax regimes and households are simulated through the tax regimes they experience. In the case of the "Stamp Duty Holiday" in line with the nature of the policy, households perfectly forecast the reversion to the previous regime after one period.

G.4 2nd Stage Estimation

Given the estimated first stage parameters, the second stage estimation selects the parameter vector $\hat{\theta}$ which minimises the GMM criterion function described in equation 24.

$$\hat{\theta} = \arg\min_{\theta \in \Theta} G(\theta)' W G(\theta) \tag{24}$$

In life cycle models of the type featured here the GMM criterion function may have multiple local minima and without analytic derivatives. It is not possible to formally establish that any optima is a global minimum and in practice Simulated Method of Moments estimates are found by employing multiple starting points for a derivative free optimisation algorithm.

As discussed above, computation of the simulated moments is costly due to the large state space of the model and multiple policy regimes. Consequently, I adopt a methodology similar in spirit to Guvenen and Smith (2014) where minimization of the GMM criterion function proceeds in two steps by combining a form of iterated grid search in the first step with a derivative free optimizer in the third step.

In the first step, I first compute 3,000 candidate parameter values and evaluate the objective function at each parameter value. The candidate values are selected by drawing from a 14-dimensional (the number of parameters to be estimated) *Sobol sequence* which is a low discrepancy quasi-random sequence. The candidate parameter values are then ranked based on the value of the objective function at these parameters. I then use the 30 highest ranked candidate parameter vectors (the 1% with the smallest value of the objective function) to generate a new hypercube on the parameter space. I take the minimum and maximum parameter value in each dimension of the parameter space and use these as new lower and upper bounds in each of the dimensions. This produces the smallest hypercube which surrounds the polytope defined by the convex hull of the 30 highest ranked candidate parameter vectors. In practice, this greatly reduces the overall admissible parameter space without necessarily producing tight bounds on any individual parameter. I compute a further 3,000 candidate parameters on this new hypercube and iterate on this procedure.[13]. Sampling points from this new hypercube (substantially larger than the convex hull) slows the rate at which regions of the parameter space are discarded and is similar to the averaging of the best estimate and new draws from a Sobol sequence in the *Tik-Tak algorithm* described in Arnoudy et al. (2019). I iterate this step 5 times. The second step uses the top 1% sample from the final set of first stage evaluation as starting values for a derivative free optimiser.

I use the BOBYQA algorithm for numerical optimization Powell (2009), a trust region based method, in the second stage. Typically, BOBYQA uses fewer evaluations of

[13] Gavazza et al. (2018) use a Sobol sequence to construct candidate parameters in a form of iterated grid search

the objective function than other derivative free methods (for example the Nelder-Mead Simplex method Nelder and Mead, 1965). By combining the BOBYQA method with the multiple starting points selected above it appears that the parameters obtain the global minimum.

At each stage of the estimation I parallelize both the calculation of the dynamic programming problem and simulation. In the first stage I also parallelize the evaluations of the candidate parameter vector and in the second stage the derivative free optimisations from different starting points using the facilities of the University College London Computer Science High Performance Computing Cluster.

G.5 Computing the Standard Errors

I use the standard formula for the asymptotic variance of the MSM estimator including adjustment for simulation error. I do not adjust for the first stage estimates - in particular, this treats the cluster determined groups as known ex-ante.

To calculate the Jacobian of the moment conditions with respect to the parameters I use numerical differentiation.

H Reverse Mortgages in the UK: Further Details

In the model presented in section 4 I assume that retired households do not have access to "Reverse Mortgages" or other home equity release products. As discussed above, in line with the results in Nakajima and Telyukova (2017), it is likely that a number of households in the model would find it optimal to use a reverse mortgage as a means of equity extraction, however, the demand for products are small. In general, older households do not have access to the same lines of credit as they typically have small incomes and large asset positions. Consequently, financial products that allow households to access wealth stored in their home without moving out of the home (home equity release products) have become increasingly popular and the focus of a burgeoning empirical literature.

In the UK market, home equity release products are issued in small volume: between 1991 and 2011 270,000 home equity plans were created for over 55 homeowners at an average of 13,500 a year (SHIP 20th anniversary report). This represents a small fraction of the over 65 population. In the UK, home equity withdrawals typically take the form of lifetime mortgages (as with HECM which capture over 90% of the US market see Cocco and Lopes) where households receive a lump sum or line of credit today, but no repayment is due until either the house is sold or the homeowners die. As with standard forward mortgages, these products have up front fixed costs which are rolled into the principle and accrue interest. However, a key difference is that households do not pay down the debt. Consequently, the compounding of fees on the initial fixed costs and earlier interest payments leads to debts that grow over time. Cocco and Lopes document a number of UK and US differences.

There are a number of reasons demand for the product in the UK may be lower (including differences in the burden of medical expenses). Cocco and Lopes document that the average loan to value (LTV) ratio of UK products is much lower than their US counterparts (the LTV ratio is typically around 20 percentage points) and that UK products are characterized by lower up front costs, but higher interest rates. The higher rates offered in the UK are higher than both standard forward mortgage products and their US counterparts. Furthermore, in this context it is important to remember that they also apply to the lower initial fixed costs. In the US, the Federal Housing Administration (FHA) underwrites HECM products (aiming to break even on average) while this is not true in the UK. It may be that this leads to differences in the adverse selection and moral hazard behaviour of product holders (although Davidoff and Wetzel, 2014, suggest that this effect is small in the US context).

It is well documented (Davidoff et al., 2017) that the limited financial literacy of potential product users contributes to the low take up of reverse mortgage products and that those who have indirect experience through peers are more likely to use reverse mortgage products. In the UK context, two major mortgage retailers offered home equity release products between 1996 and 1998 - these products were shared appreciation schemes (where home owners are insured against falls in house prices, but own progressively less and less of the equity in their home when prices rise). The shared appreciation schemes were not subject to financial regulation and subsequently were the target of negative press coverage and a class action lawsuit. In addition to cross country differences in the financial literacy of households it may be that the spillover effects of exposure are different.

