ARC Centre of Excellence in Population Ageing Research

Working Paper 2024/19

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Housing and Pensions: Complements or Substitutes in the Portfolio Allocation?*

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Abstract

We study the relation between retirement savings and housing using a life cycle model of consumption and portfolio choice with risky earnings, lumpy housing with collateralized borrowing, and financial assets inside and outside pension plans. We consistently find complementarity from pensions to housing, and substitutability in reverse. The mechanism behind this asymmetry, and especially how it unfolds across genders, stems from behavioral and housing frictions that jointly drive the timing of savings: incentivizing pension savings boosts homeownership in anticipation of a prosperous retirement, while more attractive housing absorbs pension investments. Decomposing the gender differential in lifetime savings, we show that earnings inequality and preferences drive 64.2% of the wealth gap, behavioral frictions explain another 33.5%, and housing adjustment costs, that affect males and females differently, account for the rest.

Keywords: life cycle savings, portfolio choice, pensions, housing, method of moments.
JEL Classification: H8, J26, J32.

* We are grateful to Servaas van Bilsen, Elena Capatina, Chris Carroll, James Choi, Dimitris Christelis, Uwe Dulleck, Lucas Hack, Joachim Inkmann, Fedor Iskhakov, Mike Keane, Alberto Motta, Ben Moll, Olivia S. Mitchell, Gonzalo Paz Pardo, Robert Salomone, John Stachurski, Serena Trucchi and participants at numerous conferences and workshops for helpful comments and suggestions. We also thank UniSuper staff for data access, and Sophie Yan and Andrew Wu for excellent research assistance. Research support from the Australian Research Council (ARC) LP150100608/LP190100732, and ARC Centre of Excellence in Population Ageing Research CE17010005 is gratefully acknowledged. This research was undertaken with the assistance of resources and services from the National Computational Infrastructure (NCI), which is supported by the Australian Government.

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1 Introduction

The study of why people save and how they allocate these savings across different assets has long been central to economics and finance (Gomes et al., 2021). Two pivotal asset allocations were shown to substantially impact the quality of old-age provision (Le Blanc et al., 2018). First, private retirement plans provide an important income supplement to statutory pensions (Ahmed et al., 2018, Gomes et al., 2020). Second, housing can deliver consistent shelter services while simultaneously building wealth that may be liquidated later in life (Flavin and Yamashita, 2011; Kraft et al., 2018). Although retirement savings and housing dominate people's balance sheets, a clear understanding of the life cycle interplay between these assets is lacking. In particular, we are yet to determine whether they function more as complements or substitutes (Eckardt et al., 2018), and in what circumstances.

Our paper fills this gap by directly investigating the dynamic relation between retirement savings and housing over the lifetime. To do so, we first build and estimate a structural life cycle model of optimal consumption and portfolio choice, with frictions and investments in housing, and financial assets inside and outside pension plans. The model allows us to take a comprehensive, policy-relevant approach to complementarity and substitution, examining how exogenous changes affecting one asset (caused by shifts in plan architecture or market conditions) impact the other. The complexity of multiple behavioral frictions and endogenous liquidity constraints challenges, however, traditional model solution methods (Dixit, 1992; Khan and Thomas, 2008; McKay and Wieland, 2022). We thus use the endogenous grid method (EGM, Carroll, 2006) with a novel rooftop cut approach (RFC, Dobrescu and Shanker, 2024) to solve our model, and estimate it via simulated method of moments (SMM) applied to granular data from an industry-wide retirement plan. Finally, using counterfactual experiments, we measure the lifetime consequences of changes to incentives to save. Each experiment simulates changes in either pension plans or housing conditions, showing both direct and cross-asset effects.

The life cycle setup we start with is standard: we model working individuals who earn stochastic labor income, and who consume and save to maximize expected lifetime utility. We extend this standard setup in several directions to pin down our research question. Individuals can either rent, or buy a house by taking a mortgage. When individuals adjust their housing stock, they incur non-convex costs that cause adjustments to be infrequent and lumpy. Pension wealth is determined in a rich setting that combines compulsory enrolment of new hires with reversible and (time-sensitive) irreversible plan defaults. Upon being hired, individuals are automatically defaulted in a defined benefit (DB) plan and, within the first year, they have a one-off irreversible option to switch to defined contribution (DC). Each period, plan participants can also decide to (i) voluntarily contribute (adding to mandatory employer contributions) and override a 0% default voluntary contribution rate, and (ii) opt out of the default balanced asset allocation and choose a different share of pension wealth to invest in risky assets. To switch out of plan defaults, participants must acquire information, implement the changes, and, if they make voluntary contributions, forgo the liquidity of saving outside the plan. The complications of opting out result in behavioral frictions. Finally, we include stochastic discount rates and housing preferences to account for preference heterogeneity that can potentially affect the wealth distribution and homeownership profiles.

Our setup addresses several challenges associated with estimating life cycle models. First, our rich panel data, drawn from a large number of plan participants that enter our sample at different ages, have different job tenures, and face exogenous house prices and stock returns that match those of their cohort, allows us to disentangle the age, cohort and time effects in savings (Ameriks and Zeldes, 2004). Second, we mitigate the potential measurement errors of survey data (Kapteyn and Ypma, 2007) by matching survey responses with granular data from administrative records. Third, we bypass the issue of low stock market participation (Bertaut and Starr-McCluer, 2002; Cocco, 2005; Lynch and Tan, 2011) by considering the portfolio allocations held by all plan participants, and accounting for non-choices via plan defaults. Fourth, by modeling pension plan choices jointly with financial savings and homeownership decisions that are costly to adjust, we gain insights not only into overall savings patterns but also into the associated trade-offs between allocations to the main asset classes in one's portfolio.

Preliminary reduced form analysis confirms that, while pension wealth is relatively high in our sample, females have lower balances than males, and also invest slightly more aggressively, possibly aiming to close the gap. We also see people, especially females, becoming homeowners relatively early in their working lives and holding higher housing wealth as they get older. High earners diversify their portfolios more than lower earners, and the rich hold a higher share of wealth in housing than those less rich.

Our structural analysis yields model-simulated savings patterns that are well-matched with the empirical ones, and show rising age profiles for all types of wealth and voluntary pension contributions, as well as highly persistent plan defaults. As in the real data, our simulated females save less overall due to significantly lower pension balances despite investing them more aggressively, and also investing relatively more in housing, compared to males. Fundamental to these differences is the way individuals save during their working lives. To examine the differences, we conduct counterfactual scenarios showing how alternative reforms or changes in market conditions impact portfolio allocations. The novel finding is that reforms or changes that encourage pension savings simultaneously encourage housing investments. Hence, we find a complementary relation from pensions to housing. The opposite is not true, however: reforms or changes that make housing investment more profitable also make people substitute away from pension savings into housing. These findings are remarkably consistent, being robust to differences in earnings and preferences.

The key factors that determine the asymmetry of the housing-pensions relation are the behavioral frictions in retirement choices that drive complementarity, and the housing adjustment costs that drive substitutability. These factors also contribute significantly to generating the gender wealth gap we observe. Indeed, our counterfactuals show that while changes in earnings dynamics can explain a substantial 57.53% of the wealth inequality across genders, behavioral frictions further account for 33.51% of the gender gap in total wealth. Additionally, differences in willingness to take risks (and hence asset returns) and bequest motives only contribute 5.63% and 1.01%, respectively to the wealth inequality between males and females. Finally, shutting down housing frictions completely eliminates the remaining gap.

To the best of our knowledge, this work is the first to explore whether housing and pensions are complements or substitutes for each other, and the associated implications for the gender gap in wealth. Our modeling framework aligns with recent structural dynamic studies with housing frictions (Kaplan et al., 2020; Michaud and St Armour, 2023). We extend these models by incorporating pension plan choices and defaults, alongside housing decisions, and portfolio allocations across safe and risky assets. In doing so, we also contribute to the broader life cycle theory, from Ando and Modigliani (1963) and Kotlikoff and Summers (1981) to Ameriks et al. (2011), which studies the drivers behind the typical 'hump-shaped' pattern of asset accumulation and the increasing importance of consumption smoothing during mid to later years (Gourinchas and Parker, 2002). As a result, our findings are also consistent with those in studies of housing dynamics that examine the role of adjustment costs in prompting early housing accumulation (Yang, 2009; Bajari et al., 2010) at the expense of other consumption, slower housing adjustment, and decumulation in older age (Cocco, 2005; Chetty et al., 2017; Fagereng et al., 2021), or driving the housing market's response to monetary policy (McKay and Wieland, 2022). We also extend the literature that examines how pension architecture impacts portfolio choices. Depending on their type, pension plans expose people to varying degrees of investment risk, and often include 'hard' or 'soft' defaults that affect saving behavior. These defaults can influence not only contribution rates (Choi et al., 2004; Beshears et al., 2009) and the type of plan one chooses (Madrian and Shea, 2001; Carroll et al., 2009; Goda and Manchester, 2013), but also the balance of risky versus safe financial assets, and the take up of annuities (Edwards, 2008; Horneff et al., 2009; Inkmann et al., 2011; Dahlquist et al., 2018), especially with uncertain earnings (Polkovnichenko, 2007). Importantly, defaults can influence behavior in a remarkably different way for males than for females (Joubert and Todd, 2022).

The paper proceeds in Sections 2 and 3 to describe the institutional context, our data, and the reduced form results. Section 4 presents the model, and Section 5 shows the calibration and estimation method. Structural results, the mechanisms behind the asymmetric relation between pensions and housing, and the decomposition of the associated gender gap in wealth are discussed in Section 6. Section 7 concludes.

2 Institutional context

We study the behavior of UniSuper plan participants. UniSuper is an industry-wide pension plan covering all Australians employed in the higher education and research sector. With roughly 500,000 participants and $103 billion in assets, it is the country's fourth largest pension plan. During data collection (i.e., 2010-2014), it exhibited several interesting features that enrich our setup and allow us to pin down the relation between housing and pensions. First, it was, and continues to be, one of the few remaining plans offering access to either DB or DC pensions depending on participants' employment type, earnings, and workplace agreements. Second, upon becoming a sector employee, plan enrolment was automatic and compulsory. Third, UniSuper set highly consequential defaults on plan type, contributions and investments for participants who did not make active choices; some defaults were irreversible, while others were not.

Table A.1 summarizes the main UniSuper plan features for permanent staff, that is for staff on continuing tenured contracts or contracts running for two or more years. On starting their jobs, UniSuper defaulted employees into a DB plan and then offered a one-off, irreversible choice to transition to DC within one year. Participants also started receiving employer contributions amounting to 17% of their earnings and could themselves contribute a further percentage of (post-tax) earnings as standard and/or voluntary contributions. The default standard contribution rate was 7%, irreversibly reducible down to

0%. The default voluntary contribution rate was 0%, and unlike the standard rate, this could be varied (regularly or irregularly) at any time. Finally, participants could allocate their DC account wealth into 15 investment options that differed in terms of risk and expected returns. Movement between options was possible, the default being a *balanced* portfolio with a 70:30 split between growth and defensive assets.

DC plan participants held their pension wealth entirely in DC accounts, while DB participants had both a DB and a DC account. DC balances, and final retirement benefits, depended on total (employer, standard, and voluntary) contributions and investment returns, net of taxes, fees and insurance premiums. Full DB benefits were calculated with a formula that used employer and standard employee contributions of at least 21% of earnings. Since employer contributions were 17% of earnings, the remaining 4% needed to make a 21% contribution came from employee standard contributions. This implied that (i) those with at least 4% standard contributions saw any excess over 21% (up to 7%-4% = 3%) of their employer contribution allocated to their DC account and the rest to their DB account, while (ii) those with below 4% standard contributions had all employer and standard contributions absorbed into the DB account.[1] Any voluntary contributions by DB participants went fully to their DC account, with DC balances accrued as above. Total DB plan benefits were then given by the overall entitlement across the DB and DC accounts.

Outside pension accounts, people build up considerable wealth by investing in real and financial (non-pension) assets. According to the Household, Income & Labour Dynamics in Australia (HILDA) survey,[2] the average household net worth (i.e., overall assets net of debt) was roughly $740,000 in 2014. About 57% of this net worth was housing. Notably, almost all of the (weak) growth in housing assets during 2010-2014 came from price increases rather than quantity changes. We thus see fairly stable homeownership rates at around 66%, unsurprisingly linked to earnings, wealth, and age, but also impacted by two unusual features of the local mortgage market: the existence of mortgage offset accounts and redraw options. An offset account is an at-call deposit account linked to the mortgage loan such that funds deposited into it reduce the effective outstanding loan balance (and thus the interest payable on the loan). A redraw facility allows the borrower to withdraw any excess funds they have already contributed towards their loan above the amount required by the loan contract. About 40% and 70% of total mortgages in Australia have offset

[1] Retirement and death entitlements were also reduced proportionally to the standard contribution reduction, and there was no access to income or extra life and disability insurance - see Table A.2.

[2] HILDA is a nationally representative panel study that collects comprehensive information about economic and personal wellbeing, labour dynamics and family life in Australia (Ryan and Stone, 2016).

accounts and redraw options, respectively[3] to help manage the variation in loan repayments in a mortgage market where around 80% of the loans have an adjustable (or *variable*) interest rate.

Non-housing wealth accounted for about 43% of net worth in 2014, a 4% increase compared to 2010. In contrast to housing, non-housing wealth significantly increased its average value from $320,000 in 2010 to almost $400,000 in 2014. Half of this value was held in financial wealth consisting of deposits (14%), direct equity (15%), business assets (11%), and life insurance and durable goods - e.g., motor vehicles, collectibles (10%). The other half was held in pension accounts, which made pension wealth the second largest asset in household portfolios, after housing. Interestingly, most of the 2010-2014 rise in non-housing wealth was due to pensions: account prevalence rose from 80% to 84%, and balances grew by around 4% per annum to $250,000 in 2014, largely invested in risky financial securities.

Note that our novel setting, where (i) we observe automatic enrolment into a sector-wide employer sponsored plan, (ii) enrolled participants tackle choices about plan type, contributions and investments with both reversible and irreversible default options, and (iii) opting out of defaults for each of these decisions ranges from trivially easy to very difficult (or impossible), implies broadly generalizable results.[4] Moreover, the existence of offset accounts and redraw options will allow our model to better pin down the relation between pensions and housing. With traditional mortgages, borrowers often face large penalties for additional capital repayments or payments not made on time. Offset accounts and redraw options offer borrowers the means to be able to make more active home equity decisions (jointly with pension decisions) without having to re-finance their mortgage account, effectively making mortgage balances relatively liquid. This allows people more freedom to reshuffle the assets in their portfolio, uncovering the full extent of the life cycle trade-offs between pensions and housing in a setup where wealth is less tied up and people can take advantage of suitable saving avenues when these exist. Finally, offset mortgages have recently gained tremendous popularity in the U.S. too where lenders offer similar products called all-in-one mortgages or money merge accounts, and are commonplace in the U.K. and New Zealand.

[3]Some mortgages have both an offset and redraw facility, so these figures can overlap and sum to more than 100%.

[4]Previously, only Goda and Manchester (2013) included an irreversible one-off choice between two plan types with an opt-out deadline in their structural setting. The employer they studied, however, did not allow individuals to simultaneously choose (irreversibly) their plan and (reversibly) the voluntary contributions and investment strategy within the selected plan. But their data did allow them to employ a regression discontinuity approach and tease out the causal effect of default provisions (DB or DC) for plan enrolment, while we can only estimate the effect of having DB as the default. This in turn implies that their results are valid only for ages around 45 where the policy discontinuity was active; ours are more general, covering the full life cycle.

3 Data and empirical results

We use data from UniSuper and HILDA to fit our models. UniSuper records contain extensive *individual* information on all pension choices made by a random subsample of participants. Each month, the plan also collects data on selected demographics (age, gender) and job characteristics (number of employers contributing, job tenure, annual wage), and uses it to compute pension balances. There are four sources of information about pension wealth in UniSuper, namely (i) plan type (DB or DC), (ii) employer, standard and voluntary contributions, (iii) share of pension wealth invested in risky assets across asset allocations, and (iv) cumulative pension balance (total and in DC accounts). Additionally, the plan also records whether one purchased extra life and disability insurance, as well as opted out of the default asset allocation. We have access to UniSuper data for 2010 and 2014, and restrict our sample to non-retirees.

Since UniSuper collects limited background information, we supplement the data available in our administrative records with information from the 2010 and 2014 HILDA, respectively. To do so, we follow Dobrescu et al. (2018): after selecting the relevant HILDA subsample on higher education and research sector employees, we use an iterative approach that matches UniSuper and HILDA individuals along the other nine dimensions common to both datasets: age, gender, type of work contract, wage and tenure quintiles, plan type, pension balance quintiles, and personal and spouse contributions. For the unmatched observations, the procedure then drops the last dimension and re-attempts the matching. We further employ this process three additional times, progressively excluding plan type, work contract, and personal contributions to bring across data on (i) non-durable consumption, (ii) financial wealth, (iii) housing (ownership, value, expenses), and (iv) marital status, household size, education, and household net worth (excl. pensions).[5] To get *individual* consumption and housing expenses, we follow Wachter and Yogo (2010) and compute these amounts using household spending and imputed individual-to-household spending ratios predicted from regressions of household consumption on age, gender, marital status, household size, health insurance premium, annual wage, net wealth, and net wealth interacted with age (see Tables B.1-B.2). *Individual* financial wealth includes personal wealth, as well as the apportioned value of the joint financial wealth based on individual-to-household bank accounts and credit card ratios. Finally, housing

[5]Matching is done under the assumption that since the UniSuper data contains the records of all the employees in the sector, every individual in HILDA is also in the UniSuper data. When multiple HILDA individuals exhibit the same UniSuper attributes along the nine matching dimensions, matching is done with a representative (median) individual. Variables (iv) are only used in reduced form analysis as controls; all results are robust to their exclusion.

captures the value of owner-occupied homes (i.e., main residence), and both financial and housing wealth are net of their respective debt.

