RETIREMENT SAVINGS: A TALE OF DECISIONS AND DEFAULTS*

Loretti Isabella Dobrescu, Xiaodong Fan, Hazel Bateman, Ben Rhodri Newell, A. Ortmann and Susan Thorp

This study develops a structural dynamic life-cycle model to examine the behavior of members of an industry-wide pension fund to assess both the prevalence of defaults and their impact on retirement savings. We estimate the model using the simulated method of moments on administrative data from a large Australian pension fund. Our results show that default settings strongly influence wealth accumulation. Such settings are also highly persistent, both over time and across decisions. Overall, the findings suggest that if defaults (particularly the irreversible ones) are not carefully designed, retirement savings can be severely affected.

Social security reforms around the world have increasingly put individuals in charge of their own financial well-being in retirement. At the same time, many of the required decisions (e.g. savings rates, portfolio allocations, buying health and life insurance etc.) have become more and more complex. A potential effect of these tensions is that individuals delay making financial decisions and fail to build retirement assets (Madrian and Shea, 2001; Iyengar et al., 2004). In response, many pension plans (and in some cases governments) have set default options, specifying predetermined outcomes when no choice is made for key decisions (e.g. participation, contribution rates, investment allocations, benefit type). In theory, such defaults should not matter as long as people can easily opt out. In practice, however, defaults tend to influence savings behaviour greatly (Beshears et al., 2009), being very persistent or ‘sticky’ (Madrian and Shea, 2001; Choi et al., 2002, 2004; Cronqvist and Thaler, 2004), even when they lead to inferior outcomes (Choi et al., 2011).\(^1\) So, when individuals remain passive, and if defaults are not carefully designed, suboptimal retirement outcomes may result (Carroll et al., 2009; Goda and Manchester, 2013).

In this context, we first must ask why so many individuals rely on default options in their pension choices. Is it preferences, demographic characteristics, or labour mobility? And, given the low participation in pension decisions (or high default ‘stickiness’), what is the impact of default provisions on retirement savings adequacy?

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\(^1\) See Sunstein (2013) for a review of recent literature on defaults and DellaVigna (2009) for studies documenting their effects and how they challenge the economic assumption of rational decision-making.
To answer these questions, we use administrative data from one of Australia’s largest pension funds – UniSuper, which covers all higher education and research sector employees. UniSuper is a hybrid fund that offers both defined benefit (DB) and defined contribution (DC) plans. The DB plan provides retirement benefits calculated mainly according to a set of formulae based on individual earnings, age and tenure. The DC plan provides benefits based on contributions and subsequent investment market performance. Initially, all permanent employees (i.e. employed on contracts of two years or more) are enrolled by default in the DB plan and have one year to make an irreversible change to DC. Those who do not actively opt into DC by the end of the first tenure year remain permanently in the default (DB) plan. Finally, individuals must also choose (i) an initial voluntary contribution rate (which they can change in subsequent periods), and (ii) an investment allocation for their DC balance from a menu of options (or stay with the default one).

We start our analysis by (i) documenting the relation between various defaults related to plan type, contribution levels and investment allocations, and (ii) identifying the empirical elements associated with such pension choices. Using a rich dynamic life-cycle model, we then assess the ability of these empirically motivated decision factors to explain the data.

Confirming previous findings, our empirical results show that the likelihood of selecting a DC plan increases with age, wage and contribution years and is lower for those less educated and for those who chose a default investment allocation. Married people are both more likely to opt for a DC plan and have higher account balances. Women, who are more likely to face career interruptions due to maternity leave for instance, have lower pension balances but are more likely to contribute voluntarily. Not surprisingly, being highly educated is positively related with both higher probability to voluntarily contribute and higher account balances, while having children is negatively associated to both. Finally, opting for non-default investment allocations is associated with better outcomes along all three choice dimensions (i.e. selecting a DC plan, voluntarily contributing and overall pension balance).