This appendix documents differences between the UK and US demand for reverse mortgages and their institutional context as well as suggesting some potential explanations. However, as with all financial products the product offered will reflect demand and these cross country differences. See Cocco and Lopes for an overview.

I Activities of Daily Living

In each wave of ELSA each household member is asked to whether they have any difficulties with Activities of Daily Living (ADL). They are asked about difficulties in six different categories of activities:

1. difficulty dressing, including putting on shoes and socks

2. difficulty walking across a room

3. difficulty bathing or showering
4. difficulty eating, such as cutting up food
5. difficulty getting in and out of bed
6. difficulty using the toilet, including getting up or down

Individual's may interpret these questions differently, but they are intended to capture the minimum range of daily activities typically performed by the adult population. As such, they are proxies for an individual's ability to live independently. ELSA also asks individual's about a further set of Instrumental Activities of Daily Living (IADL), including managing money and preparing meals among others, that are further proxies of an individual's ability to live alone. Both ADLs and IADLs are hierarchical, for example the last remaining ADL is typically eating, and are correlated with each other. I use experiencing two difficulties with ADLs as a threshold because this captures both mortality and medical expenditure effects (See Ameriks et al., 2018; Robinson, 1996) in a parsimonious manner.

An alternative approach is to combine these measures with further information on health conditions and health behaviours to build a frailty index (This is the approach pursued in Braun et al., 2019) as a unidimensional proxy for underlying health. There are three reasons I do not use a frailty index approach. First, both ADLs and self reported health status are inputs into standard frailty indexes and highly correlated with additional components. Consequently, the distribution of frailty indexes conditional on the parsimonious three state health status show little overlap in their distributions (they do not formally first order stochastically dominate one another). The second important reason for using an ADL based approach is that the standard inputs used in constructing frailty indices, see Searle et al. (2008) for example, are not available in all waves. Data on some comorbidities and features of physical health are collected in ELSA by nurse visits and only available in waves 2, 4 and 6. Similarly, health behaviours are missing from some waves and information about particular conditions differs across waves. This makes constructing both a time and epidemiological consistent frailty index problematic. Finally, Using a frailty index would introduce an exogenous, stochastic and continuous state variable. Accurately capturing the dynamics of frailty within a parsimonious state space is an interesting research question within itself and any attempt to discretize the frailty state space requires imposing potentially ad hoc thresholds. It is the author's belief that using an established ADL measure in this context captures the benefits of a more complicated health model while maintaining both tractability and transparency without exceeding the limits of the data.

J Computing the Bequest Share

As discussed in Section 7, it is common to report the marginal propensity to consume out of final period wealth and threshold levels of annuity consumption above which households have a positive marginal propensity to bequeath. In order to facilitate this comparison I compute the solution to the following static allocation problem for a single renter:

$$\max_{c,h^r} u(c,h^r) + \beta\phi(b) \tag{25}$$

$$\text{s.t.}$$

$$c + r^h p_h h^r + b = x \tag{26}$$

To simplify the discussion, I solve the problem expressed in terms of expenditures, e, under unit house prices. The indirect utility function is given by:

$$u^e(e) = \frac{e^{1-\gamma}}{1-\gamma} \times \left[\sigma^\sigma \Big(\frac{1-\sigma}{r^h}\Big)^{1-\sigma}\right]^{1-\gamma} = \frac{e^{1-\gamma}}{1-\gamma} \times \bar{u} \tag{27}$$

And the following maximisation problem defines the allocation between within period expenditures and bequests:

$$\max_{e \leq x} u^e(e) + \beta\phi(x-e) \tag{28}$$

The solution to this static allocation problem, where a single household knows they will die with certainty next period and faces no medical expenses, characterises the marginal propensity to bequeath and the threshold level of annuity consumption above which bequests are operative.

The first order condition for an interior solution equates marginal utility of expenditure today with the discounted marginal utility of leaving a bequest. Using the budget constraint and the first order condition delivers the following expression for the marginal propensity to expend at an interior solution:[14]

$$MPE = \frac{\bar{\phi}}{1+\bar{\phi}} \quad \text{where} \quad \bar{\phi} = \Big(\frac{\beta\phi_1}{\bar{u}}\Big)^{-\frac{1}{\gamma}} \tag{29}$$

[14] Alternatively, (e.g. De Nardi et al., 2010) this is reported as

$$MPE = \frac{1}{1+\tilde{\phi}} \quad \text{where} \quad \tilde{\phi} = \bar{\phi}^{-1}$$

	$\bar{y}$	λ_y	τ_y	R^2
Singles	556	99.1	0.468	0.90
	(737)	(24.8)	(.0213)	
Couples	5,083	7.62	0.213	0.927
	(819)	(2.32)	(0.0262)	