Our final sample consists of 10,375 individuals that provide a total of 13,867 observations across the two Unisuper waves, of which 82.24% is HILDA-matched.[6] Since opting for non-default allocations might suggest different preferences or a different understanding of available options, we present relevant sample statistics overall and split between those with and without default asset allocations.

Panel A in Table 1 shows that while about 24% of participants opt for a non-default (DC) plan overall, a much lower 6% of default allocation participants do so; in contrast, roughly 51% of non-default investors have DC plans. Similarly, only about 19% (10%) of participants contribute voluntarily (buy supplementary insurance), but about a third fewer default investors do so compared to non-default ones. These differences between default and non-default allocation participants are also reflected in earnings and wealth. Panel B in Table 1 shows unsurprisingly that people in our sample have rather long tenures, generous wages, substantial pension balances, and high wealth. Interestingly, non-default allocation participants have slightly higher wages and so, accumulate higher pension balances despite investing them less aggressively (53% vs. 70% in risky assets) and having shorter tenures (11 vs. 12 years at the median) than default participants. Finally, confirming national statistics, we find an 8-to-1 ratio of real to financial wealth, household net wealth around the million dollar mark, and annual housing expenses of about $3,000.

Table 2 reports our sample demographics. We note no significant differences between our default and non-default allocation subsamples, with an average individual being around 46 years old, married, in a 3-person household, with a Bachelor degree or more.

Clearly, UniSuper participants are rather different from typical Australians: they are older (46 vs. 38 years old), much more educated (81.6% vs. 14.8% have university education), richer ($1,008,910 vs. $687,161), and earning higher wages ($87,800 vs. $45,000) than the general population. These unique characteristics make them well suited to the task of assessing asset trade-offs for at least three reasons. First, UniSuper participants are more able to save due to higher wages, and are thus more likely to engage with portfolio allocation decisions (Attanasio and DeLeire, 2002). Second, not only are they wealthier (and have more savings to allocate), they are also more highly educated, and enter the labor market (about

[6]While those matched are 0.5 years older and 8% more likely to be males, an F-test checking pension choices and balance between those matched and unmatched shows we cannot statistically reject the hypothesis that matched status is random.

Table 1. Pension and non-pension wealth characteristics

	All		Non-Default Allocation		Default Allocation	
Panel A.	% of Members	# of Members	% of Members	# of Members	% of Members	# of Members
Plan type:						
DB	76.28	3,733	49.40	949	93.64	2,784
DC	23.72	1,161	50.60	972	6.36	189
Is voluntarily contributing	19.25	942	23.43	450	16.55	492
Has supplementary insurance	9.71	475	11.24	216	8.71	259
Is homeowner	85.84	4,201	84.23	1,618	86.88	2,583
Panel B.	Mean	Median	Mean	Median	Mean	Median
Pension wealth (in $000)	246.78	134.27	235.14	138.84	254.31	130.28
Number of employers contributing	0.92	1.00	0.93	1.00	0.91	1.00
Number of years contributing	12.40	11.25	12.03	10.83	12.63	11.67
Annual wage (estimated, in $000)	87.80	78.95	89.50	81.23	86.70	77.42
(DC) share in risky assets (%)	63.25	70.00	52.79	52.01	70.01	70.00
Financial wealth (in $000)	37.70	5.12	34.41	5.12	39.82	5.12
Housing wealth (in $000)	408.36	350.00	395.43	350.00	416.71	350.00
Housing share in total wealth (%)	47.00	45.26	46.15	45.15	47.54	47.05
Housing expenses (in $)	3,056.27	650.00	3,137.35	824.71	3,003.90	650.00
Total personal net wealth (in $000)	651.96	500.00	632.53	495.73	664.51	515.75
Total household net wealth (in $000)	1,008.91	772.75	976.30	742.06	1,029.98	774.80

Notes: Panel A presents information on all sample members ("All"), as well as on members in subsamples defined by participation in the default investment allocation ("(Non-) Default Allocation"). Panel B shows mean and median for total amount accumulated in the pension account, number of employers currently contributing, years of contribution, estimated wage, share of DC balance invested in risky assets, financial and housing wealth, share of housing in total assets, housing expenses (i.e., repairs, renovations), and total net wealth (i.e., net worth excluding pension wealth). The sample consists of members from UniSuper Wave 10, containing 4,894 permanent employees. Unisuper defaults relate to pension plan type (DB), voluntary contribution rate (0%), asset allocation (70% risky assests), and supplementary insurance (no extra cover).

Table 2. Demographic characteristics

	All	Non-Default Allocation	Default Allocation
Age	45.60	44.93	46.03
Male (%)	32.47	35.50	30.51
Couple (%)	86.47	87.09	86.08
Household size	3.01	3.04	2.99
Low education (%)	8.95	7.81	9.69
Medium education (%)	9.48	9.06	9.75
High education (%)	81.57	83.13	80.56

Notes: The table presents averages for all sample members ("All"), as well as for the subsamples defined by participation in the default investment allocation ("(Non-) Default Allocation"). The sample consists of members from UniSuper Wave 10, containing 4,894 permanent employees.

5 years) later, than the general population. This means they are likely to be better at making decisions that are complex to most people and more willing to actively save for retirement, which also makes them likely to consider much more closely the saving trade-offs. We see, in fact, about 85.8% and 19.3% of 2010 UniSuper participants becoming homeowners and voluntarily contributing to their pensions, respectively compared to less than 68.0% and 7.6% outside the sector. Finally, UniSuper is one of the few remaining plans offering access to both DB and DC pensions, which allows us to gain deeper insights into pension choice stickiness. The propensity of the UniSuper sample to save while also relying on choice defaults enables us to find a sufficient number of individuals balancing active and passive decisions in a medium-sized sample. Overall, we can thus confidently predict that there would be many more decisional constraints in the general population than for UniSuper participants, which would underestimate the relation between pensions and housing due to lack of resources or opportunities to allocate rather than willingness to do so.

3.1 Empirical estimates

We start with an exploratory analysis of the factors associated with our pension and housing choices in Tables 3A-B. The outcome variables are pension plan type, voluntary contributions, pension balance and share of risky assets owned, as well as homeownership prevalence and value. Our models control for age, gender, education, marital status, household size, and overall net wealth. For education, we use two dummies denoting whether individuals have (i) university education (Bachelor degree or above), and (ii) 12 years of education or less, respectively. To capture attitudes towards risk and defaults, we use two indicators of whether participants bought supplementary insurance or opted for non-default asset allocations. We proxy job characteristics by tenure, number of employers contributing, and annual wage.

Finally, a wave indicator captures the persistence of participants' pension decisions, and we cluster robust standard errors at the individual level. Given the systematic differences between default and non-default investors, we show separate results for each group next to overall estimates. We do this for a baseline observation defined as a 46-year-old married female, in a 3-person household, with a Bachelor degree or more, 12 years of contributions, average wage, default asset allocation, and no supplementary insurance.

Opting for a DC plan is closely related to earnings and plan engagement. A unit increase in log wage significantly increases one's chances of choosing DC by 3.5%. This effect is three times larger for non-default (6.9%) compared to default (2.3%) investors. Older, wealthier and (extra) insured participants also seem more likely to opt for DC, with the effects mostly coming again from the non-default subsample. In fact, changing the baseline from default to a non-default asset allocation correlates with 37.5% higher DC participation, in line with allocation decisions being especially relevant for DC plan participants. This is also consistent with Mitchell et al. (2006) findings that older, richer, higher earning people more actively plan for retirement and control their savings. In contrast, those relying on defaults seem to do so consistently across decisions, with very little to induce them to take control of their retirement 'pot'. As people age, however, we see voluntary contributions rise (marginal effect - m.e. of about 0.2), as they start building up their savings approaching retirement. High earners contribute more, with non-default investors having a slightly higher wage elasticity of contributions (1.1 m.e.) compared to their default peers (1.0 m.e.). So overall, those who make active decisions and can set aside funds (due to higher earnings), seem more likely to maximize retirement contributions (Hira et al., 2009), and ultimately boost pension balances. Indeed, we continue to see a positive effect of having non-default allocations on pension wealth, which also rises with age, job tenure, and earnings. For instance, wage elasticity of pensions is a sizeable 1.2 as both employer and employees contribute, with earnings flowing into pensions via both channels. This leads males to end up with significantly higher balances than females (m.e. approx. 0.2), due to both higher wages and longer tenures (APH, 2016). Being married is generally beneficial for retirement savings, while the positive effect of having extra insurance comes mostly from default investors. Wealth matters too, but associated elasticities are only around 0.1, consistent with Australians being rich, and rich people increasingly keeping the bulk of their wealth in shares or property not pensions (AGT, 2020).

Table 3B sheds further light on this, by focusing on asset allocations and homeownership decisions. We see those with shorter careers, higher wages, and extra insurance also more likely to go for non–default

Table 3A. Estimation results for pension-related decisions and outcomes

	All			Non-Default Allocation			Default Allocation		
Variable	DC Opt-In	Ln Vol. Cont.	Ln Balance	DC Opt-In	Ln Vol. Cont.	Ln Balance	DC Opt-In	Ln Vol. Cont.	Ln Balance
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Age	0.026***	0.151***	0.048***	0.060**	0.096*	0.046***	0.007	0.248**	0.050***
	(0.007)	(0.044)	(0.006)	(0.019)	(0.042)	(0.012)	(0.004)	(0.091)	(0.007)
Male	0.014	0.075	0.175***	0.028	-0.015	0.248***	0.013	0.171	0.117***
	(0.008)	(0.083)	(0.012)	(0.019)	(0.109)	(0.022)	(0.008)	(0.125)	(0.014)
Low education	-0.010	0.080	0.102***	0.009	-0.027	0.154***	-0.019	0.151	0.067*
	(0.017)	(0.148)	(0.026)	(0.046)	(0.218)	(0.046)	(0.012)	(0.205)	(0.030)
High education	0.020	0.062	0.125***	0.055*	0.144	0.184***	0.000	-0.010	0.084***
	(0.011)	(0.104)	(0.019)	(0.027)	(0.156)	(0.036)	(0.010)	(0.140)	(0.021)
Couple	-0.008	-0.007	0.144***	-0.005	-0.075	0.209***	-0.006	0.113	0.091***
	(0.011)	(0.098)	(0.018)	(0.025)	(0.134)	(0.032)	(0.009)	(0.146)	(0.020)
Household size	0.007**	-0.026	-0.028***	0.016*	-0.037	-0.044***	0.002	-0.023	-0.016**
	(0.003)	(0.026)	(0.004)	(0.007)	(0.036)	(0.008)	(0.002)	(0.038)	(0.005)
Suppl. insurance	0.031*	-0.098	0.051*	0.057*	-0.161	0.024	0.023	-0.028	0.074***
	(0.012)	(0.097)	(0.021)	(0.026)	(0.126)	(0.039)	(0.012)	(0.149)	(0.018)
Years of contribution	0.033***	0.002	0.065***	0.086***	-0.001	0.056***	0.003	0.006	0.071***
	(0.007)	(0.006)	(0.001)	(0.019)	(0.008)	(0.002)	(0.004)	(0.009)	(0.001)
Employers	0.069***	0.019	0.090***	0.147***	-0.085	0.061	0.030**	0.125	0.114***
	(0.012)	(0.131)	(0.019)	(0.029)	(0.165)	(0.031)	(0.011)	(0.214)	(0.023)
Ln annual wage	0.035**	1.024***	1.200***	0.069*	1.141***	1.116***	0.023*	1.020***	1.189***
	(0.012)	(0.146)	(0.021)	(0.029)	(0.143)	(0.036)	(0.011)	(0.165)	(0.022)
Ln net wealth	0.084***	0.284	0.119***	0.200**	0.127	0.110**	0.020	0.593	0.127***
	(0.024)	(0.149)	(0.019)	(0.064)	(0.133)	(0.036)	(0.014)	(0.317)	(0.022)
Ln net wealth X Age	-0.002***	-0.005	-0.002***	-0.004**	-0.002	-0.001	-0.001	-0.012	-0.002***
	(0.001)	(0.003)	(0.000)	(0.001)	(0.003)	(0.001)	(0.000)	(0.007)	(0.001)
Non-default allocation	0.375***	-1.258	1.088**						
	(0.009)	(1.987)	(0.345)						
Non-default alloc X Ln wage		0.127	-0.103***						
		(0.174)	(0.030)						
Observations	11,404	1,737	11,404	4,616	847	4,616	6,788	890	6,788
Model Fit	0.227	0.287	0.752	0.114	0.299	0.670	0.032	0.272	0.813

Notes: All specifications include a wave indicator and are OLS models, except for (1), (4) and (7) that are logit (marginal effects reported). The Default (Non-Default) Allocation columns present results for the subsamples who opted for (out of) the default investment allocation. Age in specifications (1), (4) and (7) denotes plan enrolment age. Standard errors (robust, clustered by individual id) are in parentheses below estimated parameters. ***p-value<0.01, ** p-value<0.05, * p-value<0.1. Including Age^2 in (3), (6) and (9) leaves results unchanged.

Table 3B. Estimation results for investment allocation and home-related decisions

Variable	All			Non-Default Allocation			Default Allocation		All
	Risky Share	Homeownership	Housing Share	Risky Share	Homeownership	Housing Share	Homeownership	Housing Share	Non-Default Allocation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Age	0.005	0.008*	0.037***	0.011	0.014*	0.043***	0.004	0.033***	0.005
	(0.003)	(0.004)	(0.004)	(0.006)	(0.006)	(0.005)	(0.004)	(0.005)	(0.005)
Male	-0.021**	-0.034***	-0.031***	-0.045**	-0.029***	-0.023**	-0.037***	-0.036***	0.034**
	(0.006)	(0.005)	(0.005)	(0.014)	(0.008)	(0.008)	(0.007)	(0.007)	(0.012)
Low education	0.011	0.022***	0.021	0.036	0.030*	0.038*	0.018**	0.012	-0.033
	(0.012)	(0.006)	(0.011)	(0.031)	(0.012)	(0.019)	(0.006)	(0.014)	(0.024)
High education	0.002	0.000	0.026***	0.006	-0.010	0.008	0.004	0.037***	-0.010
	(0.008)	(0.006)	(0.007)	(0.020)	(0.011)	(0.012)	(0.007)	(0.009)	(0.016)
Couple	-0.009	0.133***	0.063***	-0.021	0.129***	0.053***	0.134***	0.070***	-0.010
	(0.008)	(0.011)	(0.008)	(0.018)	(0.017)	(0.013)	(0.014)	(0.011)	(0.015)
Household size	0.002	0.015***	0.026***	0.005	0.021***	0.029***	0.012***	0.023***	0.002
	(0.002)	(0.002)	(0.002)	(0.005)	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)
Suppl. insurance	-0.004	0.007	-0.006	-0.011	-0.001	-0.010	0.013	-0.004	0.071***
	(0.009)	(0.006)	(0.006)	(0.019)	(0.011)	(0.010)	(0.007)	(0.008)	(0.017)
Years of contribution	-0.000	0.002***	-0.003***	-0.000	0.003***	-0.001*	0.002**	-0.003***	-0.007***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Employers	0.026**	0.003	0.010	0.075***	0.009	0.011	-0.001	0.007	0.032*
	(0.008)	(0.006)	(0.008)	(0.020)	(0.012)	(0.013)	(0.007)	(0.010)	(0.016)
Ln annual wage	0.007	-0.001	-0.082***	0.019	-0.006	-0.078***	0.002	-0.077***	0.093***
	(0.006)	(0.007)	(0.008)	(0.021)	(0.012)	(0.011)	(0.009)	(0.009)	(0.018)
Ln net wealth	0.018*	0.035**	0.129***	0.044*	0.058**	0.153***	0.022	0.114***	0.015
	(0.008)	(0.012)	(0.012)	(0.021)	(0.019)	(0.017)	(0.014)	(0.015)	(0.016)
Ln net wealth X Age	-0.000	-0.000	-0.003***	-0.001	-0.001	-0.003***	-0.000	-0.003***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Non-default allocation	-0.243	-0.005	-0.131						
	(0.185)	(0.004)	(0.128)						
Non-default alloc X Ln wage	0.006		0.012						
	(0.016)		(0.011)						
Observations	11,404	11,404	11,404	4,616	4,616	4,616	6,788	6,788	11,404
Model Fit	0.106	0.278	0.100	0.007	0.266	0.104	0.291	0.100	0.012

Notes: All specifications include a wave indicator and are OLS models, except for (2), (5), (7) and (9) that are logit (marginal effects reported). The Default (Non-Default) Allocation columns present results for the subsamples who opted for (out of) the default investment allocation. Standard errors (robust, clustered by individual id) are in parentheses below estimated parameters. ***p-value<0.01, ** p-value<0.05, * p-value<0.1.

asset allocations (column 9): (i) a unit increase in log wage is associated with 9.3% higher chances of choosing non-default portfolios, and (ii) compared to those without extra insurance, those who get it are 7.1% more likely to invest outside the default option. Notably, while males are 3.4% more likely than females to opt for non-default asset allocations, females invest across the board more aggressively possibly in an attempt to close the pension gap with males. This reversed gender investing gap is likely linked to our sample's high financial literacy (Lusardi and Mitchell, 2007), and to women's higher loss aversion (Schubert et al., 1999). We also see people becoming homeowners relatively early and accumulating a higher share of wealth in housing as they get older (Iacoviello, 2011), with once more, females doing so at higher rates than males on both counts. Education plays an interesting role, with those less educated committing more to homeownership and those higher educated affording to accumulate more value (Graham et al., 2009; AGT, 2020). Being in a couple or in a large household is, unsurprisingly, positively associated with both, while higher wages implies lower share of net wealth in housing (m.e.=-0.1) and suggests high earners use multiple savings vehicles to plan for retirement (Clark et al., 2012). In contrast, the wealthy can (and do) go for higher portfolio weights in housing (m.e.=0.13), and more so if they opt for non-default allocations rather than staying with the default one.