Next, we construct a structural life-cycle model to replicate these findings. In our model, individuals decide consumption and how much they save for retirement, in a setting that combines automatic enrolment with reversible and (time-sensitive) irreversible choices, as follows: upon employment, individuals are automatically enrolled in a DB plan and, within the first period, they have a one-off option to switch to a DC plan. Additionally, each period they can decide to (i) make voluntary contributions, effectively overriding the default (0%) contribution rate, and (ii) opt out of the default (balanced) investment allocation, by choosing a lower or a higher risk-return option. Finally, switching away from any default option is costly. Depending on the choice, this cost captures the extra effort of gathering information and completing the paperwork or the liquidity value of savings outside the pension plan. We assume individuals will select the arrangement (i.e. plan type, contribution schedule and investment allocation) that maximises their expected lifetime utility.

To the best of our knowledge, ours is the first structural study to consider simultaneously choices related to plan type, contributions and investments, with both
reversible and irreversible default options, some of which also have strict opt-out deadlines. This (structural) setup allows us to conduct detailed policy simulations and evaluate the potential welfare implications of multi-default provisions for members of an industry-wide pension fund. We thus use UniSuper data and estimate the model via the simulated method of moments.

The structural results are consistent with the empirical ones: first, we find that defaults are sticky, both over time and across decisions. We estimate a monetary-equivalent cost of switching to DC of roughly $32,000 at the median, with opting out of balanced investments 34% cheaper for women and almost twice that for men. This leads to only few people opting out of the default (DB) plan and more than half remaining in the default (balanced) investment allocation. Second, we also find an increasing incidence and level of voluntary contributions with age, in line with the data. Third, we measure the effect of default stickiness on retirement savings by performing several counterfactual experiments to study what would have happened to an individual’s retirement wealth had the defaults (or the choice timing) been different. Specifically, changing the default plan from DB to DC leads to a 10.13% and 18.34% net increase in total pension wealth for men and women, respectively. This dramatic difference derives from the DC investment performance reported by UniSuper and emphasises the potentially severe costs of irreversible defaults and opt-out deadlines. In fact, being able to switch from DB to DC irreversibly in any period would increase pension wealth by 1.48% (11.66%) for men (women), whereas allowing people to switch back and forth between DB and DC would bring a difference of 10.47% (for men) and 5.91% (for women). Note that in all these scenarios, women appear to benefit more from switching to a market-contingent DC plan as this would partly mitigate their shorter tenure and lower wages (compared to men). Additionally, defaults continue to be sticky when the standard investment option is either the low or the high risk allocations, with the former leading to slightly less accumulated wealth (up to 2%) and the latter generating up to 7% more retirement savings. Finally, allowing people to switch freely between plans and between investments brings a substantial pension wealth gain, comparable to a high risk-DC default. This is not surprising since generally, if one abstracts from default opt-out costs, DC plans are superior to the DB ones.

All in all, these findings contribute to understanding both the determinants of retirement plan selection and the role of multi-default provisions (related to plan type, voluntary contributions and investment allocation) on retirement savings behaviour. So far, the consensus from studies of plan selection has been that the main drivers of retirement wealth are individual risk preferences, demographic characteristics and job tenure (Clark and Pitts, 1999; Clark et al., 2006; Manchester, 2010; Brown and Weisbenner, 2014).

2 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 our study 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 is active. Ours are more general, covering the entire life cycle.

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Our empirical results are consistent with these findings. Some international evidence, however, also supports the notion that a large number of choice options causes confusion, which leads to high rates of default (Choi et al., 2004; Tapia and Yermo, 2007; Vanguard, 2008; Benartzi et al., 2011; Bateman et al., 2014). Our simulations confirm this theory in the context of the Australian higher education sector and quantify the large impact of default provisions on savings. In this respect, our article is closely related to studies of pension plan choice (Bodie et al., 1988; Blake, 2000; Gerrans and Clark-Murphy, 2004; Brown et al., 2004; Cocco and Lopes, 2011; Gerrans and Clark, 2013) and on the role of defaults in decisions regarding participation (Madrian and Shea, 2001; Beshears et al., 2009; Goda and Manchester, 2013), contribution rates (Choi et al., 2004; Beshears et al., 2009), investment allocation (Hedesstrom et al., 2004; Choi et al., 2005; Beshears et al., 2009) and distributions from DC plans (Mitchell et al., 2009). Additionally, we also contribute to the recent literature investigating the relevance of individual heterogeneity in designing and implementing default provisions in the context of plan enrolment (Carroll et al., 2009; Handel, 2013; Sunstein, 2013; Goda and Manchester, 2013; Chetty et al., 2014).