Table A.8: Tax Function Parameter Estimates

The threshold value of final period wealth above which bequest motives become operative (or the annuity value of consumption) is given by:

$$c_{beq} = \bar{\phi} \times \phi_2 \tag{30}$$

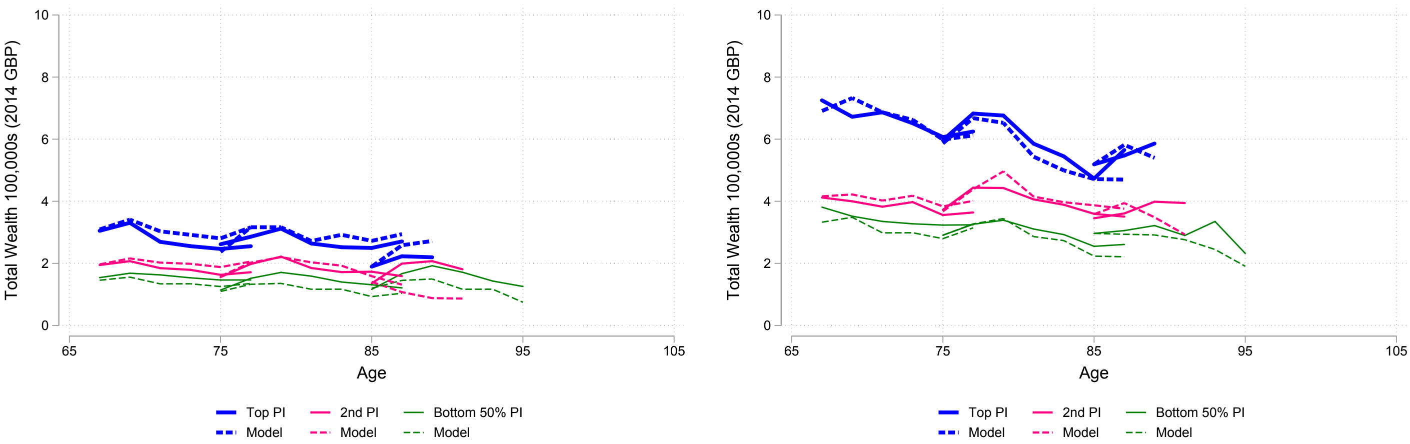
Finally, to generate the results in Figure 11 the author must take a stand on how to bring their differing frameworks in line with the model estimated in this paper. This is requires two assumptions. First, I assume that (in line with the model in this paper) bequest utility is discounted by the time preference β and liquid assets do not earn a return when the value of consolidated wealth that enters bequest utility is calculated. Second, of the papers from the related literature presented in Figure 11, only Nakajima and Telyukova (2018) estimate a model with housing. Consequently, for all other papers I use the non-housing share of consumption from the baseline estimates to calculate $\bar{u}$ while continuing to use their own estimate of the coefficient of relative risk aversion, γ. These assumptions generate minor differences between the MPC reported in a given study and the MPE used in this paper, but do not change any of the qualitative implications for the strength of the bequest motives estimated here when compared to other estimates in the literature. The final step adjusts the curvature of the bequest motive to homogenize the studies for a 2014 price level.

K Additional Estimation Details

K.1 The Income Tax Function

$$\tilde{y} = \bar{y} + \lambda_y y^{1-\tau_y}$$

I combine data from TAXBEN, a microsimulation model of the UK tax and benefit system (for further details see Waters, 2017), with individual household data for my ELSA sample in order to estimate the tax function. The tax function includes both taxes and benefits including those that are means tested, for example pension credit, and provided to all older household, such as winter fuel allowance (which motivates the inclusion of an additional constant in after tax income).



(a) 25th Percentile (b) 75th Percentile

Figure A.9: Model Fit - Total Wealth Profiles (Initial Owners)

K.2 Model Fit for Untargeted Moments

I present the model fit for two additional sets of moments that were not included in the estimator. This form of out validation is common in exercises that estimate structural models.

These results are presented in Figure A.9. I choose the 25th percentile and 75th percentile of total wealth holdings amongst initial owners to demonstrate that the model matches within PI heterogeneity.[15] The cross-sectional distribution of households is important ingredient in determining the quantitative implications of the model. The model is able to capture differences across the conditional wealth distribution and captures higher order moments of the wealth distribution well despite not being constrained to match these moments.

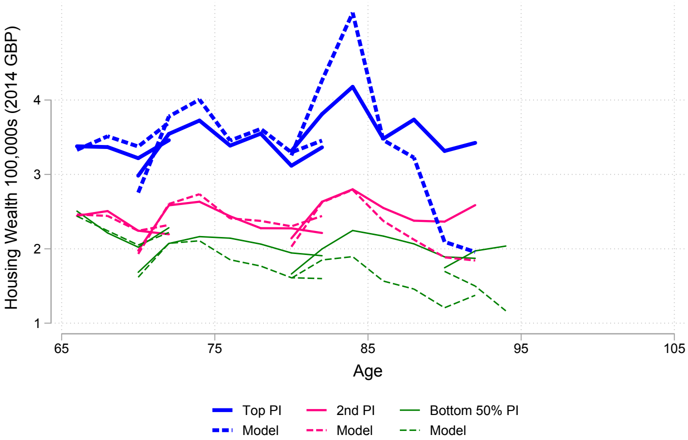
K.3 Model Fit for Alternative Birth Cohorts

Figures A.10 - A.12 display the corresponding data and simulated moments for the alternative set of birth cohorts not included in 8 - 10.

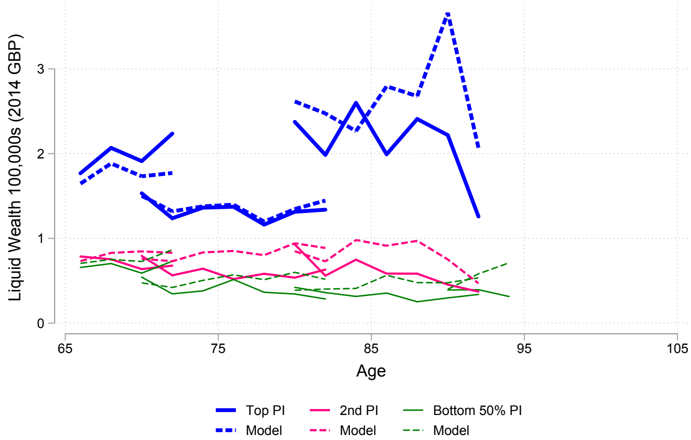
The model produces a similar level of fit to the wealth holdings as for the cohorts presented in the main text and captures the same features of the data. The model is unable to correctly match the liquid wealth and housing wealth holdings of the second oldest cohort in their early 90s. However, these two data moments are imprecisely estimated due to volatility in the reported wealth of the richest households. Under alternative sample selection the model does not exhibit this divergence from the data.