4 The model

To understand how the significant factors from our preliminary analysis determine the relation between pensions and housing, we build a rich life cycle model. To start, consider an individual who begins working at age t_0, retires at age T_R (exogenous and deterministic), and lives up to age T. The model consists of a series of one-year periods indexed by t. Each period, the individual has a survival probability p_t and, if alive, wishes to maximize her expected lifetime utility by choosing non-durable consumption and housing services through renting or owning. She supplies labor inelastically, faces uninsurable idiosyncratic earnings risk, and makes decisions about non-durable and housing consumption, pension contributions, homeownership (including mortgage debt), and savings. The pension system is designed to incorporate a wide range of choices and defaults that will allow us to explore key aspects of the interplay with the housing market. Buying a mortgage-financed home requires a minimum down payment, housing purchases and sales incur transactions costs, and houses require maintenance.

A. Preferences. Individual preferences are given by the per-period utility function

$$u(c_t, S_t) = \frac{\left[(1-\alpha_t)c_t^{\rho} + \alpha_t S_t^{\rho}\right]^{\frac{1-\gamma}{\rho}} - 1}{1-\gamma}, \tag{1}$$

where $c_t > 0$ is consumption of non-durables, $S_t > 0$ is consumption of housing (or shelter) services, $\alpha_t \in (0,1)$ is the relative taste for housing services, $1/(1-\rho)$ measures elasticity of substitution between consumption and housing services, and $1/\gamma$ is the intertemporal elasticity of substitution.

Housing services can be consumed by either renting or owning a house (Sommer and Sullivan, 2018), with H_t denoting the housing stock owned at time t.[7] Renters (with $H_t = 0$) must purchase housing services at a rental rate P_t^S, while homeowners (with $H_t > 0$) benefit from housing services in linear proportion to the housing stock they own. To account for the impact of persistent and time-varying preferences on housing adjustments, we consider future preferences for housing services to be uncertain (Ngai and Sheedy, 2020). To do so, we first assume the parameter governing housing tastes (and affecting housing demand) follows a two-point Markov chain, corresponding to a low and a high housing preference state, and obtained as a discrete approximation of an AR(1) process $\alpha_t = \overline{\alpha}^{(1-\rho_\alpha)} \alpha_{t-1}^{\rho_\alpha} e^{\varepsilon_{\alpha_t}}$, with $\varepsilon_{\alpha_t} \sim N(0, \sigma^2_{\varepsilon_{\alpha_t}})$. Next, we allow individuals in the low preference state to also hold different beliefs about their likelihood to transition to the high preference state. To implement this, we partition the probability of transitioning from the low to the high preference state by assuming that individuals in the low preference state experience a binary independent and identically distributed (i.i.d.) shock to their expectations about future housing demand. Like Kaplan et al. (2020), this shock can take two values, associated with (i) a state of *conviction* occurring with probability q^η, and (ii) a contrasting state of *hesitation* occurring with probability $(1-q^\eta)$. When in a state of conviction (hesitation), individuals experience a higher (lower) chance of transitioning from the low to the high preference state by a factor of η. A shift between the low and the high preference state captures an actual preference shock. In contrast, a shift between conviction and hesitation captures a change in beliefs about future housing preferences.

[7] Here housing stock level incorporates both the size and the quality of the dwelling, with housing depreciation and investments appearing simply as decreases and increases in H_t, respectively.

At death, any remaining wealth is bequeathed to one's heirs, with an associated warm-glow utility

$$b(B_t) = \theta \frac{(B_t + k)^{1-\gamma}}{1-\gamma}, \tag{2}$$

where θ captures the strength of the bequest motive, k the extent to which bequests are luxury goods (De Nardi et al., 2010), and B_t includes all real and financial assets, inside and outside pension accounts.

B. Endowments. While working, individuals and their spouses receive idiosyncratic earnings y_t and y_t^s, respectively. Consider y_t to have (i) a deterministic component related to age and work tenure $y(t,\tau)$ common to all individuals, and (ii) a stochastic component ξ_t following an AR(1) process in logs with persistence ϕ and innovation $u_t \sim \mathcal{N}\left(0, \sigma_u^2\right)$ capturing some level of wage persistence among individuals,

$$\ln y_t = y(t,\tau) + \xi_t. \tag{3}$$

Spousal earnings follow a similar structure, with the deterministic component also including individual's earnings $y^s(y_t, t, \tau)$, and the stochastic one ξ_t^s parameterized by ϕ^s and $u_t^s \sim \mathcal{N}\left(0, \sigma_{u^s}^2\right)$ (French, 2005). Individuals start with no endowment of housing or pension wealth of their own, while their initial financial wealth is based on liquid savings that correlate with enrolment age t_0.

C. Pensions. Individuals choose the plan type p, the voluntary contribution rate v_t, and the risky asset allocation π_t as follows: at t_0, they are automatically enrolled into a (default) DB plan and can irreversibly switch to DC within the first period, otherwise they continue in DB. Then, employers and employees start contributing. The employer mandatory contribution v_E and the standard employee contribution v_S are (fixed) shares of y_t.[8] Voluntary employee contribution rates v_t start from a default of $v^d = 0\%$ and can be changed each period. Similarly, the risky asset share π_t that individuals choose for their DC balances can be dialled up or down from a default investment allocation with risky asset share $\pi^d = 70\%$. Finally, switching away from any default incurs a cost u_i (with $i \in \{p, v, \pi\}$) modelled in terms of utility lost as

[8] We calibrate standard contribution rates from the data due to limited heterogeneity, thus effectively accounting for them in the empirical analysis, and when structurally constructing the pension balances profiles.

$$
\begin{aligned}
u_p &= \psi + \exp\left(\nu_0^p + \nu_1^p t_0 + \nu_2^p t_0^2\right), \\
u_{\nu_t} &= \psi + \exp\left(\nu_0^y + \nu_2^y (t - \nu_1^y)^2 + \nu_3^y \max\{0, \ln(a_t)\}\right), \\
u_{\pi_t} &= \psi + \exp\left(\nu_0^r + \nu_1^r t + \nu_2^r t^2 + \nu_3^r \max\left\{0, \ln\left(a_t^{dc}\right)\right\} + \nu_4^r u_p\right),
\end{aligned} \tag{4}
$$

where ψ captures an inherent preference for defaults, and the ν's relate to (i) the effort of researching, comparing options, and filing forms that vary with age (current t or at employment t_0), (ii) the liquidity value of savings outside pension plans a_t, and (iii) the DC balance at stake in investment decisions a_t^{dc}.[9]

While DB participants hold both DB and DC accounts, they accumulate pension wealth primarily through the DB account based on a formula related to age, work tenure, employer and standard contribution rates, and average earnings over the last three years of continuous employment (UniSuper, 2012). DB account balances are thus calculated as

$$
\begin{aligned}
a_t^{db} &= f_t^{ACF}(\nu_S) \cdot f^{LSF}(t) \cdot f^{ASF} \cdot \tau \cdot \bar{y}_t, \text{ with} \\
f^{LSF}(t) &= \max\{18,\ \min\{23,\ 23 - 0.2(65 - t)\}\}/100, \\
\bar{y}_t &= \frac{1}{3}\left[y_t + g(y_{t-1}) + g(y_{t-2})\right],
\end{aligned} \tag{5}
$$

where f_t^{ACF} is a ν_S-related average contribution factor over the entire tenure span, f^{LSF} is an age-related lump sum factor (with $f^{LSF}(t \leq 40) = 18\%$ and $f^{LSF}(t \geq 65) = 23\%$), f^{ASF} is the average service factor (with f^{ASF}=100% as permanent staff are assumed to work full-time), and $\bar{y}_t$ is the average wage over the last three years of continuous employment (see Appendix C.1). DB plan participants also have a separate DC account where a share (1-o) of employer contributions and all voluntary contributions will accumulate, with overall DB wealth being the total wealth across both accounts. In contrast, DC participants only have one (DC) account in which all employer and employees contributions accumulate. The DC wealth (accumulated in either the DC account of a DB plan or within a DC plan) builds up according to the chosen asset allocation. As mentioned, allocation options differ in terms of the share of funds invested in risky

[9] See Steel (2007), Ebersbach and Wilkening (2007), Agarwal et al. (2009), Besedes et al. (2012). As voluntary contributions and investment allocations can be changed annually, the associated switching costs for non-defaulters will also be per period.

and conservative assets, and thus DC account balances are calculated as

$$a_{t+1}^{dc} = \begin{cases} \left[\pi_t R_t^r + (1-\pi_t) R_t^s\right] \cdot \left[a_t^{dc} + ((1-o)\,v_E + v_t)\,y_t\right] & \text{if in a DB plan,} \\ \left[\pi_t R_t^r + (1-\pi_t) R_t^s\right] \cdot \left[a_t^{dc} + (v_E + v_S + v_t)\,y_t\right] & \text{if in a DC plan,} \end{cases} \tag{6}$$

where R_t^r (R_t^s) are returns on risky (conservative) assets, and we account for intertemporal effects of time-varying financial returns on asset allocation (Campbell and Viceira, 1999; 2002) by modeling them as

$$\ln R_t^i = r_t^i = r^i + i\varepsilon_t^d, \tag{7}$$

with $i \in \{r, s\}$ a scaling factor that can amplify ($r > 1$) or dampen ($s < 1$) asset market shocks, and $\varepsilon_t^d \sim N(0, \sigma^2_{\varepsilon_t^d})$ the returns shock of the default allocation with constant mean return r^d, and $r^s < r^d < r^r$.

D. Housing. Each individual in our model may decide to rent or own a home. Markets for rental and owner-occupied housing are competitive and immediate, meaning that any renting or buying or selling transactions do not take time. The per-unit price of housing is denoted by P_t, while the rental rate of a unit of housing P_t^S is a fixed (and constant) share φ^S of the market unit price P_t of the house being rented.

All individuals start as renters and must choose between continuing to rent and buying a house. Renters "purchase" housing services at the rental rate P_t^S in each period they continue to rent, incur no per-period housing maintenance costs, and can adjust the size of their house without paying any transaction costs. For those who decide to buy a house, housing plays a dual role. First, it is a durable consumption good that yields instantaneous utility and for simplicity, we assume homeowners receive one unit of housing services S_t for each unit of housing stock H_t they own (i.e., $S_t = H_t$). Being a severely illiquid form of wealth, housing can only be traded by incurring a transaction cost $\tau_H P_t H_t$ where $\tau_H \in [0,1)$,[10] and $P_t H_t$ is

[10] In Australia, what is commonly referred to as *property tax* is a range of taxes and charges related to property ownership, namely (i) land tax: a tax applied on the value of investment and commercial property land owned, (ii) stamp duty, also known as transfer duty: this tax applies to a property's price or market value when traded, (iii) capital gains tax (CGT): applied to the capital gain (the difference between the sale and purchase price, after accounting for expenses and concessions) from selling an investment property, and (iv) council rates: levied by local councils on residential and commercial properties, depending on the property's value. Owner-occupied homes are CGT-exempt, while exemptions from land tax and council rates vary by state and territory but they all generally include owner-occupied homes. We thus account for transfer duty through τ_H.

time-t housing value.[11] Once transaction costs are paid, housing accumulates as

$$H_t = (1-\delta)H_{t-1} + h_t, \tag{8}$$

so individuals enter period t with an initial housing stock H_{t-1}, which depreciates at constant rate $\delta \in [0,1)$ and replenishes via housing investments (i.e., maintenance expenses) $h_t > 0$, with $h_t < 0$ if downsizing.[12] Second, housing is an investment good with capital value P_t bringing returns R_t^h (Yogo, 2016)

$$R_t^h = (1-\delta)P_t/P_{t-1}. \tag{9}$$

To purchase a house, individuals can take out a mortgage m_t that must be paid back at an interest rate r_t^m that correlates with the conservative asset returns (Justiniano, 2021)

$$r_t^m = \beta^m r_t^s + \kappa \varepsilon_t^d, \tag{10}$$

where β^m is the markup of the mean mortgage over the mean conservative asset returns, and κ scales the mortgage volatility over that of conservative asset returns.[13] Borrowers may choose their next period debt position m_{t+1} at time t, when they must satisfy the collateral constraint

$$m_{t+1} \leq (1-\varphi^C)P_t H_t, \tag{11}$$

where $\varphi^C \in (0,1)$ is the homeowner deposit (or down payment) share, which ensures that borrowers must have a minimum equity $\varphi^C P_t H_t$ if they hold a mortgage.

Assume mortgages can be costlessly refinanced by those adjusting their housing stock (Yang, 2009) and so, for housing adjusters, only constraint (11) must hold. For non-adjusters, costless variation of their mortgage position can still occur each period up to a limit ι, with $m_{t+1} - R_t^m m_t \leq \iota$. This approximates our

[11] After time-t transaction costs have been paid, housing can be adjusted continuously within the period. Since these costs are non-convex and must be paid each period housing is adjusted, they will impose a friction that results in lumpy investments.

[12] See Harmenberg and Oberg (2021) and Berger and Vavra (2015). Note that here housing depreciation accounts for a substantive change (deterioration) in housing stock over the long run that affects housing services although it might not be immediately rectified via annual expenses; to reduce complexity, we thus abstract from very minor repairs.

[13] Note that unlike Sommer and Sullivan (2018), we capture Australian mortgages by linking r_t^m to the stochastic (rather than constant) conservative asset returns to allow for variation while keeping the model state space computationally feasible.

institutional setup that features mortgages with offset accounts and redraw facilities that allow for some liquidity in mortgage accounts but only up to a certain limit. In our model, the fixed withdrawal limit also means that some individuals will hold liquid assets and mortgages at the same time.[14]

E. Budget constraint. Let $\mathbb{1}_{\{h_t \neq 0\}}$ be an indicator function equal to one if time-t housing expenses deviate from zero. Assuming individuals enter period t with some amount of financial wealth a_t, and there is only one risk-free asset in which to save a_t that yields constant gross returns R,[15] the per-period financial wealth after consumption, renting and housing expenses is

$$a_{t+1} = Ra_t + (y_t + y_t^s)\tau^m - (v_t + v_S)y_t - c_t - P_t^S S_t - P_t h_t - \mathbb{1}_{\{h_t \neq 0\}}\tau_H P_t H_t + m_{t+1} - R_t^m m_t, \tag{12}$$

with mortgage interest $\ln R_t^m = r_t^m$, and τ^m the share of household earnings received by the individual (Keane and Wolpin, 2010). Housing wealth is thus $a_t^h = P_t H_t$, while total (net) non-pension wealth is

$$A_{t+1} = a_{t+1} + (1-\delta)P_{t+1}H_t - m_{t+1}. \tag{13}$$

At age T_R, people access their (share of combined household) pension balances, so the intertemporal budget constraint becomes

$$A_{t+1} = \\ = \begin{cases} Ra_t + (y_t + y_t^s)\tau^m - (v_t + v_S)y_t - c_t - P_t^S S_t - P_t h_t + (R_{t+1}^h - \mathbb{1}_{\{h_t \neq 0\}}\tau_H)P_t H_t - R^m m_t & \text{if } t < T_R, \\ (a_t^{db} + a_t^{dc} + a_t^{dcs})\tau^m + Ra_t - c_t - P_t^S S_t - P_t h_t + (R_{t+1}^h - \mathbb{1}_{\{h_t \neq 0\}}\tau_H)P_t H_t - R^m m_t & \text{if } t = T_R, \\ Ra_t - c_t - P_t^S S_t - P_t h_t + (R_{t+1}^h - \mathbb{1}_{\{h_t \neq 0\}}\tau_H)P_t H_t - R^m m_t & \text{if } t > T_R, \end{cases} \tag{14}$$

[14]The literature often assumes unlimited withdrawals (up to the collateral constraint) to reduce the state space, as mortgages and liquid assets can be combined into a single net asset state (Yang, 2009). In contrast, our motivation for costless but limited withdrawals not only approximates the Australian mortgage market but also enables us to identify the gross mortgage position in one's asset portfolio. In our institutional setup, individuals can make extra payments into their mortgage account that they can later withdraw costlessly via offset accounts or redraw facilities, which makes mortgage balance relatively liquid (Price et al., 2019). To avoid adding mortgage repayment schedules as an additional state space, we capture this mortgage balance liquidity by assuming the redraw limit is constant each period at ι.

[15]This is consistent with equity market participation outside DC accounts being less than 2.5% in Australia (ABS, 2019), not unlike in many other advanced developed economies (Gomes et al., 2021); this helps keep things computationally feasible.

where housing has a stochastic return $R_t^h = (1+r_t^h)$, with $r_t^h = r^h + \varepsilon_t^h$ and $\varepsilon_t^h \sim N(0, \sigma^2_{\varepsilon_t^h})$. Equation (9) then determines the housing price P_t dynamics, with initial (2010) price levels normalized to $P_0 = 1$. Finally, we assume (i) spouse account balances a_t^{dcs} to be a function of the individual's pension balance, age, and work tenure, and include a stochastic component $\varepsilon_t^{dcs} \sim N(0, \sigma^2_{\varepsilon_t^{dcs}})$, and (ii) no borrowing associated with financial wealth and so $a_{t+1} \geq 0$ in each period t.

F. Timing of events and Bellman equation. The dynamic problem can be viewed as a two stage optimization. At the start of the first period, each individual with financial wealth a_{t_0} and labor income shock ξ_{t_0} irrevocably chooses their pension plan. Thus, the time-t_0 Bellman equation is

$$V_{t_0}(X_{t_0}) = \max_{\{DB,DC\}} \left\{ V_{t_0}(X_{t_0}|DB) + \zeta_{db}, V_{t_0}(X_{t_0}|DC) - u_p + \zeta_{dc} \right\}, \tag{15}$$

where $X_t = \left(\tau, \xi_t, a_t, a_t^{dc}, \{DB,DC\}, (1-\delta)H_{t-1}, P_t, m_t, \alpha_t, \beta_t\right)$ is the vector of state variables and $\{DB,DC\}$ captures the set of plan types.[16] We further include an unobservable utility component in each option $\zeta_{\{DB,DC\}}$, following a type I extreme value distribution with scale parameter σ_p,[17] to allow for unobservables that might affect one's decision. Thus, the probability of choosing DC is (Rust, 1987)

$$Pr(DC) = \frac{\exp\left[\left(V_{t_0}(X_{t_0}|DC) - u_p\right)/\sigma_p\right]}{\exp\left[V_{t_0}(X_{t_0}|DB)/\sigma_p\right] + \exp\left[\left(V_{t_0}(X_{t_0}|DC) - u_p\right)/\sigma_p\right]}. \tag{16}$$

In each subsequent period, individuals choose (i) voluntary contribution v_t from the set $\{v_i, i = 1, 2 \ldots N_v\}$, (ii) asset allocation π_t from the set $\{\pi_i, i = 1, 2 \ldots N_\pi\}$, and (iii) optimal consumption c_t, housing services S_t, and housing expenses h_t, to maximize the discounted present value of lifetime utility

$$\hat{V}_t(X_t, v_t) = V_t(X_t, v_t) + \zeta_{v_t}. \tag{17}$$

Here, ζ_{v_t} is the unobservable utility of the v_t choice, and the deterministic value $V_t(X_t, v_t)$ is

$$V_t(X_t, v_t) = E\left\{ \max_{\pi_t} \hat{V}_t(X_t, v_t, \pi_t) \right\} - u_v \cdot \mathbb{1}\{v_t \neq v^d\}, \tag{18}$$

[16] State space includes P_t as it defines the relative price of housing in terms of consumption, which is time dependent. We also retain mortgages m_t as a state variable to allow us to run the counterfactual that removes mortgage frictions.