The remainder of the article is organised as follows: Section 1 gives an overview of the UniSuper pension scheme. In Section 2, we describe the data and present the reduced form results. Section 3 develops the dynamic model and Section 4 presents the parameter calibration and the estimation method. Results from the structural model are presented in Section 5 and counterfactual experiments are reported in Section 6. Section 7 concludes.

1. The UniSuper Pension Scheme

Australia has roughly 200 large pension (or superannuation) funds. Among them, UniSuper is the only fund for higher education and research sector employees. It is also one of Australia’s largest pension funds with roughly 460,000 members and $50 billion in assets.

The UniSuper pension plan features for permanent staff are summarised in Appendix A. Note that upon employment, permanent staff on long-term (two years or more) or continuing (tenured) contracts are automatically enrolled in a DB plan. They are then offered an irreversible choice to switch to DC (also known as Accumulation 2), within the first 12 months of tenure. If they do not switch within this time interval, they will permanently remain DB members. Employees also receive employer contributions (typically 17% of earnings) and can make ‘standard contributions’ as a further percentage of their wage (see Appendix A).

UniSuper members who opt for a DC plan hold individual accounts with balances that depend on total contributions and investment earnings, net of taxes, administrative and investment management fees, and insurance premiums. Members receive life, total and permanent disability insurance coverage by default but may vary their level of coverage, may elect to also receive income insurance or may opt out entirely.

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make additional `voluntary contributions`, which may attract tax benefits.\(^6\) Such contributions can be made regularly or irregularly and, for low income earners, they may attract an annual government co-contribution of up to $1,000. Finally, DC members may also select from a menu of 15 investment options varying by projected returns and risk, asset allocation and management fees. Limited movement between investment options is allowed. If new members do not select an option, however, their contributions go to a default investment option. The default is a diversified `balanced` investment, with a 70:30 split between growth and defensive assets.

Standard DB plan benefits are based on an aggregate (employer and employee) contribution of at least 21% of after-tax earnings. If employees who receive 17% employer contributions choose the default (maximum) standard contribution of 7%, then 3% of their employer contribution is allocated to a DC component, leaving an earnings contribution rate of 21% for the DB component. Employees choosing a lower standard contribution rate have first their DC benefits and then their DB benefits reduced. Appendix A provides the detailed schedule. Employees with a lower standard contribution rate are also ineligible for optional insurance coverage. The decision to reduce standard contributions cannot be reversed. Regardless of their standard contribution rate, in each period employees can make voluntary contributions, which are always assigned to the DC component. Since for DB members, part of the standard contributions and any voluntary ones are allocated to the DC component (usually earning uncertain returns), part of their final retirement benefit is also uncertain.

2. Data and Empirical Analysis

In our analysis we combine two data sets:

(i) UniSuper records on pension plan choices, and
(ii) the Household, Income & Labour Dynamics in Australia Survey (HILDA).\(^7\)

The first data set consists of individual administrative data on a random subsample of UniSuper members on permanent contracts. As mentioned, UniSuper is a large pension fund covering all employees of Australia's higher education and research sector. Each month, the fund collects data on demographics, voluntary contributions and pension plan type, as well as some job (mobility) indicators. We use two waves of UniSuper data, corresponding to May and September 2012. We restrict our sample to individuals who were active members in Wave 1, according to whether they (or their employers) made any contributions to the fund over the previous four months. After merging Waves 1 and 2 of UniSuper data, our sample consists of 7,331 individuals that provide a total of 10,421 observations across waves (2,308 individuals appear only in Wave 2, forming the refresher sample drawn for that wave).

There are three sources of information about pension accounts in the UniSuper data set: the type of pension plan, the cumulative pension balance and whether...

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\(^6\) Individuals making contributions from the before-tax (i.e. gross) income are taxed at significantly lower tax rates (only 15%) compared to the income-specific progressive rates.