As with the other birth cohorts the model generates a moving rate that is higher than the observed moving rate. For the youngest cohorts this moving rate is closer than

[15] I have already that the model matches well the relative portfolio shares of households

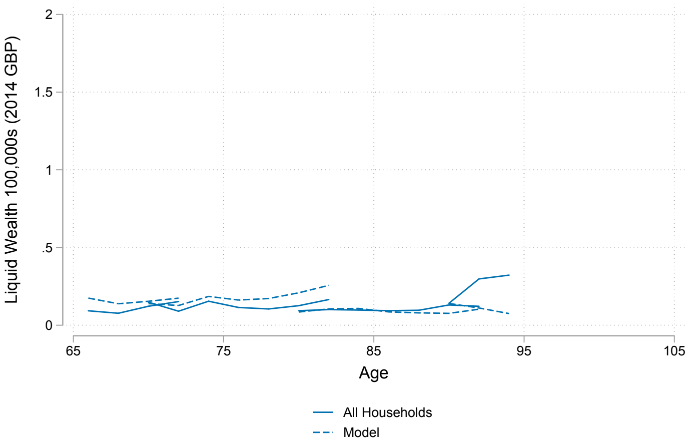


(a) Mean Housing Wealth

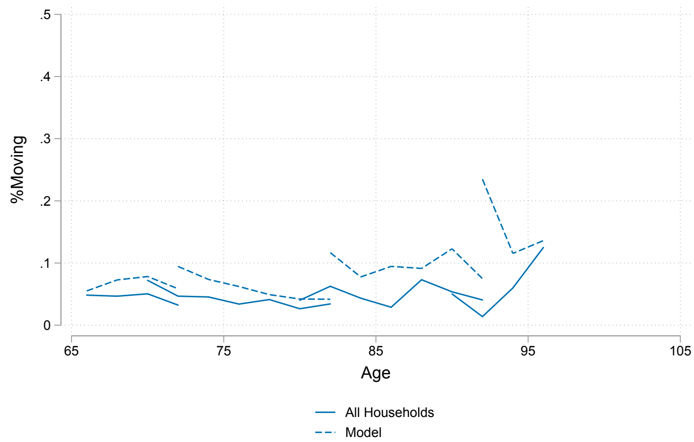


(b) Mean Liquid Wealth

Figure A.10: Model Fit - Wealth Profiles (Initial Owners)

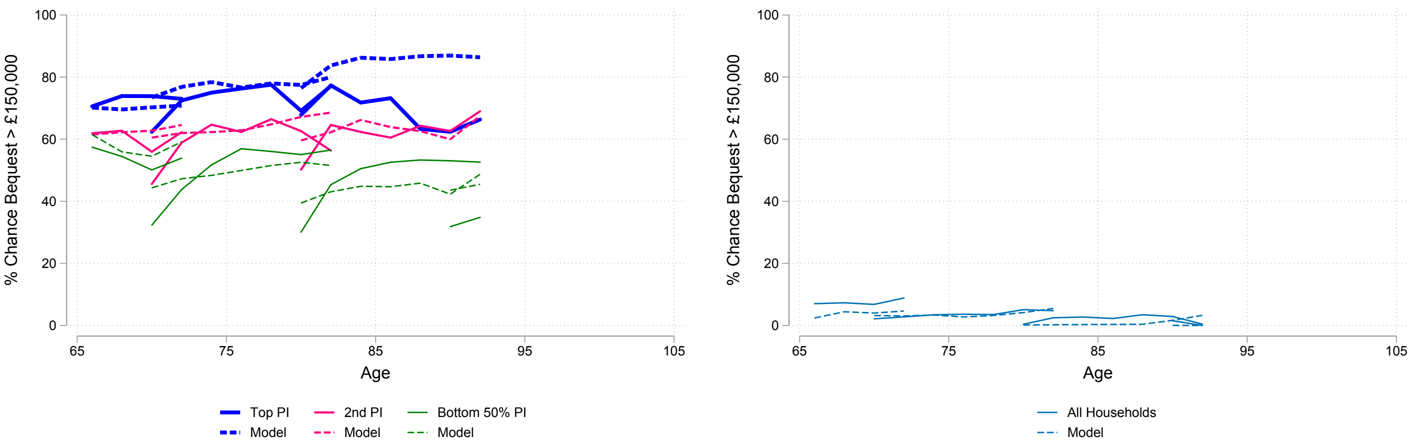


(a) Mean Liquid Wealth (Initial Renters)



(b) Moves in the last 2 years

Figure A.11: Model Fit - Home Moving Rates and Renters



(a) Initial Owners

(b) Initial Renters

Figure A.12: Model Fit - Subjective Bequest Probabilities

other birth cohorts, but for the oldest cohort the model struggles to replicate the high levels at age 95 without generating large deviations from the data at earlier ages. Again, due to the smaller number of households sampled at these ages these moments are more imprecisely estimated in the data.

Finally, figure A.12 plots the data and simulated profiles for the subjective bequest probabilities. The results for these moments are very similar to the results presented in the main text.