[17] The variance of the distribution of $\zeta_{\{DB,DC\}}$ is therefore $\frac{\pi^2}{6}\sigma_p^2$, and note that in our framework, it is more convenient to select the scale of the shock than to multiply the value functions by scaling parameters.

where $\hat{V}_t(X_t, v_t, \pi_t)$ is the value of a portfolio with π_t invested in risky assets, defined as

$$\hat{V}_t(X_t, v_t, \pi_t) = V_t(X_t, v_t, \pi_t) + \zeta_{\pi_t}. \tag{19}$$

Similar to ζ_{v_t}, ζ_{π_t} is the unobservable utility component for the π_t choice, with observable part

$$V_t(X_t, v_t, \pi_t) = \max_{c_t, h_t, S_t} u(c_t, S_t) - u_\pi \cdot \mathbb{1}\{\pi_t \neq \pi^d\} + \beta_t E_t[p_t V_{t+1}(X_{t+1}) + (1-p_t) B_{t+1}], \tag{20}$$

subject to budget constraint (14), collateral constraint (11), $S_t = H_t$ if $H_t > 0$, and

$$V_{t+1}(X_{t+1}) = E\left\{ \max_{v_{t+1} \in \{v_i\}_{i=1}^{N_v}} \hat{V}_{t+1}(X_{t+1}, v_{t+1}) \right\}. \tag{21}$$

Krusell and Smith (1998) show that time preference heterogeneity is crucial for generating the higher order moments of the wealth distribution. We thus allow our discount factor β_t to follow a three-state AR(1) process, fluctuating around a long-run stationary value $\overline{\beta}$ with convergence rate ρ_β (Dobrescu et al., 2012). Similar to α, an initial value for β that lies significantly below $\overline{\beta}$ coupled with a fast convergence (a small value of ρ_β) is indicative of an individual placing more weight over time on future consumption and housing when deciding present consumption and housing, helping us capture the joint dynamics of various asset distributions in the data. Note that individuals know β_t, but they are uncertain about future values β_s, where $s > t$. Because today's individual controls all future allocations, the issue here is uncertain future desires (preference uncertainty), not time inconsistency.

Assume both ζ_{v_t} and ζ_{π_t} follow type I extreme value distributions independently, with scale parameters allowed to differ across plan types (so $\sigma_v^{DB} \neq \sigma_v^{DC}$ and $\sigma_\pi^{DB} \neq \sigma_\pi^{DC}$) and simplify as follows[18]

$$V_t(X_t) = \sigma_v^j \log\left\{ \sum_{v_h \in \{v_i\}_{i=1}^{N_v}} \exp\left[\frac{V_t(X_t, v_h)}{\sigma_v^j}\right] \right\}, \tag{22}$$

[18]The position parameters of ζ_{v_t} and ζ_{π_t} are assumed to be $-\sigma_v \gamma_E$ and $-\sigma_\pi \gamma_E$, where $\gamma_E = 0.57721$ is the Euler constant. Since voluntary contributions and investment choices are not relevant at ages beyond 65, we estimate the scale parameters directly (instead of normalizing them to 1 and multiplying the corresponding deterministic value functions by $1/\sigma_v$ or $1/\sigma_\pi$, respectively, for ages below 65). This is essentially a nested logit model (Berkovec and Rust, 1985).

$$V_t(X_t, v_t) = \sigma_\pi^j \log\left\{\sum_{\pi_h \in \{\pi_i\}_{i=1}^{N\pi}} \exp\left[\frac{V_t(X_t, v_t, \pi_h)}{\sigma_\pi^j}\right]\right\} - u_v \cdot \mathbb{1}\{v_t \neq v^d\}. \tag{23}$$

The discrete choice probabilities are thus

$$Pr(v_t = v_i) = \frac{\exp\left[V_t(X_t, v_i)/\sigma_v^j\right]}{\sum_{v_h \in \{v_i\}_{i=1}^{N_v}} \exp\left[V_t(X_t, v_h)/\sigma_v^j\right]}, \tag{24}$$

$$Pr(\pi_t = \pi_i) = \frac{\exp\left[V_t(X_t, v_t, \pi_i)/\sigma_\pi^j\right]}{\sum_{\pi_h \in \{\pi_i\}_{i=1}^{N\pi}} \exp\left[V_t(X_t, v_t, \pi_h)/\sigma_\pi^j\right]}, \tag{25}$$

where $j \in \{DB,\, DC\}$. Because there is no analytical solution, we solve the problem numerically via backward induction. Further details are presented in Appendix C.2.

5 Calibrations and estimation approach

To ease the computational load of structurally estimating all parameters together, we first calibrate those that appear as instruments for our dynamic programming model. Next, we run the model and use these imputed data generating processes to simulate life cycle profiles for a large number of hypothetical individuals. Finally, we iterate to find the parameters that match the simulated profiles with the actual data.

We calibrate gender-specific survival probabilities p_t using the Human Mortality Database corresponding levels averaged across 2010 and 2014, set enrolment age $t_0 = 17$ and retirement age $T_R = 65$ to match UniSuper data, and allow individuals to live up to maximum age $T = 100$.[19] Next, we follow Kaplan et al. (2020) to parameterize the i.i.d beliefs shock as $q = 0.4$ and $\eta = 80$, and also set the bequest shifter k to the weighted average of its marital status-specific parameters from Ding (2013). To derive the parameters for individual earnings, spousal earnings and spousal pension balances, we employ OLS models with a quartic in age and a quadratic in work tenure years, also adding individual-level earnings and balances to the spouse processes. We further calibrate τ^m from the data, and discretize ξ_t via a discrete Markov process with $N_\xi = 5$ gridpoints.[20] For pension wealth, we set (i) $f^{ACF} = 86.0\%$ to match its data mean

[19]Setting a common enrolment age reduces the state of the model during estimation; experimenting with varying enrolment age in the simulations did not significantly alter our key results.

[20]We abstract from unemployment risk as for permanent higher education staff, the sector full-time equivalent count of employees has only experienced a systematic upward trend in 2010-2014 (AG-DOE Higher Education Statistics, Table 1.2), with on average an extra 4% unfilled job vacancies (see ABS, 2022). Sector exit was also very low (2.8% in ABS, 2022), while

and so $v_S = 2.35\%$, (ii) $v_E = 17\%$, and so $o = 100\%$ (as $v_s = 2.35\%$), and (iii) the interest rate parameters for the risky, conservative, and default allocations to the risk and return targets reported in the UniSuper product disclosure statements, and so $r^s = 1.93\%$, $r^r = 4.76\%$, $r^d = 2.88\%$, s=0.54, r=1.68, $\sigma_{\varepsilon_t^d}$=0.064.

Turning to housing, we take $\tau_H = 0.08$ from Yogo (2016), and set $\varphi^S = 0.06$ to replicate the average rental yield in Gitelman and Otto (2012). Based on equation (9), housing returns are estimated using the Bank for International Settlements series on real residential property prices for Australia (BIS, 2023), with depreciation $\delta = 1.1\%$ (Fox and Tulip, 2014). The real housing return rate, deflated by CPI for all items, has a mean of 3.2% and standard deviation of 4.2% from 1982 to 2014, so we set $r^h = 0.032$ and $\sigma_{\varepsilon_t^h} = 0.042$. Based on the Reserve Bank of Australia lending rates for 1982-2014, we find a mean real mortgage rate (using median inflation) of 0.0649, with 0.021 standard deviation (RBA 2024 - Table F5). Thus, we set $\beta^m = 3.36$, $\kappa = 0.33$, $\varphi^C = 20\%$ (Guest, 2005), and limit the costless redraw $\iota = \$120,000$ to reflect the average balance of offset accounts in our data, calculated using (i) the national statistics on the average extra payments made into mortgage accounts as a proportion of total mortgage debt and the ratio of debt to average income (RBA, 2018), and (ii) the average earnings in our data.

Finally, financial wealth has a constant return of $R = 1.0097$, in line with the average real return for long-term (indexed) Treasury bonds for the period 1982-2014. We also predict initial levels of gender-specific financial wealth using the second order age polynomial coefficients of an OLS regression on available (financial wealth) data for gendered subsamples. (All other HILDA-UniSuper matching dimensions were irrelevant at enrolment age.) There is no initial pension wealth, initial housing stock is a negligible \$1, and the initial real house price is such that the 2010 house prices are normalised to \$1.

Using SMM, we estimate

$$\phi \;=\; \left\{\overline{\alpha}, \rho_\alpha, \sigma_{\alpha\varepsilon_t}, \rho, \theta, \gamma, \overline{\beta}, \rho_\beta, \sigma_{\beta\varepsilon_t}, \psi, \nu^p_{i=\overline{0,2}}, \nu^v_{i=\overline{0,3}}, \nu^r_{i=\overline{0,4}}, \sigma_p, \left\{\sigma^j_v, \sigma^j_r\right\}_{j\in\{DB,DC\}}\right\} \;\in\; \mathbb{R}^{27}, \quad (26)$$

by matching the real moments related to wealth and plan choices to the corresponding moments of the same variables in the simulated sample. The objective is to find the vector of preferences $\widetilde{\phi}$ that simulates the distributions such that they fit the data best. To this end, we match (i) first order moments related to consumption, pension wealth, financial and housing wealth, voluntary contributions, and risky assets share

within-sector job changing could affect earnings but not the pension setup as UniSuper was the sector-wide compulsory plan.

- overall and above default levels; (ii) second order moments of consumption, financial and housing wealth, as well as quartiles of overall wealth; (iii) lagged correlations of consumption, financial and housing wealth; (iv) correlations between consumption and housing wealth, voluntarily contributing and opting for DC, and switching to DC and opting for non-default allocations; (v) plan-specific second order moments of pension wealth, risky assets share and voluntary contributions; (vi) plan-specific correlations between pension wealth and voluntary contributions (amount and prevalence), between pension wealth and risky assets share (level and prevalence of opting for riskier-than-default allocations), and between voluntarily contributing and having non-default allocations, and (vii) proportions of participants in DC, voluntarily contributing and with non-default allocations. We discuss the identification below.

For efficiency reasons, we estimate our models for males and females separately, using our two waves of UniSuper data. For each model, we calculate the age-specific empirical (real) moments for each sub-sample (i.e., males or females) as follows: first, we assign individuals into 5-year age cohorts, with the first cohort consisting of individuals with ages below 25 in 2010, the second containing those age 25-29 in 2010, and so on. Next, we take cell means by cohort for the balanced panel in each wave to generate the data moments. For the simulated moments, we then simulate $N = 10,000$ paths of individual choices, collect the simulated values for each path, and compute N sets of simulated moments, conditional on the initial values of the state variables X_{t_0} and on the parameters $\widetilde{\phi}$. Finally, the SMM estimator minimizes the distance between the empirical moments and the average of the N sets of simulated moments.[21]

5.1 Identification

To explain how we identify the parameters of interest, we start with the intuition behind why each parameter might significantly affect only a subset of moments. Since an analytical proof of identification is not possible, we validate this reasoning by showing identification in the neighborhood of a subset of parame-

[21] The last cohort labelled "60+" also contains a few observations on individuals older than 65 but their (wealth, consumption, contributions, allocations) data is not very different from the "60-64" cohort data and so including them does not significantly alter the empirical moments. We deal with housing outliers by excluding their 99th percentile. Using more than 10,000 paths to compute moments did not change results materially. To minimize the SMM objective function, we use the cross-entropy method (De Boer, 2005, Botev el al., 2011). We start with a uniform draw of 600 parameter vectors and evaluate the SMM objective function across each of them. From this initial draw, we select the top 10% performing parameters and use them to fit a multivariate distribution over the parameter space, from which we sample the next iteration of 600 parameter vectors and again evaluate the SMM objective function. We repeat the process until the covariance matrix of the parameter sample distribution satisfies a predetermined tolerance.

ters via simulation.[22] Changing one parameter, however, can affect multiple data moments. For instance, risk aversion, bequest weight, and discount factor parameters are jointly identified by cohort-specific first order financial wealth moments: a high γ makes individuals save more; a high β means people are more future oriented and decumulate more slowly; and a high θ (strong bequest motive) leads to higher wealth. We further identify these parameters by requiring the model to also match the observed first order moments of pension wealth and housing wealth, by cohort. The rationale is provided by the Euler equation: ignoring bequests, the Euler equation tightly shapes the liquid savings profiles (i.e., financial wealth before retirement). These financial wealth profiles are largely set by a combination of time discounting β and taste for smoothing γ. In the case of β, however, this equation identifies the product $\beta_t p_t R$, not its individual elements. Therefore, lower values of R and/or p_t can lead to higher β_t estimates. To check whether the returns rate can be separately identified, we set its value to the maximum rate observed for the riskiest asset allocation available in our data and re-estimate the models. We find that realized returns are, on average, higher than our benchmark assumption (of 2.23%) and our β is lower. We thus conclude that we can only identify $\beta_t R$, but not each term separately. Given the autoregressive nature of the underlying β process, we acquire additional identification by also requiring the model to match the variance and first order autocorrelation of financial wealth. To further pin down γ we also use the correlation involving non-default choices on voluntarily contributing and plan type. Intuitively, this might bias downwards our risk estimates as we identify them based only on the *active* sample when presumably default participants have certain attitudes towards risk too. Hence, to acquire extra identification, we use the proportion of DC wealth invested in riskier (than default) assets across both the DB and DC subsamples. Then, going back to the Euler equation, note that bequest motives are related to the total amount of resources that could be passed on as bequeathable wealth. Thus, bequest weight θ will apply to all (pension, financial and housing) wealth, and so we additionally identify this parameter via the age-profile of mean pension and housing wealth, and use the quartiles of overall wealth to further help fix the curvature of the function. Lastly, we identify α and ρ by noting that the within-period utility function is CES between consumption and housing wealth: α gives the share of resources corresponding to housing rather than consumption, while ρ captures the within-period substitution between the two. We thus identify AR(1) α parameters

[22] To do so, we compute the moments and fit the value function at and around estimated parameter values. Next, we check whether the resulting simulated profiles fit the empirical ones as we vary the value of each parameter and verify the fitted function shape in a neighborhood of the selected parameter value.

via the mean, variance and lagged correlation of consumption and housing wealth, and use the correlation between these two series to pin down ρ.

Turning to the switching costs, we note that identification comes from observations where individuals actually switched away from defaults. Hence, we identify the latent factor ψ via plan-specific correlations involving non-default choices on voluntary contributions and asset allocations. To identify the $\nu^{p}_{i=\overline{0,2}}$ parameters of u_p, we match the age-specific proportion of individuals that switched to DC, while for u_v, we match the age-specific proportion of individuals contributing (to identify $\nu^{v}_{i=\overline{0,2}}$) and the mean level of voluntary contributions by age (to identify ν^{v}_{3}). As for u_π, we identify the parameter ν^{r}_{3} of $\ln\left(a^{dc}_{t}\right)$ by the mean risky asset share, and ν^{r}_{4} by the correlation between opting for non-default allocations and opting for DC, with the age coefficients $\nu^{r}_{i=\overline{0,2}}$ once again identified by the proportion of individuals with non-default investment allocations by age. To identify the unobservable utility components associated with the three pension choices, we proceed as follows: first, we identify the scale parameter σ_p that determines the variance of ζ_{db} and ζ_{dc} using the variability in pension wealth by plan type. Second, since people choosing DB or DC might value liquidity differently or have different attitudes toward risk, we allowed the relative weight of ζ_{v_t} and ζ_{r_t} to differ across plan types. As a result, to identify the parameter σ_v we use the plan-specific variance of voluntary contributions and the correlation between pension wealth and voluntary contributions (both amount and prevalence). Similarly, we can identify σ_r by plan-specific measures of risky assets share variability and by the correlation between pension wealth and risky asset share (both level and prevalence of opting for riskier-than-default allocations).

Importantly, we use the correspondence between the empirical and simulated profiles for homeownership prevalence as an informal overidentification test. While we do not directly fit this variable, our results show that the model is very successful in endogenously replicating the high rates of homeownership observed in the data. We discuss this in more detail in the next section.