\(^7\) http://www.melbourneinstitute.com/hilda/

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individuals contributed voluntarily. To capture attitudes towards risk, we also use a variable denoting whether one purchased supplementary (disability) insurance. And to account for any ‘stickiness’ across decisions, we include an indicator that captures the default (i.e. balanced) investment allocation choice. We use the number of employers currently contributing to one’s plan, the length of tenure (in years) and the annual wage to account for job characteristics. Finally, UniSuper data also provides information on a member’s age and gender.

Since UniSuper collects limited background information on its members, we supplement these administrative records with a set of variables from HILDA Wave 10, which is the closest (to 2012) available HILDA wave containing wealth and job information. Specifically, we use HILDA’s additional information on consumption and wealth (i.e. net worth excluding pensions), as well as health, education, marital status and number of children. (Note that besides these variables, HILDA also contains data on age, gender, wage and type of employment contract (i.e. permanent versus casual), pension plan type and balance, contribution years and spouse contributions, which can be also found in the UniSuper records).

To match HILDA data to UniSuper records, we first select the relevant subsample among HILDA respondents (i.e. individuals employed in the higher education and research sector) and then use an iterative procedure that first matches the UniSuper and HILDA individuals along eight common individual dimensions (as captured by variables present in both data sets, namely age, gender, quintiles for wage, pension account balance and years of contribution, whether the spouse contributes, type of pension plan selected and type of employment contract). For the observations unmatched in the first stage, the procedure drops one dimension (e.g. spouse contributions) and attempts the matching again. After this second matching along seven dimensions, we employed the procedure two additional times, progressively excluding the plan type and finally the type of employment contract. We thus match 46% of our full sample, and 100% (71%) of our panel sample when importing wealth (consumption).

One final remark about the HILDA variables. As shown below, we only use health, education, marital status and number of children in the empirical analysis to confirm previous findings. Our results are robust to their exclusion. Additionally, only wealth is used in our simulations, while consumption is solely employed in an informal identification test.

2.1. Descriptive Statistics

In frameworks such as ours, choosing an investment allocation other than the default implies at least some understanding of the various options available. This holds for us abstract from the decision to make standard contributions and calibrate their level from the data, effectively accounting for the amount of these contributions:

(i) when empirically analysing the pension balance; and
(ii) in the structural model when constructing the pension benefit functions.

Health status is captured by a dummy equal to 1 if self-reported health is excellent or very good. We use two dummies denoting whether individuals have university level education (bachelor or honours, graduate and postgraduate diploma) and whether they have 12 years of education or less.

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understanding might translate into active choices regarding other financial decisions, like plan type or voluntary contributions. In fact, 72% of non-default (DC) plan members opt for non-default investment allocations too. As a result, we split the sample by whether individuals choose to stay with the default investment or not and examine the two groups separately.

Panel (a) in Table 1 shows that this is indeed the case. Looking at those who opted for the default investment allocation, we find that DC prevalence is roughly one-tenth of DB prevalence. Among those with non-default allocations however, the situation is more balanced, with 46% of them enrolled in a DC plan. Hence, plan and investment defaults appear to be highly persistent (i.e. ‘sticky’). Notably, this stickiness does not extend to other financial options offered by the fund. For instance, among those who contribute voluntarily or purchase supplementary insurance, there is an almost 50:50 split between default and non-default investment members. Overall, however, the members who take advantage of these opportunities are very few (i.e. roughly 17% and 10%, respectively).

These differences between default and non-default members are also reflected in the pension accounts. Panel (b) in Table 1 reports mean and median account balance (in AU$), contribution period and contribution sources, also split by investment options. As expected, university employees appear to have substantial pension balances, at least one employer contributing, considerable periods of contribution,