	Band around cut-off				
Order of polynomial	10%	15%	20%	25%	30%
Data					
Linear	-0.0445**	-0.0475***	-0.0207*	-0.0200*	-0.0250**
	(0.0181)	(0.0160)	(0.0114)	(0.0116)	(0.0110)
Quadratic	-0.0365	-0.0450**	-0.0270**	-0.0218*	-0.0265**
	(0.0241)	(0.0193)	(0.0133)	(0.0130)	(0.0112)
N	1224	1559	3023	3233	3979
Model					
Linear	-0.0737	-0.0556	-0.0491	-0.0568	-0.0578
Quadratic	-0.0785	-0.0570	-0.0441	-0.0563	-0.0578

All regressions additionally control for wave fixed effects, a polynomial in age, household demographics, a polynomial in permanent income and region dummies. Following Kolesár and Rothe (2018), Standard Errors are clustered by household. * $p < 0.10$, ** $p < 0.5$, *** $p < 0.01$

Table A.12: The Effect of Transaction Taxes on Household Mobility: Model and Data

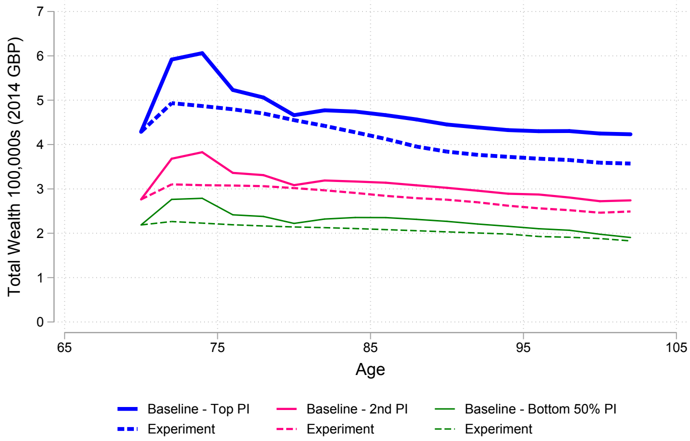


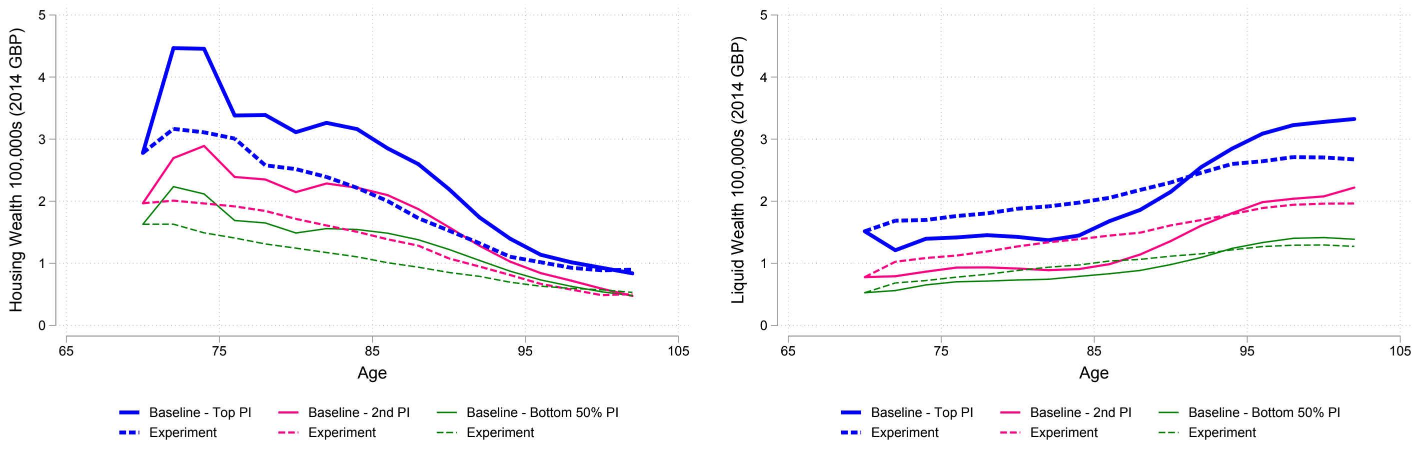
Figure A.13: Experiment A1- Total Wealth

L Decomposing Savings Motives

To determine the quantitative importance of different savings motives, I use the estimated parameters and change one feature of the model at a time. For each of these different environments, I compute the new household policy functions, simulate the model and compare the resulting asset accumulation profiles to the asset profiles generated by the baseline model. I display asset profiles for households who are age 68 in the first wave of ELSA. Throughout, I focus on the wealth of initial homeowners because the wealth of renters is negligible.

First, I fix house prices at their 2002 level as in the main text, but also change household expectations. In this counter-factual, households now know that there are no returns on housing and that houses bear no risk. Figure A.13 plots the simulate profiles of total wealth for initial owners. Compared to the wealth profiles in the baseline simulated economy, total household wealth decrease at all ages. The effect is largest at younger ages where the baseline profiles include the rapid house price appreciation of the early 2000s, but also has effects at older ages. Relative to the experiment holding prices constant in the main text, there are even larger cross sectional differences with much of the effect on total wealth concentrated at the top of the permanent income distribution. Figure A.14 breaks the total wealth into its two components.

Housing wealth decreases when house prices are held constant. The left panel shows housing wealth. There is a large reduction in the housing wealth held by households due to the mechanical effect of eliminating house prices as well as the behavioural response as simulated households re optimize. The right panel shows the corresponding effect on their liquid wealth. For the top 50% of lifetime incomes, liquid wealth increases for much of their retirement which dampens the overall deccumulation of wealth. Households continue to maintain large levels of wealth as buffers against future shocks and substitute from consumption to saving in order to offset the wealth effect of decreased house prices.