6 Structural results

6.1 Structural estimates

Table 4 reveals economically reasonable SMM estimates. For instance, the life cycle literature finds relative risk aversion parameters between 1 and 6 (Chetty, 2006). Our estimated γ is roughly 4.62 for males and 4.04 for females, in line with Cagetti's (2003) estimates for U.S. college graduates. Additionally, the (statistically significant, p-val=0.01) gender difference in γ confirms prior findings on the male-female risk-taking gap narrowing for those who are highly educated (Gerrans and Clark-Murphy, 2004; Drupp et al., 2020). Turning to time preferences, we find βs of roughly 0.91 that are well within the range reported in the literature (Cocco et al., 2005; Dobrescu et al., 2012). Similarly, we find a utility weight of housing versus consumption α of around 0.59, slightly higher than Kaplan et al. (2020) but lower than Yogo (2016). As for the intra-period substitution between the two, we estimate ρ to be -1.04 for males and -1.16 for females that implies an elasticity of substitution slightly above 0.45 – at the lower end of the range of estimates in the literature (Ogaki and Reinhart, 1998; Pakos, 2011; Albouy et al., 2016) but close to recent ones in McKay and Wieland (2022). These estimates also suggest that compared to males, females are somewhat less willing to substitute housing for consumption, which is also consistent with the ABS (2018) report on homeownership rates (see Table 2.15), and with our reduced form analysis in Section 3. Turning to the intensity of the bequest motive, we find θ parameters of roughly \$3,641 for men and \$30,977 for females. This marked (and statistically significant, p=0.05) gender differential might be due to the stronger intergenerational altruism of females and so, to their greater propensity to save for heirs (Seguino and Floro, 2003).[23]

The bottom panel in Table 4 presents the default switching cost estimates, which F-tests confirm are significantly different between males and females. To ease interpretation, we express these costs as the net present value of the additional DC balance (at retirement) required to compensate for the associated utility loss. Figure 1 plots these monetary equivalents. First, we note the downward sloping profile of all three cost types, suggesting that switching away from defaults becomes cheaper over time: more years of employment can help individuals learn the importance of retirement savings. We would thus expect them to take increasing control of their wealth accumulation, particularly near the end of their careers. Second, note that the highest switching costs are related to opting out of the default pension plan. This irreversible choice costs on average about \$21,215 for males and \$24,795 for females, which represents roughly 26.20% of annual earnings as also estimated by Luco (2019). Switching away from the default 0% voluntary contribution rate is cheaper, costing females about \$16,885 and males \$19,434. This more

[23] It may also relate to the likelihood that couples hold major assets jointly so that only after the last member dies - probably the female partner - does the majority of wealth register as a bequest.

Table 4: Parameter estimates

		Males		Females		
		Estimates	S.E.	Estimates	S.E.	P-value
CRRA	γ	4.618	0.155	4.038	0.114	0.004
Housing share	$\overline{\alpha}$	0.587	0.052	0.601	0.030	0.820
	ρ_α	0.859	0.031	0.874	0.024	0.710
	$\sigma_{\alpha\varepsilon_t}$	0.008	0.006	0.017	0.006	0.305
CES parameter	ρ	-1.040	0.282	-1.164	0.236	0.739
Bequest	$\ln(\theta)$	8.200	0.697	10.341	0.812	0.050
Time discount	$\overline{\beta}$	0.914	0.012	0.909	0.010	0.751
	ρ_β	0.637	0.040	0.624	0.034	0.804
	$\sigma_{\beta\varepsilon_t}$	0.028	0.002	0.017	0.004	0.019
Switching costs:						
Voluntary	v_0^v	14.433	10.746	21.688	7.557	0.583
contributions	v_1^v	44.844	5.350	38.092	3.145	0.281
	$v_2^v \times 10^3$	0.102	0.233	-16.973	8.646	0.057
	v_3^v	-0.130	0.233	-0.411	0.161	0.323
	$\sigma_{DB}^V \times 10^3$	1.242	7.644	12.825	6.464	0.251
	$\sigma_{DC}^V \times 10^3$	15.931	10.904	1.124	4.073	0.210
Asset	v_0^r	6.067	6.202	17.588	3.824	0.119
allocations	v_1^r	-0.053	0.023	-0.044	0.018	0.774
	$v_2^r \times 10^3$	0.550	0.239	0.438	0.000	0.643
	v_3^r	0.131	0.033	0.105	0.026	0.539
	v_4^r	2.163	0.423	1.879	0.484	0.660
	$\sigma_r^{DB} \times 10^3$	4.472	8.070	4.383	3.823	0.992
	$\sigma_r^{DC} \times 10^3$	11.055	10.321	8.358	4.992	0.815
Plan	v_0^p	11.318	10.738	-0.462	2.524	0.292
type	v_1^p	-0.121	0.011	-0.123	0.011	0.875
	$v_2^p \times 10^2$	0.813	0.044	0.785	0.038	0.632
	σ_p	0.084	0.034	0.102	0.036	0.717
Default preference	$\ln(\psi)$	-0.877	1.613	-1.743	0.832	0.635

subtle difference confirms estimates in Section 3 on voluntary contributions being rather similar for males and females. In contrast, gender differences in adjustment costs are significantly more marked for the decision to choose non-default asset allocations, being 30.95% cheaper for males to do so compared to females. Given the high risky asset share in the default allocation, switching out means lower chances for high returns and with smaller balances to invest, females will see their pension wealth drop.

While these adjustment costs might seem substantial, recall that they are compounded up to a variation to DC account balance at retirement. They do not mean that an average individual would not switch for this amount in cash, but that they would not switch for this amount in their DC account upon retirement. An alternative way to understand their impact is to see how wealth would have changed over time had

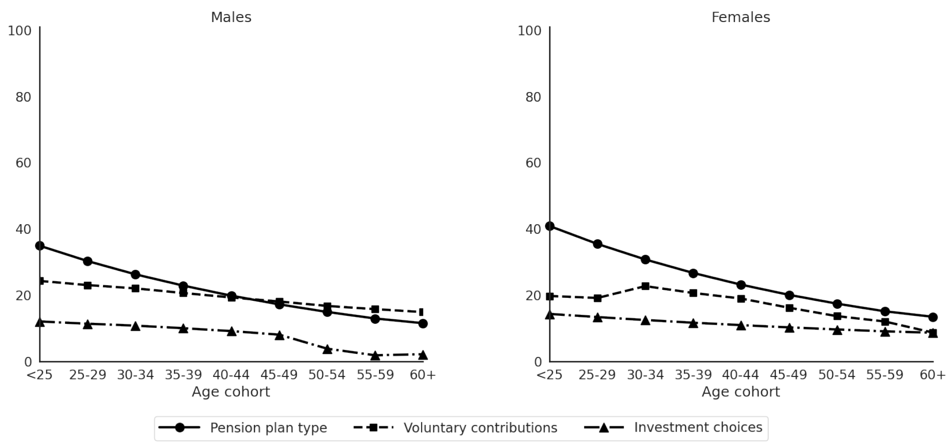

Figure 1: Mean switching costs by cohort (thousands of $)

switching been costless. We do this exercise in Section 6.2.

6.1.1 Data patterns and model fit

The model replicates the life cycle wealth profiles, the patterns of pension choices, and the timing of homeownership very well. In particular, we have successfully replicated (i) the increasing age profiles of wealth for all three types of assets accumulated (in Figures 2 - 4), (ii) the overall gender-specific plan opt-in levels (in Figure 5), (iii) the stable risky asset share over working life (in Figure 6), (iv) the increasing rates and amounts of voluntary contributions over prime working years (in Figures 7 - 8), and (v) the mildly-increasing hump-shaped consumption profiles (in Figure 9) that we observe in the data. The goodness of fit between the simulated and the empirical (data) moments is assessed via a χ^2-test (or corresponding $p-value$). In all instances, a χ^2-test of goodness of fit confirms that we cannot reject the null that the simulated and empirical moments are the same at standard significance levels.

Let us take a closer look at wealth, with Figures 2 - 4 showing the pension, financial and housing wealth profiles. As mentioned, all types of wealth increase with age, but females appear to accumulate 25.06% less in their pension account than males. This might be due to their earnings: females work fewer hours, are more likely to have career interruptions and thus shorter tenures, and potentially face slower wage growth (2013 COAG Reform Council). The lower earnings of females compared to males will be also compounded, however, by the missed opportunities for high return investments due to generally small take-up of DC plans (Figure 5) – i.e., 19.51% for females and 22.05% for males, which confirms the

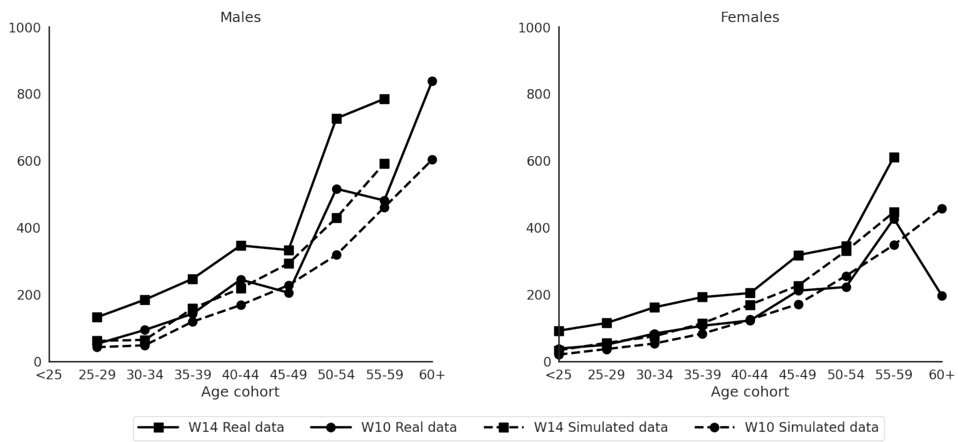

Figure 2: Mean pension wealth by cohort (thousands of $)

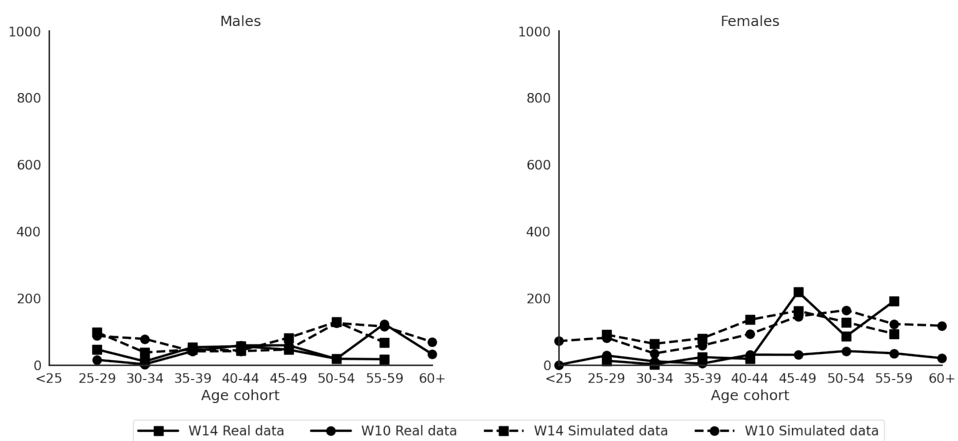

Figure 3: Mean financial wealth by cohort (thousands of $)

positive (although statistically insignificant) gender effect for DC opt-in decisions in Section 3. Note also that while only one in five of all participants pursue riskier-than-default allocations, females try to make up for lost returns by holding on average 11.31% riskier portfolios than males (Figure 6). Overall, we see relatively flat age profiles for risky asset shares, with very slight portfolio rebalancing away from risk for the oldest cohort. In higher education, the drop in the stock of human capital with age is arguably milder, and associated with more stable incomes and less employment risk. These characteristics of academic earnings are consistent with continuing exposure to risky assets later in working life (Haliassos et al., 2001; Cocco et al., 2005).

One way to supplement pension wealth is via voluntary contributions. Like Beshears et al. (2009),

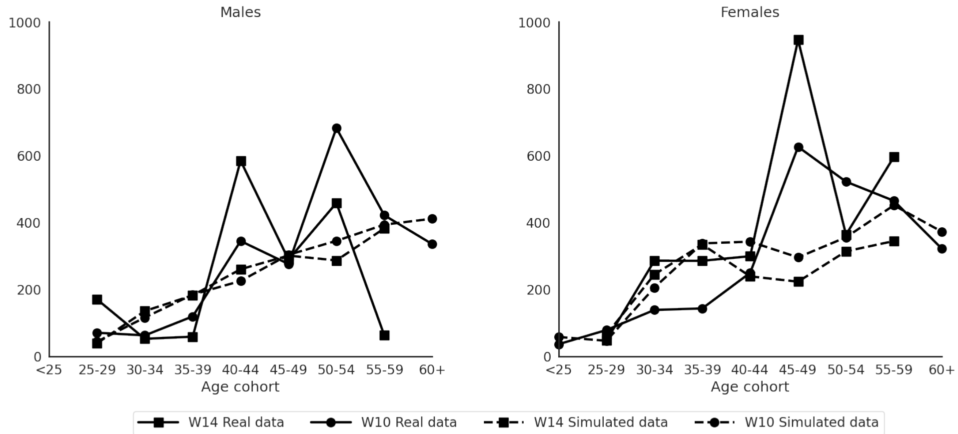

Figure 4: Mean housing wealth by cohort (thousands of $)

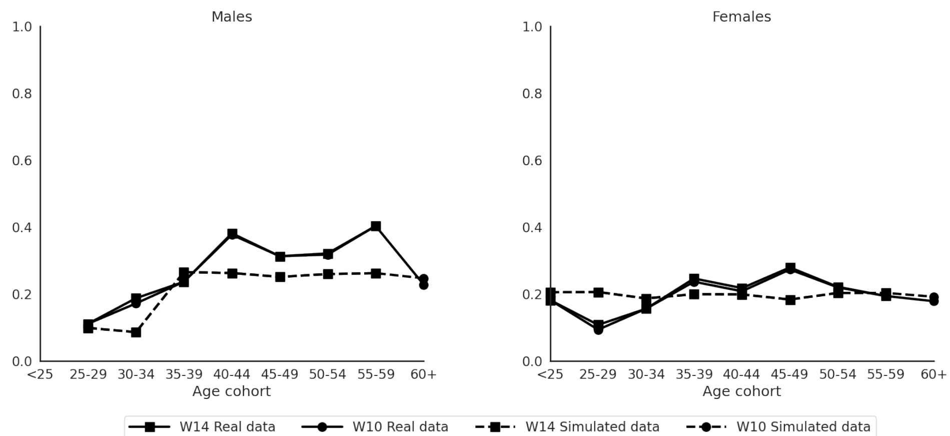

Figure 5: Share of participants choosing DC plans by cohort

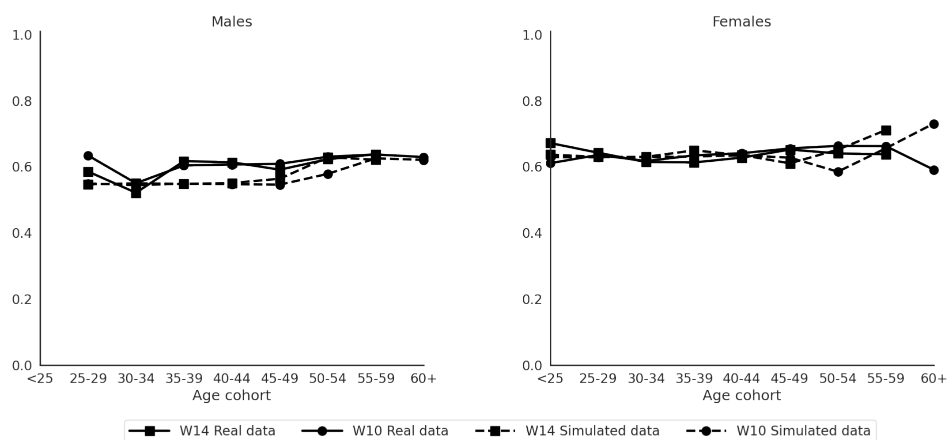

Figure 6: Mean risky assets share by cohort

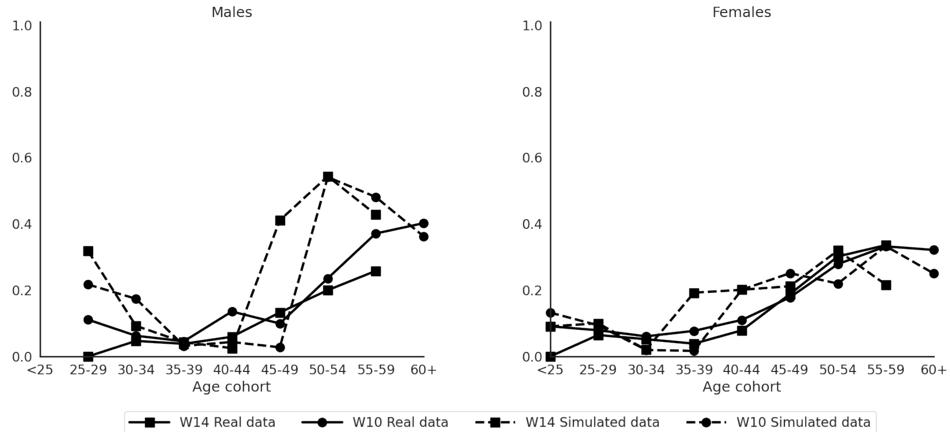

Figure 7: Share of participants voluntarily contributing by cohort

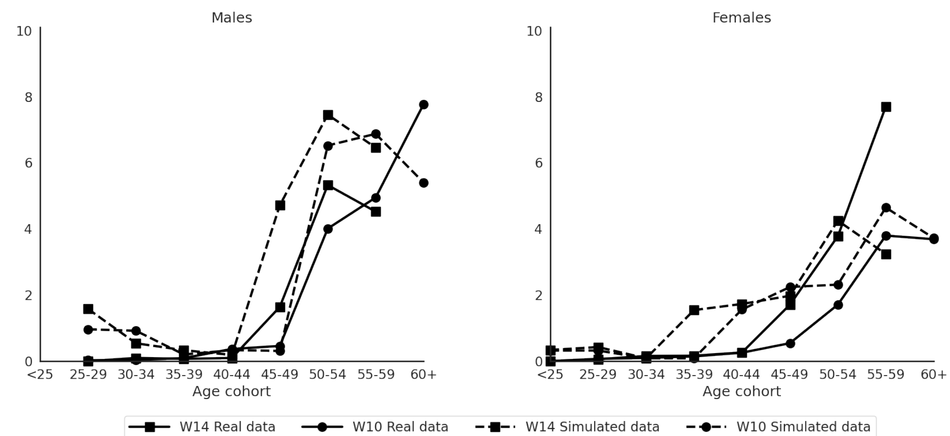

Figure 8: Mean voluntary contributions by cohort (thousands of $)

we find that most participants stay at the default voluntary contribution rate of 0%. Towards the end of their career, about 30-40% of participants contribute extra, while for most of their active lives fewer than 15% make voluntary contributions (Figure 7). Surprisingly, females rely only slightly more than males on voluntary contributions to build their retirement savings (Figure 8), confirming results in Section 3.