(a) Mean Housing Wealth

(b) Mean Liquid Wealth

Figure A.14: Experiment A1- Portfolio

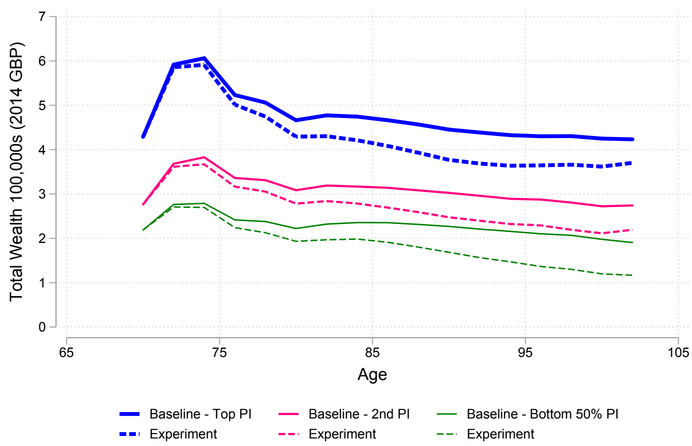
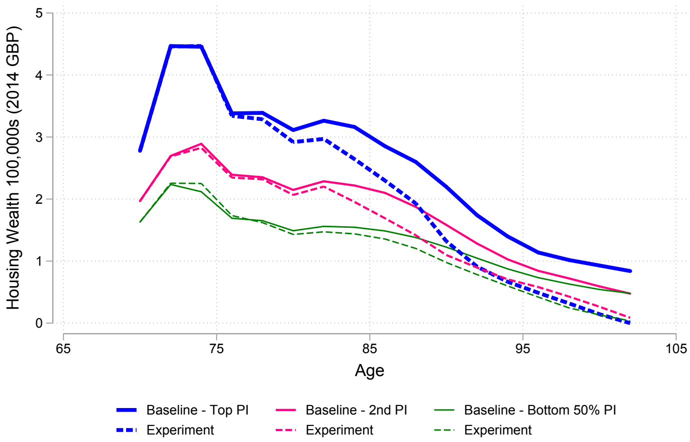


Figure A.15: Experiment A2- Total Wealth

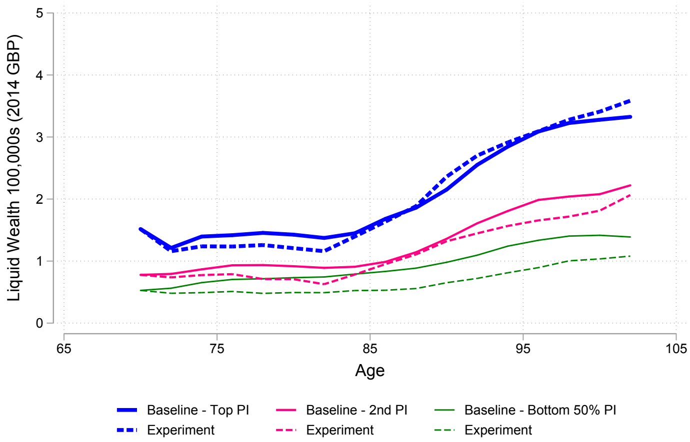
Averaged across the households' remaining life span liquid wealth balances increase due to the effect on high PI households at younger ages (17%) while housing wealth declines (15%). Relative to the baseline, when households don't experience periods of house price appreciation, they reduce the frequency with which they move home (by 18%). This transmits into lower consumption by the household and smaller bequests

In the next experiment I eliminate both bequest motives and their heterogeneity. As the estimated bequest motive for the Type 1 household is close to zero across the support of Type 1 wealth this is approximately equivalent to giving every household they Type 1 bequest motive. Figure A.15, shows that the difference in total wealth between the experiment and the baseline is small (9%) , however, for survivors this grows with age. The effect on total wealth obscures the effect of bequest motives on household portfolios.

Eliminating bequest motives has a large effect on the composition of household assets and the extent of this effect varies with age. For older households, eliminating the bequest



(a) Mean Housing Wealth



(b) Mean Liquid Wealth

Figure A.16: Experiment A2- Portfolio

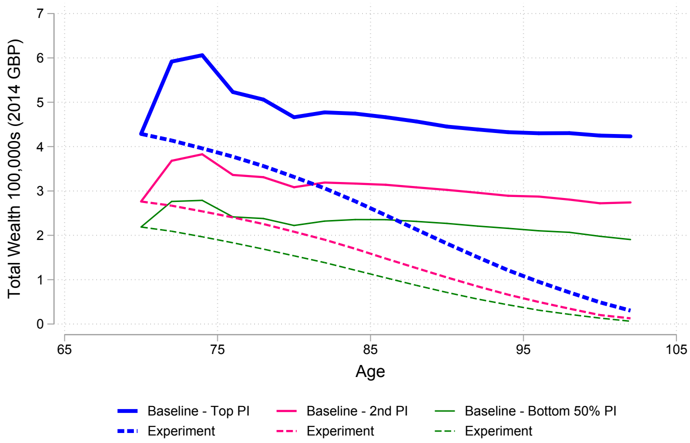


Figure A.17: Experiment A3- Total Wealth

motive makes saving in a house less attractive. However, they still face substantial costs to adjusting their housing wealth and consuming more today. The size of these adjustment costs means that there is an effect on both the intensive and extensive margins. Those who move home in the baseline economy release more equity and especially those who move at older ages.

Next, I look at the interaction of housing and bequest motives. To understand the interaction of these saving motives, I return to the second experiment in the main text which eliminated the housing asset and additionally eliminate bequest motives. This is shown in figure A.17.