Outside pension wealth, we also see females holding 30.81% more financial assets than males, possibly counteracting lower wages by accumulating more precautionary savings (Seguino and Floro, 2003). As for housing wealth, we find that females accumulate roughly 6.18% more wealth in housing than males. This higher real assets path for females, particularly given their financial wealth, is consistent with females deriving higher utility from housing than males (Goldsmith-Pinkham and Shue, 2023).

Unsurprisingly, these wealth patterns generate very reasonable consumption profiles that fit those observed in the data (Figure 9). The profiles display the usual mildly-increasing hump-shape, with males'

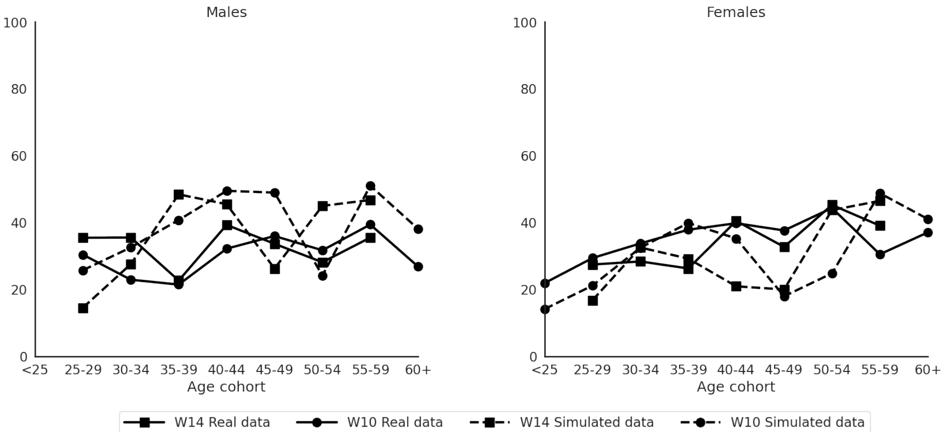

Figure 9: Mean consumption by cohort (thousands of $)

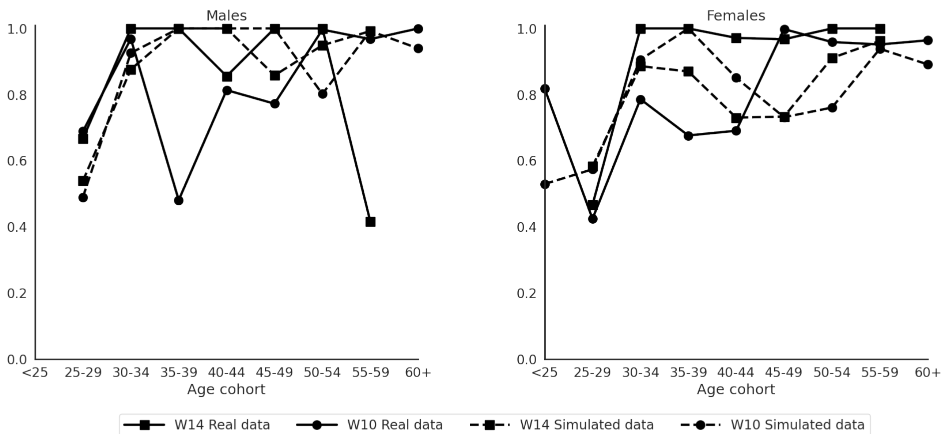

Figure 10: Share of homeowners by cohort

slightly lower than females'. The larger gap between males' simulated and empirical profiles might be caused by limiting males' consumption to non-durables, and therefore under-estimating it. Indeed, the gap is smaller for females, for whom non-durables (e.g., fuel, power, clothing, etc.) take a larger budget share than for males (Bradbury, 2004). Finally, note that our estimation procedure did not include fitting shares of homeownership. Figure 10 shows the model's fit to this variable, which amounts to an informal overidentification test. Remarkably, we find that both the male and female models were able to endogenously generate cohort-specific rates of homeownership that are close to the actual data.

6.2 How do pension and housing investments interact?

To study the relation between pensions and housing, we first conduct six counterfactual experiments that consider either policy interventions or changes in market conditions. Specifically, we consider how people's saving behavior would have changed over time had they (i) been able to freely switch away from the three pension defaults ("Costless switching"), (ii) earned 4.5% higher returns for their risky pension assets ("Growth investment"), (iii) incurred 60% higher returns risk for all DC pension assets ("DC volatility"), (iv) faced 10% lower prices in the housing market ("Affordable housing"), (v) experienced a 10% increase in housing returns risk ("Riskier housing"), and (vi) faced a 10 percentage point rise in the collateral required to purchase a house ("Credit tightening"). Next, we re-run scenarios (i), (ii) and (iv) above without the pension (PF) and housing frictions (HF) to clarify the mechanisms behind the relation between pensions and housing. Each simulation modifies the key parameters associated with a particular scenario, solves the model numerically, and generates the corresponding wealth patterns. Table 5 shows how counterfactual wealth allocations compare with their baseline counterparts.

Table 5: Counterfactual scenarios

	Opting for DC Plans	Opting to Contribute	Risky Assets Share	Pension Wealth	Financial Wealth	Housing Wealth	Overall Wealth
	% of participants		%	% change from baseline			
Panel A. Males							
Baseline	26.453	25.338	56.798	-	-	-	-
Costless switching	36.782	61.106	47.635	47.774	-5.383	18.539	25.785
Growth investment	38.631	55.207	58.349	53.595	4.398	8.821	23.463
DC volatility	23.484	19.183	55.897	-7.530	3.707	-2.192	-3.347
Affordable housing	31.467	24.456	58.636	-1.015	7.140	17.356	12.251
Riskier housing	28.418	31.323	58.290	2.960	1.938	-12.344	-5.602
Credit tightening	27.467	10.164	57.934	-12.157	31.578	-1.567	-1.014
Affordable housing^{PF}	37.271	35.700	32.300	5.349	6.167	4.987	4.379
Growth investment^{HF}	27.467	23.717	57.664	76.631	12.053	-4.359	36.853
Costless switching^{HF}	40.960	53.674	43.353	53.608	6.793	-8.980	22.714
Panel B. Females							
Baseline	19.742	16.876	63.899	-	-	-	-
Costless switching	31.129	75.823	73.574	59.431	-14.297	41.328	40.353
Growth investment	29.156	58.162	75.058	68.476	-5.827	23.678	33.003
DC volatility	17.182	10.407	62.847	-10.588	19.995	-13.418	-9.000
Affordable housing	21.187	15.634	73.569	-7.235	20.391	19.247	11.679
Riskier housing	24.125	21.769	67.678	6.348	-14.678	-8.567	-8.725
Credit tightening	22.478	8.441	64.792	-25.678	14.475	-8.102	-9.479
Affordable housing^{PF}	35.403	78.815	75.588	13.460	-13.216	6.127	6.610
Growth investment^{HF}	29.547	65.896	60.484	47.180	3.589	-1.920	16.833
Costless switching^{HF}	29.858	30.614	61.045	84.324	2.414	- 1.080	31.136

Notes: The table shows individual percentage changes averaged across the life cycle.

6.2.1 The pensions – housing complementarity

Our first "Costless switching" scenario tests the effect of plan architecture by eliminating pension switching costs. We uncover a complementarity relation from pensions to housing that is stronger for females than for males. Consider, say, an information campaign by the pension plan that is fully effective, so that plan participants can make optimal decisions without behavioral frictions. The higher flexibility and opportunities for diversification of non-default options generate a sizeable pension wealth boost, averaging 47.77% for males and 59.43% for females. This boost is caused by both higher DC take-up (by about a third of the baseline rates),[24] and significantly larger chances for participants to voluntarily contribute (double the baseline rate for males, and four times for females). As expected, financial savings drop (by about 9.84% overall) but interestingly, males (females) accumulate 18.54% (41.33%) more housing in response to their higher lifetime wealth. Expecting higher wealth in retirement, people will opt to smooth future housing consumption and bring some of it earlier into their working years. Overall, this leads to 25.79% and 40.35% higher life cycle wealth for males and females, respectively – the largest increase among the scenarios we investigate. More important still, the heterogeneity in wealth effects by gender means that changes to pension plan architecture have significant potential – by a sizeable 48.46% – to alleviate gender wealth inequality.

To further test the pension-housing complementarity, we explore a scenario that increases risky pension returns by 4.5% to match the yield of the UniSuper *High growth* investment option over the past decade ("Growth investment"). Higher returns boost pension wealth (by about 53.60% for males, and 68.48% for females), due to higher prevalence of DC plan choices, higher voluntary contributions, and more risk taking, all of which are now more rewarding options. Consistent with our finding above, we continue to find complementarity from pensions to housing, and a stronger relation for females than for males. Indeed, higher pension balances lead to 8.82% higher housing investments for males, and 23.68% for females. Interestingly, the increase in housing occurs mostly during early years and also as 'upsizing' before retirement (Figure 11). The effect of high returns on raising voluntary contributions, however, is present throughout the life cycle and rises with age (Figure 12), a pattern consistent with our preliminary results. So while we observe an early increase in housing, a more significant increase in pensions occurs

[24]Note that even with costless switching, a sizeable share of people might prefer DB plans. This is mainly due to the sector's long tenures and high earnings (particularly towards the end of a career), which mean the DB formula pays generous benefits.

relatively later in life. Overall, these effects translate into roughly 23.46% and 33.00% higher total wealth for males and females, and further contribute to narrowing the gender gap in wealth by 36.43%.

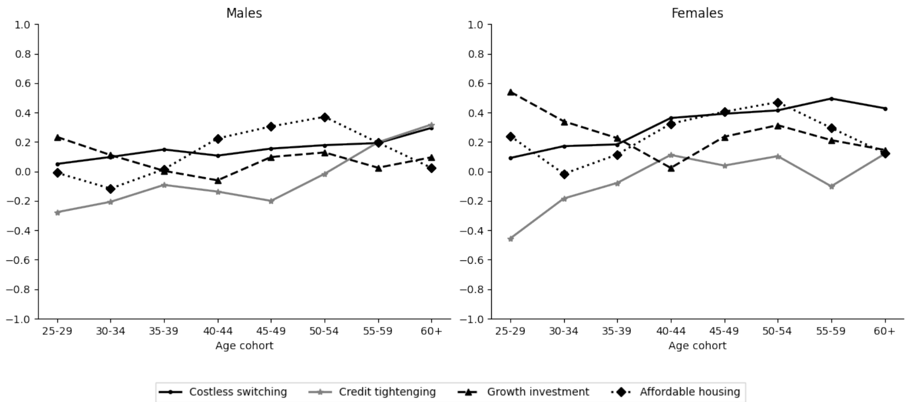

Figure 11: Additional gross housing wealth by cohort (proportional change w.r.t. baseline)

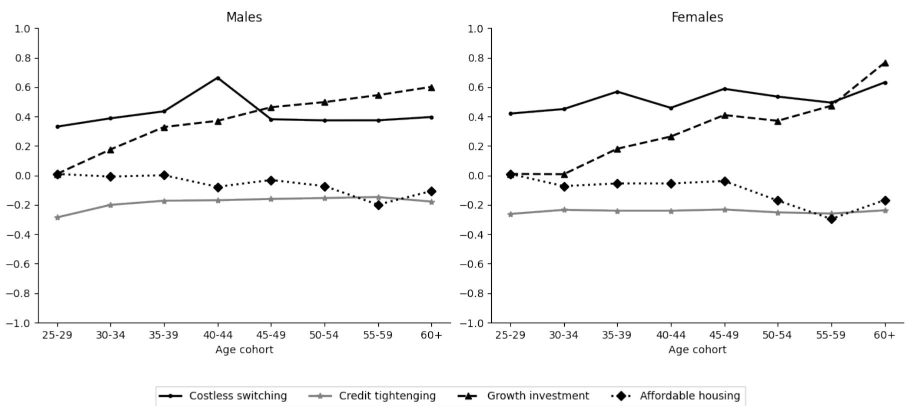

Figure 12: Additional pension wealth by cohort (proportional change w.r.t. baseline)

As a reverse check, we confirm that complementarity holds under unfavorable financial conditions. Consider a 60% increase in DC plan investment return volatility, on par with the surge in the equity market risk index (VIX) during the 2000 dot-com crash. The heightened risk makes individuals shift away from pensions towards outside savings, with males (females) accumulating 7.53% (10.59%) less pension wealth. The shift is the result of both genders contributing less, opting less for DC benefits, and slightly reducing their exposure to risk, forgoing higher returns in the process. Concurrently, we see all individuals cutting back on housing, with males lowering investments by 2.19% and females, once more, reacting strongly with a 13.42% reduction. First, with smaller pension balances, individuals anticipate a lower level of consumption (including housing consumption) post-retirement, and so they slow down housing accumulation during working years to smooth consumption. Second, since housing returns are also risky, they further decrease housing investments to mitigate the rise in overall risk associated with post-retirement consumption. Third, females have lower pension balances, and so worse plan conditions will mean a relatively larger drop in pension wealth for females than for males. This leads to larger overall wealth effects for females than for males (9.00% vs. 3.35%), but, as expected, negative for both groups.

The extent to which changes in pension plan architecture and investment conditions cause co-movement between retirement savings and homeownership is one of the main contributions in this study. These results, however, also raise the question of whether the same positive co-movement occurs when housing (rather than pension) conditions change. Changes to housing market and credit conditions can generate price fluctuations that will affect the timing and value of homeownership, which will likely affect in turn the pace and manner in which retirement wealth is built. Below we propose three counterfactuals to flesh out these effects.

6.2.2 The housing – pensions substitutability

We start from an "Affordable housing" scenario that assumes a 10% reduction in housing prices, consistent with a policy that eases zoning restrictions in circumstances where such restrictions have previously led to a tight housing supply (Quigley and Raphael, 2004; Glaeser and Gyourko, 2018). Housing becoming more affordable moves individuals at the margin towards homeownership or upsizing, which ultimately translates into males (females) accumulating 17.36% (19.25%) more housing wealth, consistent with females placing a higher value on bequests. As people build up their housing, they will have less liquidity available to allocate to the other assets. We thus observe a drop in pension wealth, higher for females (7.23%) than males (1.02%) due to tighter budget constraints brought by lower earnings. Overall, better housing conditions will sum up to roughly 12% higher total wealth for both males and females.

This scenario highlights a significant asymmetry: while the gains from successful information campaigns or favorable plan conditions boost pension wealth and in turn housing, a housing wealth increase does not reciprocally raise pension savings. The reason behind this asymmetry is evident in Figure 11, which shows the largest rise in housing wealth occurring during the prime working years (i.e., age 35-50). On the one hand, recall that a fall in house prices implies lower housing adjustment costs. The lower cost promotes an increase in housing purchases on the extensive margin but also on the intensive margin, with more people choosing to upsize later in life. On the other hand, mid-working-life individuals tend to stop undervaluing their post-retirement future and become more likely to voluntarily contribute. Reduced liquidity due to higher housing will reduce extra contributions on the intensive margin. We thus see housing affordability boost real wealth for these cohorts even as they substitute away from pensions (Figure 12). We verify this intuition in Section 6.2.3 below.

Next, we confirm the housing to pensions substitution effects using a "Riskier housing" scenario. Here, housing appeal is reduced by increasing the volatility of returns to housing by 10%, similar to the rise in house price index volatility experienced in the decade after the Subprime Crisis (Shiller et al., 2019). The extra volatility, together with limits on borrowing, a risk-free liquid saving option (financial wealth), and an (unchanged) illiquid saving alternative (pensions), motivates smaller housing holdings by about 12.34% (8.57%) for males (females) – a differential response consistent with females being less risk averse and valuing bequests more. As allocations to housing fall, people move wealth into pensions: females increase pension balances by 6.35% and males by 2.96%. While both males and females are more likely to contribute (by 5.99% and 4.89%, respectively), females choose riskier allocations and DC plans at double the rates of males. The shift to DC allows all individuals to better manage their post-retirement risk exposure, taking advantage of the variety of investment choices available. For females, the extra risk remains aligned with their preferences and need to compensate for the earnings differential. All in all, we see that higher housing market volatility hurts total wealth, with a larger drop for females (8.76%) than males (5.60%) and wealth inequality rising as in the "DC volatility" scenario above.

Finally, we also explore a scenario that is not price-related, deviating somewhat from the economic definition of complementarity and substitution that focuses on how price changes in one asset affects investments in another asset. To do so, we assume an increase in the collateral required for a mortgage from 20% to 30% ("Credit tightening"), possibly coming from a macroprudential implementation of a more stringent loan-to-value (LTV) ratio (Justiniano et al., 2019). The higher collateral constraint will bind for more individuals, making it harder to become a homeowner, lowering total wealth, and widening the wealth gap between females and males by 12.98%. Younger cohorts are the most severely affected (Figure 11), as they have yet to amass sufficient funds for the higher down payment (Ortalo-Magnè and Rady, 2006). Their response is to increase financial wealth, and higher earnings will allow males to do so at rates that are almost double those for females (31.58% vs. 14.48%). Their higher financial wealth will allow males to buy a house earlier than females, leading to a significantly smaller drop in housing wealth for them (1.57%) compared to females (8.10%). Diverting resources to meet higher down payments results, however, in lower liquidity available to build up pensions. While both males and females try to compensate for lower contributions by choosing DC plans and riskier investment options, pension holdings decrease by 12.16% (25.68%) for males (females) – by far the largest drop in our scenarios so far.

Taken together, our results show that housing complements pensions, while pensions act as a substitute for housing. Moreover, whether pensions and housing are complements or substitutes has different implications for the gender wealth gap: complementarity in situations when savings are incentivized reduces wealth inequalities, while substitutability might not. When saving becomes more difficult, however, complementarity exacerbate the gap more than substitutability. This asymmetry has important implications about when, where, and how much people save.