As with the previous experiment eliminating housing, the wealth trajectory in retirement is very different from the baseline economy. Eliminating bequest motives has a small effect on the profile of this wealth deccumulation during early retirement, but a large effect for the oldest households. Under this experiment, the wealth of those who

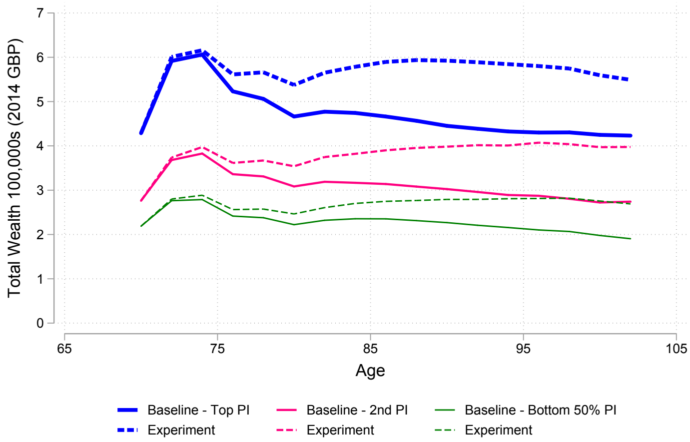


Figure A.18: Experiment A4- Total Wealth

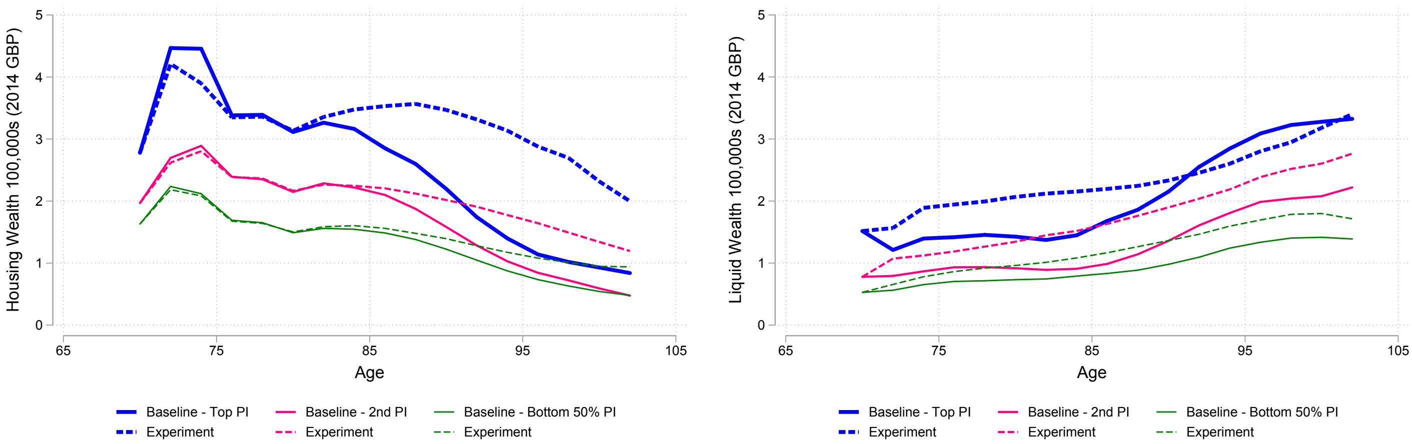
survive to age 100 is approximately 75% lower for the richest households who have the largest bequest motives, while for lower PI groups the effect is closer to 60%. Because these differences grow with age the average reduction in total wealth during the whole retirement period is 20% lower when compared with the experiment where only housing is eliminated. In contrast, the average reduction in bequests between the two experiments is close to 50%.

Taken together, these results suggest that bequest motives interact with the portfolio choices of households. Housing has a larger effect on wealth in retirement, but bequest motives are still important and have a large effect on how households allocate their wealth across different asset classes as they age as well as the wealth holdings of households in the absence of this portfolio choice.

In addition to eliminating bequest motives I now show how large the effect of increasing bequest motives is by endowing each household with the strongest estimated bequest motives. This has a large effect on wealth holdings increasing average wealth for those who survive to age 96 by over £100,000 or over 40% of wealth in the baseline economy.

In this counter-factual, households retain higher levels of housing wealth. For older households, eliminating the bequest motive makes saving in a house more attractive and paying the adjustment costs to capture trapped equity even less attractive. There is a decline on both the intensive and extensive margins of housing adjustment. However, increasing bequest motives also has a large effect on their liquid wealth savings even as they release less equity from their home. Relative to bequests lifetime consumption is less attractive and households increase their savings in all forms of wealth which they finance by decreasing their lifetime consumption.

As in Lockwood (2018), bequest motives are important for households portfolio choice (in Lockwood - the decision over LTC insurance products), however, here the effect on total wealth is stronger. The role of heterogeneous bequest motives is also highlighted in



(a) Mean Housing Wealth

(b) Mean Liquid Wealth

Figure A.19: Experiment A4- Portfolio

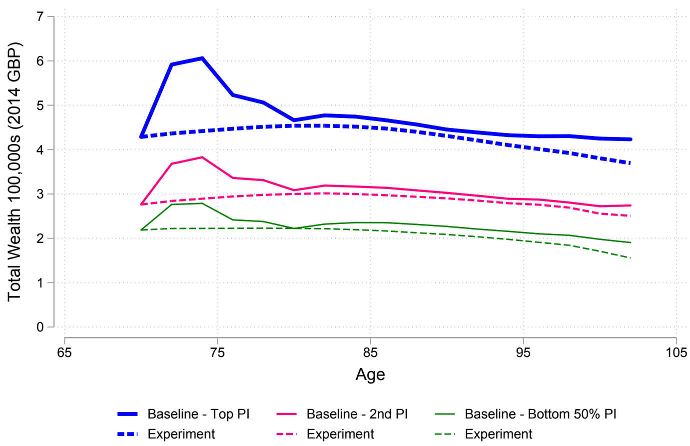


Figure A.20: Experiment A5- Total Wealth

this experiment- the effect of eliminating or increasing bequest motives varies with the level of household permanent income and the level of wealth. The intensity of bequest motives also varies along these dimensions and experiment 3 highlights that effect of bequests is not homogeneous.

Finally, I look at the interaction of housing and bequest motives. To understand the interaction of these saving motives, I return to the second experiment which eliminated the housing asset and additionally eliminate bequest motives. This is shown in figure A.20.

This single asset version of the model misses the cyclical role of house prices in total wealth, but is able to reproduce near identical levels of wealth. This shows that one of the advantages of accurately modelling housing is to eliminate one potentially large source of bias in estimating bequest motives. Without housing the model would require a substantially larger role for bequests or precautionary savings motives.

	Ratio Relative to Benchmark Model							
	Total Wealth	At Age 96	Housing Wealth	Liquid Wealth	Cons	Bequests	Home Moves	Δ Home Value
Two Asset Model								
2002 Prices	0.893	0.859	0.880	0.926	0.962	0.899	0.776	0.879
2002 Prices & No Uncertainty	0.899	0.886	0.762	1.167	0.938	0.920	0.826	1.415
No Bequests	0.905	0.791	0.920	0.873	1.063	0.837	1.461	1.177
Max Bequests	1.160	1.406	1.081	1.315	0.860	1.298	0.623	0.693
One Asset Model								
Base	0.724	0.429	0.000	2.074	1.593	0.619	n/a	n/a
No Bequests	0.606	0.128	0.000	1.735	1.730	0.396	n/a	n/a
Max Bequests	0.922	0.946	0.000	2.639	1.357	1.004	n/a	n/a

Table A.20: Contribution of Alternative Model Mechanisms to Aggregate decisions

	Change Relative to Benchmark	
	Total Wealth	At Age 96
Two Asset Model		
2002 Prices	-28,175	-35,611
2002 Prices & No Uncertainty	-26,479	-28,944
No Bequests	-24,988	-53,046
Max Bequests	41,969	102,880
One Asset Model		
Base	-72,314	-144,657
No Bequests	-103,395	-220,857
Max Bequests	-20,538	-13,807

Table A.20: Contribution of Alternative Model Mechanisms to Aggregate decisions

Shock		Marginal Propensity to Consume	Marginal Propensity to Bequeath
Income	Type 1	0.295	0.526
	Type 2	0.294	0.526
	Type 3	0.274	0.566
	Type 4	0.076	0.785
	Type 5	0.043	0.838
House Price	Type 1	0.023	0.413
	Type 2	0.023	0.413
	Type 3	0.023	0.425
	Type 4	0.028	0.359
	Type 5	0.025	0.339

Simulated responses for a single birth cohort to a one-time 10% increase in income and a one-time 10% increase in house prices. In both simulations the shock arrives at age 70 and the MPC is measured contemporaneously. Preference parameters for each type are taken from the estimation results above. In order to separate the role of preferences the correlation between preference type and initial conditions is set to 0.

Table A.20: Household Responses to Unanticipated Shocks by Preference Type

Tables A.20 summarizes these results and shows how key economic aggregates change for this cohort of retirees. These are displayed as shares relative to the baseline economy (the solid lines in each graph). Additional results are provided in Table A.20 which summarizes the average deviation in total wealth across the whole retirement period and for those who survive to age 96. This is provided in levels.

M Additional responses to unanticipated shocks

In this appendix, I show additional results for the household responses to unanticipated shocks discussed in Section 7.3 of the main text.

I begin by expanding on Table 11 by also including the results for House Prices in Table A.20.

Focussing on the variation in MPCs and MPBs to the house price shock across preference type reveals a very different picture. The obvious correlation in the case of the income shock has all but disappeared. The differences in the MPB out of a house price shock by preference type are smaller than in the case of the income shock because of the importance of the interaction between housing and bequests - bequests dampen household incentives to adjust portfolios. However, the sign of the MPB with respect to the strength of the Bequest motive is less clear.

Shock		Marginal Propensity to Consume	Marginal Propensity to Bequeath
Income	Type 1	0.177	0.758
	Type 2	0.468	0.673
	Type 3	0.195	0.363
	Type 4	0.069	0.721
	Type 5	0.074	0.972
House Price	Type 1	0.061	0.307
	Type 2	0.028	0.392
	Type 3	0.0125	0.469
	Type 4	0.012	0.352
	Type 5	0.025	0.396

Simulated responses for a single birth cohort to a one-time 10% increase in income and a one-time 10% increase in house prices. In both simulations the shock arrives at age 70 and the MPC is measured contemporaneously. Preference parameters for each type are taken from the estimation results above.

Table A.20: Household Responses to Unanticipated Shocks by Preference Type and Heterogeneity in Initial Conditions

Household decision rules feature regions of inaction[16] and when households have operative bequest motives this shrinks the regions for which they find it optimal to move. When house prices appreciate and the returns to downsizing increase for households, those who are less likely to move in the baseline (these Type 4 and 5 households) may have a larger extensive margin effect due to the combination of shock size and preference parameters. This generates the non-monotonic response by preference types because more households cross the boundary of their inaction region on the housing adjustment margin. Extensive inspection reveals that this non-monotonicity is not a general feature of the model and only occurs for particular parameter values and thus it is not emphasized in the main text as the intuition is similar to the difference in the aggregate response to house prices and income shocks. However, this is instructive in that it highlights the potential for asymmetric responses to these shocks that arise from non-linearities in household decision rules.

To elaborate on the interaction between these shocks and individual heterogeneity, I reintroduce the correlation between preference type and initial conditions. These results are documented in Table A.20.

These results highlight that households with the same preferences such as Types 1 and 2 (or close to in the case of Types 3 and 4) behave very differently when differences in their

[16](S,s) policy rules are common in applications with durable goods, such as housing

distribution of initial state variables are accounted for. Indeed, the non-monotonicity is now also present in the household response to income shocks. The model estimated in this paper has rich household level heterogeneity which generates policy rules that are non-linear in multiple dimensions. As highlighted by Kaplan and Violante (2014) and Attanasio (2000) the combination of non-linear decision rules and idiosyncratic shocks can generate varied properties for aggregate dynamics.

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