6.2.3 Explaining the asymmetry in pension and housing investments

We now evaluate, using our model and the counterfactuals above, the key drivers of the asymmetry of the relation between pensions and housing. In particular, we ask whether it is behavioral frictions in retirement choices that drive the complementarity from pensions to housing, housing frictions that drive substitutability, or a combination of both that is required.

To answer these questions, we start from our main counterfactuals in Table 5 and examine how the relation between pensions and housing changes in three situations. First, we remove behavioral frictions from the "Affordable housing" scenario that shows the substitutability from housing to pensions. Second, we remove housing frictions from the "Growth investment" scenario that shows the complementarity from pensions to housing. Third, we remove housing frictions from the "Costless switching" scenario to evaluate the impact of overall frictions on the link between pensions and housing.

In the "Affordable housing" scenario in Table 5, we see housing becoming cheaper and so people will want to 'consume' relatively more housing; females will do so more than males, consistent with them placing a higher value on bequests, of which housing is the main vehicle. This leaves everybody with fewer resources to invest in other assets, which will impact first on those choices most affected by liquidity constraints – i.e., voluntary contributions. The fall in voluntary contributions will overpower strategies to build back these savings through extra returns from riskier allocations (females) and higher DC take-up (males), as also shown in Section 3. When facing liquidity constraints and switching costs, individuals will underinvest in pension accounts. Costless switching will allow them, however, to follow through with strategies to exploit higher returns, decreasing outside financial holdings as they transfer this wealth into pensions ("Affordable housing^{PF}"). Larger pension balances will then allow for higher non-durable and housing consumption in retirement. Substitutability will be reversed, with (i) 5.35% (13.46%) higher pension wealth for males (females) pairing now with 4.99% (6.13%) more housing than in the starting scenario (baseline without pension frictions), and (ii) total wealth rising by 4.38% for males and 6.61% for females, and confirming the positive effect of complementarity on the gender gap.

Consider now the "Growth investment" scenario that makes pension holdings more profitable, particularly later in life, and also boosts early housing (see Figure 11-12). The timing difference in these responses is due to the behavioral hurdles associated with early-life financial decisions: individuals are already inclined towards adjusting their housing early in life (Yang, 2009), and so they face no significant hurdle to marginally increase housing in response to anticipated future wealth. The pension-housing complementarity is thus only reinforced by housing frictions, prompting the young to secure larger houses early on rather than adjust their housing stock throughout their lives (and incur further adjustment costs). These same people face, however, considerable behavioral hurdles to build up their pensions, with a significant share of the young not contributing. A marginal increase in the rate of return leads therefore to a delayed increase in pension savings that does not otherwise crowd out early homeownership. Without housing transaction costs ("Growth investment^{HF}"), people will adjust their housing stock smoothly, with relatively less early housing accumulation and more upsizing later in life. This reduces the positive effect of higher pension returns on housing accumulation and reverses complementarity into substitution, with (i) 76.63% and 47.18% higher pension wealth being paired with 4.36% and 1.92% lower housing for males and females, respectively compared to the original scenario (baseline without housing frictions), and (ii) total wealth rising by 36.85% for males and 16.83% for females, and showing that unlike complementarity, substitutability in situations when savings are incentivized might not necessarily reduce wealth inequality.

Finally, consider the joint effects of eliminating both housing and pensions frictions in scenario "Costless switching^{HF}". Since the original "Costless switching" scenario is one of the counterfactuals showcasing complementarity, the impact of eliminating the housing transaction costs will largely follow the same economic intuition as for "Growth investment" above. Complementarity will be reversed into substitution, with housing dropping by 8.98% (1.08%) for males (females), pensions rising by 53.61% (84.32%), and substitution having, once more, a more moderate impact on the gender wealth gap than complementarity.

6.3 Implications for gender inequality in wealth accumulation

Now that we have an understanding of the key factors that drive the asymmetric relation between pensions and housing and how it unfolds across genders, the last step is to evaluate how they affect gender wealth inequality. For instance, is the wealth gap arising because females' characteristics (e.g., being more prone to defaults) are less well rewarded in pension terms than males', which complementarity amplifies at the total wealth level too? Or is it because females have less rewarding characteristics, such as smaller wages or more volatile labour market participation rates? For instance, the average earnings of the males in our sample is 23.66% higher than for females, and they also have 25.63% more net wealth. At first glance this may suggest that wages almost single-handedly drive the gender gap in wealth.

To answer this question, we decompose the gender gap in wealth by evaluating the relative contributions of six key elements: earnings inequality and volatility, risk and bequest preferences, costs of active participation in retirement choices, and housing adjustment costs. These are the only significant differences across genders; by counterfactually changing them one one at the time we can thus quantify their relative contribution to the difference in wealth between males and females.

To isolate the labor market impact, we run a counterfactual in which we assign the earnings process of the males to the females, keeping all other elements constant. By doing so, we find that 57.53% of the gender difference in total wealth can be accounted for by earnings inequality, with no further significant effects coming from wage volatility. Not all of this effect is because of earlier home-buying: changes in earnings dynamics still have important effects during mid-working life on housing, and afterwards on pensions. Results are robust to scenarios that highlight the two-way relation between pensions and housing within the parameters of our counterfactual experiments above.

Second, the literature (Dominitz and Manski, 2007; Croson and Gneezy, 2009; Niederle, 2016) has also shown that gaps in pension assets are related to gender differences in personal traits. Our estimates show that males tend to invest more safely and assign a lower value to leaving bequests, which can give rise to gender differences in investment strategies. These two traits will thus make females save less, ultimately widening the gender gap by 5.63% and 1.01%, respectively.

Third, more active plan participation by females can be rationalized with smaller default switching costs, which reflects the easier information acquisition that seems to apply for males. Without behavioral frictions, pension wealth will rise. Facing a more prosperous retirement, and consistent with complementarity, females will also increase housing because of the value they place on housing, for their services, and because it allows them to benefit from capital gains. Our model thus predicts that lower behavioral frictions in retirement choices will narrow wealth inequality by about 33.51%.

In a parallel scenario that additionally considers a frictionless housing market, we find transaction costs to be more important than preferences, but not more important than behavioral frictions, in driving the gender gap in wealth. Shutting down housing frictions, that affect males and females differently, leads to females accumulating 21.65% more housing than males, ultimately wiping out the gender gap in wealth.

Overall, our model shows that changes in labor market income dynamics, risk and bequest preferences, behavioral costs and housing market frictions have substantial effects on life savings. In the longer term, these factors can influence the distribution of income and wealth, intergenerational mobility, and the effects of policies. Within this setup, we do not need to assume any other preference changes to explain the smaller wealth of females.

6.4 Structural robustness checks

In this section, we present several robustness checks that further verify the direction of our effects. We start from the counterfactual with the highest beneficial effect on the gender gap in wealth, and cancel the behavioral costs associated with plan type, voluntary contributions and asset allocations one-by-one. We find that the effect of each adjustment cost on overall wealth goes hand in hand with their respective magnitude, as shown in Figure 1. In particular, removing the switching cost associated with opting for DC plans has the largest positive effect on wealth for both males and females, followed by the cost associated with voluntarily contributing, and then adjusting risky assets share. Importantly, the consistent complementarity from pensions to housing is robustly maintained in each of these scenarios.

Next, we consider a robustness check that fully eliminates housing frictions, and another that completely removes the ability to redraw from mortgage accounts. Without housing transaction costs, investments in housing will rise and pension savings will drop. The decrease in pension contributions aligns with the analysis in our main counterfactuals, where housing affordability increases housing and displaces pension contributions, highlighting the substitutability that runs from housing to pensions. The overall effect of eliminating transaction costs on total wealth continues to be positive and stronger for females.

In contrast, preventing mortgage redraws lowers borrowing and decreases housing, with females lowering their stock more than males. Since housing displaces pensions, pension contributions will rise, highlighting again the substitutability and bringing positive wealth effects across the board. The same would occur in a situation parallel to the "Growth investment" scenario, in which we consider a higher rate of capital gain on housing: more attractive housing will displace pensions, giving rise to the substitutablity. The positive wealth effects look stronger for females than for males (21.69% vs. 12.71% boost), with the gender gap in housing returns narrowing by 9.25% the gender gap in wealth.

Finally, note that our model includes preference heterogeneity and uncertainty in the time discount factor, time-varying preferences for housing services, and time-varying beliefs about those preferences going forward. Removing them makes our profiles more sensitive to other shocks and worsens the fit of certain aspects of the data, in particular in terms of cross-sectional distributions and auto-correlations over time. However, this leaves all our main conclusions unchanged.

7 Conclusions

This study examines an overlooked aspect of how people save, namely the two-way relationship between pension and housing investments over the life cycle. Using a structural model of optimal consumption and portfolio choice estimated on granular data from a large industry-wide pension plan, we ask whether pensions and housing are complements or substitutes in people's portfolios of assets during their lives. We also investigate the channels that lead to the relations we see, and how they impact the gender wealth gap.

Results show that housing complements pensions, with environments that motivate pension savings also encouraging more investment into housing. For instance, eliminating behavioral frictions on retirement choices delivers high wealth gains, with the sizeable rise in pension balances further stimulating housing accumulation during working years as people anticipate a wealthier retirement. The opposite is not true, however: encouraging housing investments crowds out pension savings. Improving housing affordability, for instance, makes people add to housing savings in later working years, at a time when they should increase their pension contributions. The mechanisms behind this asymmetry, and especially how it unfolds across genders, are related to behavioral and housing frictions largely driving complementarity and substitutability, respectively. As a result, we show that while the gender gap in wealth is unsurprisingly associated with gender differences in personal characteristics per se, it is also considerably explained by gender differences in returns to personal characteristics. The latter refers not so much to risk or bequest preferences, but plan choices access costs. In particular, although there are marked differences between males and females in their lifetime earnings, these differences account for only 57.53% of the overall wealth gap between the genders. Behavioral frictions, on the other hand, explain a significant 33.51%, preferences add a further 5.63% (risk aversion) and 1.01% (bequest motives), and a frictionless housing market would completely eliminate the remaining gap.

As a rising share of the population grows older, lives longer and relies more on private pension savings, life cycle portfolio decisions – and in particular the interplay between housing and retirement savings – become crucial in determining retirement wellbeing. By highlighting the heterogeneity in when, where, how much and how people save, our results contribute to the policy debates on designing adequate welfare programs. They also lend support to models of saving behavior that allow for different assets to display different life cycle patterns, some following more and others less the standard life cycle theory predictions.

Given the rich framework of our model, one potential avenue for further research involves investigating the heterogeneous effects we might see for certain groups. While our findings provide key intuitions on the life cycle wealth accumulation of males and females, one could similarly evaluate the implications for high and low earners, or for individuals at different points in the wealth distribution, as well as examining, for example, housing value by plan type, the differential in homeownership by decision to voluntarily contribute, the risk exposure in pensions vs. housing wealth by age, earnings and wealth, etc. Additionally, analyzing the impact of other international pension-housing settings on portfolio decisions could provide very useful insights. Relatedly, as pensions and housing form a substantial fraction of total assets in an economy, studying the wider macroeconomic effects of pension and housing incentives within a general equilibrium framework could also provide valuable intuitions. In particular, the way in which related policies influence economies' responses to aggregate shocks is a promising area for future research. Lastly, while we provide a quantitative analysis of joint asset accumulation, formal theoretical results on comparative statics between different asset types in a general dynamic setting with frictions and various sources of risk are yet to be tackled.

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Appendix (online only)

A Retirement plan features

Table A1. Pension plan features

	Mandatory	Default Option	Alternative Options
Enrolment	✓	-	-
Plan type	-	*DB*	*Irreversible choice to DC (within 1 yr)*
Employer contributions	✓	*17%*	-
*Employee contributions**			
Standard rate	-	*7%*	*Irreversible choice to decrease*
Voluntary rate	-	*0%*	*Reversible choice to increase*
Investment options	-	*Balanced*	*Reversible choice of other 14 options*
Insurance	-	*Life and disability*	*Reversible choice to change cover*

Notes: The table presents the key features of UniSuper - the pension fund we study. Bold indicates the choice dimensions that we model. Recall all UniSuper members make investment allocation choices as both DB and DC plans have a DC account. *An additional choice dimension (that we do not model here) is that employee contributions can be made pre- or post-tax.

Table A2. Pension standard contribution schedule

Standard Contribution Rates (%)		ACF (%)	Employer Contribution to DB Account (%)
Pre-tax	Post-tax		
8.25	*7.00*	*100.00*	*82.30*
5.25	*4.45*	*100.00*	*100.00*
4.70	*4.00*	*97.40*	*100.00*
3.55	*3.00*	*91.70*	*100.00*
2.35	*2.00*	*86.00*	*100.00*
1.20	*1.00*	*80.20*	*100.00*
0.00	*0.00*	*74.50*	*100.00*

Notes: The table presents the UniSuper standard contribution rates that an employee can opt for, before- or after-tax, along with the corresponding Average Contribution Factor (ACF) and share of employer contributions to the DB account.

B HILDA spending imputation estimates

Table B1. Share of individual-to-household consumption

	Wave 10				Wave 14
	(1)	(2)	(3)	(4)	(5)
Age	0.289*	0.258	0.141*	0.254	0.323*
	(0.140)	(0.142)	(0.063)	(0.141)	(0.128)
Male	-6.116***	-6.095***	-6.121***	-5.842***	-4.828**
	(1.480)	(1.503)	(1.478)	(1.493)	(1.543)
Couple	-2.258	-2.598	-3.063	-3.868	0.744
	(1.764)	(1.893)	(1.916)	(1.971)	(2.074)
Household size		1.107	1.350*	1.165*	1.819**
		(0.587)	(0.568)	(0.581)	(0.688)
Health insurance premium	0.001*		0.002*	0.001*	0.000
	(0.001)		(0.001)	(0.001)	(0.000)
Ln annual wage	-0.374	-0.261	-0.215	-0.336	0.509
	(0.654)	(0.627)	(0.618)	(0.632)	(0.720)
Ln net wealth	1.228*	1.029		1.058	-0.138
	(0.553)	(0.557)		(0.557)	(0.550)
Ln net wealth x Age	-0.019	-0.013		-0.016	0.004
	(0.013)	(0.013)		(0.013)	(0.012)
Constant	76.168***	74.504***	81.193***	75.041***	62.434***
	(9.041)	(8.794)	(6.862)	(8.776)	(8.300)
Observations	504	504	510	504	633
AIC	4172.9	4174.8	4220.8	4170.3	5452.9

Notes: All specifications are OLS models. Specifications (4)-(5) are the final ones used for the imputation of individual-to-household consumption share in Wave 10 and Wave 14, respectively. Note that compared to Wave 10, Wave 14 misses (i) holiday and travel costs, and (ii) new vehicles, computers, audio visual equipment, household appliance and furniture. To adjust Wave 14 consumption for these missing categories, we compute the Wave 10 ratio of missing to non-missing consumption categories, where these categories are identified based on whether they appear in Wave 14 or not. We then use the coefficients of specification (4) run on this Wave 10 ratio to impute the value of missing Wave 14 consumption categories and add it to Wave 14 raw consumption to get total consumption. Since net wealth contains negative values, log net wealth is the log of adjusted net wealth, where *Adjusted net wealth= (net wealth - min net wealth) +1*. Robust standard errors are in parenthesis below estimated parameters. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table B2. Share of individual-to-household housing expenses

	Wave 10				Wave 14
	(1)	(2)	(3)	(4)	(5)
Age	0.372	0.459	0.308	0.471	-1.974
	(1.198)	(1.205)	(0.198)	(1.213)	(1.179)
Male	7.127	7.103	7.262	7.069	1.305
	(5.051)	(5.026)	(5.084)	(5.036)	(5.382)
Couple	3.885	5.573	7.055	6.285	1.187
	(4.806)	(5.899)	(6.176)	(6.264)	(6.734)
Household size		-1.599	-1.531	-1.642	2.842
		(1.962)	(1.905)	(1.970)	(2.019)
Health insurance premium	-0.001		-0.001	-0.001	-0.002
	(0.001)		(0.001)	(0.001)	(0.001)
Ln annual wage	3.557*	3.523*	3.623*	3.555*	2.176
	(1.445)	(1.423)	(1.439)	(1.433)	(1.645)
Ln net wealth	1.422	1.827		1.857	-8.963*
	(3.536)	(3.608)		(3.624)	(4.445)
Ln net wealth x Age	-0.013	-0.023		-0.023	0.193*
	(0.092)	(0.094)		(0.094)	(0.094)
Constant	28.649	28.322	43.049*	27.704	162.298**
	(46.542)	(46.306)	(18.987)	(46.564)	(56.973)
Observations	413	413	419	413	505
AIC	4267.5	4266.7	4326.5	4268.5	5357.8

Notes: All specifications are OLS models. Specifications (4)-(5) are the final ones used for the imputation of individual-to-household housing expenses share in Wave 10 and Wave 14, respectively. Since net wealth contains negative values, log net wealth is the log of adjusted net wealth, where *Adjusted net wealth= (net wealth - min net wealth) +1*. Robust standard errors are in parenthesis below estimated parameters. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

C Computation

This appendix provides the computational details of our model solution and estimation. We start by describing how we discretize our model in Section C.1. Next, Section C.2 describes the backward induction using the inverse Euler equation method and RFC algorithm. Finally, Section C.3 discusses the parallel computation of our model solution and estimation.

C.1 Constructing the computational grids

Wages. For the average wage over the last three years of continuous employment $\bar{y}_t$, we have that

$$g\left(y_{t-j}\right)=\frac{1}{Pr\left(\xi_t\right)}\sum_{i=1}^{N_\xi}Pr\left(\xi_i\right)\cdot P\left(\xi_i,\xi_t\right)\cdot exp\left[\lambda_0+\sum_{k=1}^{4}\lambda_k\left(t-j\right)^k+\sum_{k=1}^{2}\lambda_{4+k}\left(\tau-j\right)^k+\xi_i\right].$$

This is derived from the reverse of the ξ_t Markov process (Chung and Walsh, 1969), with N_ξ discrete state points, distribution $Pr(\cdot)$ and transition matrix $P(\cdot,\cdot)$ and allows us to reduce computational burden and not carry (ξ_{t-2},ξ_{t-1}) in the state space.

State space. We create state space grids for each age as follows. For $t>T_R$, we have

$$\hat{\mathbb{X}}_t=\hat{\mathbb{A}}\times\hat{\mathbb{B}}\times\hat{\mathbb{S}}\times\hat{\mathbb{H}}\times\hat{\mathbb{M}}\times\hat{\mathbb{Q}},\tag{79}$$

while for $t\leq T_R$, we have

$$\hat{\mathbb{X}}_t=\hat{\mathbb{Z}}\times\hat{\mathbb{A}}\times\hat{\mathbb{B}}\times\hat{\mathbb{S}}\times\hat{\mathbb{S}}_{DC}\times\hat{\mathbb{H}}\times\hat{\mathbb{M}}\times\hat{\mathbb{Q}}\times\hat{\mathbb{T}}^t\times\{DB,DC\},\tag{80}$$

where $\hat{\mathbb{S}}$ is the financial wealth grid, $\hat{\mathbb{H}}$ is the housing wealth grid, $\hat{\mathbb{Q}}$ is the housing price grid, $\hat{\mathbb{S}}_{DC}$ is the DC pension wealth grid, $\hat{\mathbb{M}}$ is the mortgage asset grid,[25] $\hat{\mathbb{Z}}$ is the wages shock grid, $\hat{\mathbb{T}}^t$ is the set of possible tenure levels at age t, $\{DB,DC\}$ is the plan type, $\hat{\mathbb{A}}$ is the grid for housing preferences α, and $\hat{\mathbb{B}}$ is the grid for time preferences β. We also let $\hat{\mathbb{V}}$ denote the voluntary contribution grid and define an extended grid with the discrete choices as follows:

$$\bar{\mathbb{X}}_t=\hat{\mathbb{Z}}\times\hat{\mathbb{A}}\times\hat{\mathbb{B}}\times\hat{\mathbb{S}}\times\hat{\mathbb{S}}_{DC}\times\hat{\mathbb{V}}\times\hat{\mathbb{H}}\times\hat{\mathbb{M}}\times\hat{\mathbb{Q}}\times\hat{\mathbb{T}}^t\times\{DB,DC\}.\tag{81}$$

We discretize (i) financial wealth, housing wealth, (DC) pension wealth, and mortgage space into 35 grid-points each, and (ii) housing price space into 11 grid-points. The wage term ξ_t is discretized into a 5-state Markov process following Kopecky and Suen (2010). The α and β preference processes are also discretized into 3-point Markov process each, asset returns are discretized to two grid-points for low and high risk alternatives, and finally the housing price shock is discretized into three grid-points. The tenure years state space τ is integer and ranges from 0 to 48 $(=65-17)$. Finally, we consider five different levels

[25] In the subsequent computational discussion, both the pension grid and the mortgage grid represent the time t state after the stochastic returns at the start of time t have been realised.

of voluntary contribution rates (besides the 0% default) and five different levels for the risky assets share (besides the 70% default). Experiments with the grids fineness suggested that the ones we used produce reasonable approximations.

Note that our specification of mortgage redraws is designed to reduce dimensionality and make our estimation feasible, while preserving the features of the institutional context in our data. The discussion below equation (11) captures the Australian mortgage market setup, where individuals can costlessly withdraw from their mortgage accounts if they are ahead of their repayment schedule (up to the amount of extra payments made). To avoid adding the repayment schedule as an extra state, our model assumes that redraws are available up to a fixed limit ι, and we calibrate ι accordingly based on the amounts by which individuals are, on average, ahead of their mortgage repayments (RBA, 2018) - see also Kaplan et al. (2020). This assumption, however, means we do not capture how the marginal benefit of access to redraws in the future affects the mortgage repayments people make. Regardless, we calibrate redraw limit ι such that each period, individuals face the same redraw constraints as the mean individual in our data.

C.2 Solution method

C.2.1 Sequential problem setup

Each period, we collect the problem's variables into a shock vector e_t, a vector of continuous states w_t, continuous post-states x_t, and discrete choices d_t. Define $e_t :=\left\{y_t, R_t^r, R_t^s, P_t, \alpha_t, \beta_t, \{\xi_t^v\}_{v\in\mathbb{V}}, \{\xi_t^v\}_{v\in\Pi}\right\}$ as the set of shocks realized at the start of period t. The continuous state variables are (i) financial wealth after returns are realized $w_{a,t}$, (ii) housing wealth after depreciation $w_{H,t}$, (iii) pension wealth after returns are realized $w_{a^{DC},t}$, and (iv) mortgage liabilities after mortgage interest is realized $w_{m,t}$. The continuous post-states are (i) end-of-period financial wealth $x_{a,t} := a_{t+1}$, (ii) end-of-period housing wealth $x_{H,t} := H_t$, and (iii) end-of-period mortgage liabilities $x_{m,t} := m_{t+1}$. The discrete choices of the model are (i) whether or not to rent $d_{HS,t}$, (ii) whether or not to adjust housing $d_{H,t}$, (iii) voluntary contributions $d_{v,t} := v_t$, and (iv) risky asset shares $d_{\pi,t} := \pi_t$. We let $w_t = (w_{a,t}, w_{H,t}, w_{a^{DC},t}, w_{m,t})$, $x_t = (x_{a,t}, x_{H,t}, x_{m,t})$, and $d_t = (d_{S,t}, d_{H,t}, d_{v,t}, d_{\pi,t})$.

The continuous state space W_t can be defined as a compact subset of $\mathbb{R}^4$ and the post-state space X_t can be defined as compact subset of $\mathbb{R}^3$. Moreover, $D_t := \{0,1\}^2 \times \mathbb{V} \times \Pi$, where $\mathbb{V}$ and Π are the sets of discrete choices for the voluntary contributions and risky assets share, respectively.

C.2.2 Constrains, transitions and payoffs

To characterise the constraints, we will define a function $g_t : E_t \times W_t \times D_t \times X_t \to \mathbb{R}^{N_g}$, where N_g is the number of constraints. The constraints are the mortgage collateral constraint, mortgage redraw constraint, the non-negativity constraint for financial wealth, the non-negativity constraint for housing wealth, the non-negativity constraint for mortgages, and a rental choice constraint which ensures agents can rent if they own no housing capital. The constraints are defined by

$$g_{mc,t}(e_t, w_t, d_t, x_t) = -x_{m,t} + \phi^C x_{H,t} P_t, \tag{82}$$

$$g_{mr,t}(e_t,w_t,d_t,x_t) = (1-d_{H,t})(w_{m,t}-x_{m,t}+\iota), \tag{83}$$

$$g_{a,t}(e_t,w_t,d_t,x_t) = x_{a,t}, \tag{84}$$

$$g_{H,t}(e_t,w_t,d_t,x_t) = (1-d_{H,t})(w_{H,t}-x_{H,t}), \tag{85}$$

$$g_{m,t}(e_t,w_t,d_t,x_t) = x_{m,t}, \tag{86}$$

and

$$g_{S,t}(e_t,w_t,d_t,x_t) = -d_{HS,t}x_{H,t}. \tag{87}$$

We say (d_t,x_t) is feasible if $g_t(e_t,w_t,d_t,x_t) \geq 0$.

Transition equations. The transition functions for the continuous state are

$$F_{a,t}(e_t,w_t,d_t,x_t) = \left[\pi_t R^r_{t+1} + (1-\pi_t)R^s_{t+1}\right] \cdot \left[x_{a^{DC},t} + (v_t+v_S+v_E)\,y_t\right],$$

$$F_{DC,t}(e_t,w_t,d_t,x_t) = Rx_{a,t},$$

$$F_{H,t}(e_t,w_t,d_t,x_t) = (1-\delta)x_{H,t},$$

and

$$F_{m,t}(e_t,w_t,d_t,x_t) = (1+r^m_{t+1})x_t.$$

Payoffs. Each period, payoffs are given by a real-valued function

$$\Xi^u(e_t,w_t,d_t,x_t): \;=\; p\hat{u}\big(c_t,S_t;\alpha_t\big) + \nu_v \mathbb{1}_{d_{v,t}\neq 0} - \nu_\pi \mathbb{1}_{d_{\pi,t}\neq \pi^d} + \xi_{t,v} + \xi_{t,\pi} + (1-p)b(B_t), \tag{88}$$

where $\hat{u}(c_t,S_t;\alpha_t) = u(c_t,S_t;\alpha_t)$ if $c_t > 0$ and $S_t > 0$, or $\hat{u}(c_t,S_t;\alpha_t) = -\infty$ otherwise.[26]

We let consumption be denoted by

$$c_t = w_{a,t} + (1-d_{v,t}-v_S)\,y_t - P_t(x_{H,t}-w_{H,t}) - d_{H,t}\tau_H P_t x_{H,t} - H^S_t P^S_t - w_{m,t} + x_{m,t}, \tag{89}$$

and bequests by

$$B_t = w_{a,t} - w_{m,t} + w_{H,t} + w_{a^{DC},t}. \tag{90}$$

Housing services are given by

$$S_t = d_{HS,t}H^S_t + (1-d_{S,t})x_{H,t}, \tag{91}$$

[26] In equation (88), the survival probability p is the probability that one survives and enters the period to earn payoffs $\hat{u}\big(c_t,S_t;\alpha_t\big)$; $(1-p)$ is then the probability that one does not enter the period alive and thus earns payoffs $b(B)$, where B is the start-of-period wealth after all returns have been accrued.

where H_t^S is the rental value of housing services (for renters).

The stochastic dynamic optimization problem is defined by

$$V_0(e_0, w_0, d_0, x_0) : = \max_{(d_j, x_j)_{j=0}^T} \mathbb{E}_{e_t} \left[\sum_{j=0}^{T} \tilde{u}_t(e_t, w_t, d_t, x_t) \right], \tag{92}$$

where per-period payoff is given by

$$\tilde{u}_t(e_t, w_t, d_t, x_t) : = \hat{p}_t \hat{\beta}_t \Xi^u(e_t, w_t, d_t, x_t), \tag{93}$$

s.t. (i) $\hat{\beta}_t = \Pi_{k=0}^{t} \beta_k$, $\hat{p}_t = \Pi_{k=0}^{t-1} p_k$, (ii) $w_{t+1} = F_t(e_t, w_t, d_t, x_t)$, and (iii) $g_t(e_t, w_t, d_t, x_t) \geq 0$ for all $t \leq T$.

C.2.3 Euler equations

We use the S-function (Dobrescu and Shanker, 2024) to derive the Euler equations for the model. First, the Euler equation for financial wealth is

$$\partial_c u(c_t, S_t, \alpha_t) - (1 - p_t) b'(B_{t+1}) - \mu_{a,t} = \beta_t p_t (1 + r_{t+1}) \mathbb{E}_{e_t} \partial_c u(c_{t+1}, S_{t+1}, \alpha_{t+1}), \tag{94}$$

with $\mu_{t,a} > 0$ if $g_{a,t}(e_t, w_t, d_t, x_t) = 0$. Second, the Euler equation for mortgages is

$$\begin{aligned} &\partial_c u(c_t, S_t, \alpha_t) - (1 - p_t) b'(B_{t+1}) - \mu_{mc,t} - \mu_{mr,t} + \mu_{m,t} \\ &\qquad = \beta_t p_t \mathbb{E}_t (1 + r_t^m) \partial_c u(c_{t+1}, S_{t+1}, \alpha_{t+1}), \qquad 0 \leq m_{t+1} \leq \phi^C H_{t+1}, \end{aligned} \tag{95}$$

with (i) $\mu_{mr,t} > 0$ if $g_{mr,t}(e_t, w_t, d_t, x_t) = 0$, (ii) $\mu_{mc,t} > 0$ if $g_{mc,t}(e_t, w_t, d_t, x_t) = 0$, and (iii) $g_{m,t}(e_t, w_t, d_t, x_t) = 0$ if $\mu_{m,t} > 0$. Third, the Euler equation for housing if an adjustment is being made at time t is

$$\begin{aligned} P_t \partial_c u(c_t, S_t, \alpha_t) - (1 - d_{HS,t}) \partial_S u(c_t, S_t, , \alpha_t) + \mu_{mc,t} \phi^C &= \mathbb{E}_t \hat{s}_t^\tau \hat{\beta}_t^\tau (1 - \delta)^{\tau - t} P_\tau \partial_c u(c_t, S_t, \alpha_t) \\ &\quad + \mathbb{E}_t \sum_{l=t}^{\tau} \hat{\beta}_t^l \hat{s}_t^l (1 - s_l) b'(B_{l+1}) P_l, \end{aligned} \tag{96}$$

For the shadow values of the state, we have

$$\Lambda_{a,t} = \partial_c u(c_t, S_t, \alpha_t) - \mu_{a,t}, \tag{97}$$

$$\Lambda_{m,t} = \mu_{a,j} + \Lambda_{a,j} - \mu_{m,j} + \mu_{mr,j}. \tag{98}$$

Now recursively define Λ_t^H as follows: given Λ_{t+1}^H and μ_{t+1}^H, define

$$\Lambda_{H,t} = d_{H,t} P_t \partial_c u(c_t, S_t, \alpha_t) + (1 - d_{H,t}) \beta_t p_t \mathbb{E}_{e_t} \Lambda_{t+1}^H + (1 - p_t) \mathbb{E}_{e_t} P_{t+1} b'(A_{t+1}). \tag{99}$$

C.2.4 Inverting the Euler equation

To approximate the policy functions that characterize the agent's continuous post-state decision, we invert the Euler equation above over an exogenous grid of post-states and controls (Dobrescu and Shanker (2024). The inverse problem is solved separately for each feasible housing-related discrete choice: $d_{t,S} = 1$ (renters), $d_{t,H} = 1$ (housing adjusters), and $d_{t,H} = 0$ (non-adjusters). For each housing discrete choice, we solve policy functions given the exogenous shocks e_t and pension state $w_{a^{DC},t}$ fixed.[27] Once the optimal continuous policy function conditional on these discrete choices is approximated, the choice probabilities over these discrete choices can be computed using equations (15)-(20).

Renters. Starting with renters, note that the only continuous active state affecting their problem is *total liquid wealth* $\bar{w}_{t,lw} :\, = w_{t,a} - w_{t,m} + P_t w_{t,H}$. As a result, the relevant Euler equation for renters is the financial wealth Euler equation (94). Renters make decisions over two constrained regions: (i) a region where the financial constraint $g_{a,t}$ binds, and (ii) a region where this constraint does not bind.

The exogenous grid must be one-dimensional since the active state-space is one dimensional. For renters in the financially constrained region, the exogenous observable is consumption ($\cong \mu_{a,t}$) and the relevant Euler equation is (94). For renters in the unconstrained region, the exogenous variable is the financial wealth post-state $x_{a,t}$. For both regions, Euler equation (94) can be inverted analytically to recover values for the active state $\bar{w}_{t,lw}$ and form an endogenous grid. The RFC algorithm Dobrescu and Shanker (2024) can then be applied to recover the optimal upper envelope over the endogenous grid and approximate the policy function on the grids defined in Section C.1.

Non-adjusters. The three possible continuous active states are total liquid wealth $\bar{w}_{t,lw} :\, = w_{t,a} - w_{t,m}$, mortgage $\bar{w}_{t,m} :\, = w_{t,m}$, and housing wealth $\bar{w}_{t,H} :\, = w_{t,H}$. The relevant exogenous observables are consumption and the mortgage post-state. Non-adjusters make eight possible constraint choices, defined by combinations of the financial wealth and mortgage constraint binding. However, instead of interpolating separate policy functions for each of these possible eight constraint choices, we use Theorem 1 by Dobrescu and Shanker (2024) to invert from the eight different regions such that equations (94) -(99) hold. This allows us to construct a single grid of endogenous and exogenous points over which we apply RFC and interpolate only once to approximate the optimal policy function.

Adjusters. The continuous state affecting the adjuster's problem is total liquid wealth $\bar{w}_{t,lw} :\, = w_{t,a} - w_{t,m} + P_t w_{t,H}$. The relevant Euler equation is the financial wealth Euler equation (94), the Euler equation for housing wealth (96), and the mortgage Euler equation (95). Since the number of active states is less than the number of post-states, the exogenous grid can be constructed from a uniform grid of housing values by finding multiple roots of $x_{a,t}$ and $x_{m,t}$ for each value of the housing post-state. RFC can then be applied to recover the optimal upper envelope and approximate the policy function (see Application 2 in Dobrescu and Shanker, 2024).

[27] Since pension wealth is determined only by discrete choices, we can consider them as a discrete state and fix them as a fixed variable.

C.3 Estimation on HPC cluster

Despite significantly reducing the numerical steps required to compute a solution by inverting the Euler equation, the dimensionality of the life cycle model imposes a significant computational burden on the SMM estimation. Monte Carlo methods such as the cross-entropy method (Botev el al., 2011) are well suited to minimising irregular objective functions such as the SMM objective function. However, since we estimate 27 model parameters, the cross-entropy method requires up to 1,000 parameter draws per iteration. Thus, we proceed to estimate the model on a high performance computing (HPC) cluster, where we distribute the model solution and estimation across CPUs.

As a first step, we separate the solution conditioned on pension plan type (DB/DC) as plan specific decision rules can be solved independently. However, conditional on DB/DC choice, further paralellization proved to be challenging. This is because there is a significant serial component to the backward induction algorithm. Moreover, many of the numerical evaluations in the backward induction algorithm are 'fast' compared to the time taken for message passing interface (MPI) operations used for inter-CPU communication. The backward induction algorithm also contains steps to 'combine' large arrays by evaluating conditional expectations to generate the final policy function, which could be slowed down due to MPI array broadcasting. As such, we find assigning two CPUs to each plan specific solution yielded good scaling with a scaling efficiency of approximately 70%.

Finally, to implement cross-entropy, for each iteration, we distribute 600 parameter draws. Each parameter draw solves both DB and DC decision rules, and so we create 600 groups of 4 CPUs, with each group handling one parameter draw. Even with over 10,000 CPUs used to implement the cross-entropy method, efficiency remains over 80%.