| Table 1 |
| Job and Pension Account Features |

<table>
<thead>
<tr>
<th>Panel (a)</th>
<th>All</th>
<th>Default allocation</th>
<th>Non-default allocation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No. of members</td>
<td>Percentage of members</td>
<td>No. of members</td>
</tr>
<tr>
<td>Plan type</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DB</td>
<td>3,831</td>
<td>76.27</td>
<td>2,861</td>
</tr>
<tr>
<td>DC</td>
<td>1,192</td>
<td>23.73</td>
<td>212</td>
</tr>
<tr>
<td>Is voluntarily contributing</td>
<td>854</td>
<td>17.00</td>
<td>424</td>
</tr>
<tr>
<td>Has supplementary insurance</td>
<td>536</td>
<td>10.67</td>
<td>270</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel (b)</th>
<th>All</th>
<th>Default allocation</th>
<th>Non-default allocation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Median</td>
<td>Mean</td>
</tr>
<tr>
<td>Account balance</td>
<td>2,56,430</td>
<td>1,48,313</td>
<td>2,59,825</td>
</tr>
<tr>
<td>Number of employers contributing</td>
<td>1.22</td>
<td>1.00</td>
<td>1.17</td>
</tr>
<tr>
<td>Years of contribution</td>
<td>12.55</td>
<td>11.91</td>
<td>12.25</td>
</tr>
<tr>
<td>Annual wage (estimated)</td>
<td>97,048</td>
<td>90,328</td>
<td>94,795</td>
</tr>
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</table>

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 the total amount accumulated in the pension account, number of employers currently contributing, years of contribution and estimated salary. The sample consists of members from the first (May 2012) UniSuper wave, containing 5,023 permanent employees.

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and quite high salaries. Interestingly, however, members with default investments have lower salaries and so, lower pension balances despite contributing for longer than the non-default members (at the median).

Table 2 reports the demographic characteristics of our sample. We note that the average UniSuper member with a permanent contract is around 45 years old, employed, married, with 1.8 children. As expected, a vast majority have a Bachelor/Honours degree or above. The conditional statistics in Table 2 show, however, no further significant differences between those who do and do not default to the balanced investment option.

2.2. Empirical Analysis

We examine the association between pension choices and risk, demographics and job characteristics by estimating linear models that correlate pension savings with measures of such factors. The estimation methods that we use include ordinary least squares (OLS) and logit models. In all our main specifications, the outcome variables are the three indicators of pension decisions (i.e. pension plan type, pension balance and whether an individual contributes voluntarily). To tease out the attitudes towards risk and defaults, we use two variables indicating whether an individual purchased supplementary insurance and whether he opted for a non-default investment allocation, respectively. In terms of demographics, we include age, gender, marital status, number of children, whether in good health, and education as described before. Finally, for job characteristics variables, we include the log of annual wage, number of employers contributing, and years of contribution. We also add an indicator for the survey wave, as pension decisions tend to be sticky. In all specifications, we present robust standard errors clustered at individual level.

Table 3 reports the results. The first three columns present marginal effects (m.e.) from (i) a logit model of individual decisions to participate in a DC plan (rather than

| 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 the first (May 2012) UniSuper wave, containing 5,023 permanent employees. |

11 The 2012 median (mean) salary for full in-time jobs was roughly $60,000 ($72,000) – Australian Bureau of Statistics Report (ABS) (2012).
<table>
<thead>
<tr>
<th>Variable</th>
<th>All Default allocation</th>
<th></th>
<th>Voluntarily contributing</th>
<th>All Non-default allocation</th>
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<th>Voluntarily contributing</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DC participation (1)</td>
<td>Ln balance (2)</td>
<td>Voluntarily contributing (3)</td>
<td>DC participation (4)</td>
<td>Ln balance (5)</td>
<td>Voluntarily contributing (6)</td>
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<tr>
<td>Age/10</td>
<td>0.013***</td>
<td>0.315***</td>
<td>0.122***</td>
<td>0.005</td>
<td>0.282***</td>
<td>0.102***</td>
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<tr>
<td></td>
<td>(0.006)</td>
<td>(0.013)</td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.017)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Male</td>
<td>-0.008</td>
<td>0.072***</td>
<td>-0.018**</td>
<td>-0.017*</td>
<td>0.075***</td>
<td>-0.027**</td>
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<tr>
<td></td>
<td>(0.010)</td>
<td>(0.021)</td>
<td>(0.009)</td>
<td>(0.009)</td>
<td>(0.027)</td>
<td>(0.011)</td>
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<td>Married</td>
<td>0.051***</td>
<td>0.340***</td>
<td>0.016</td>
<td>0.011</td>
<td>0.336***</td>
<td>0.021*</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.028)</td>
<td>(0.010)</td>
<td>(0.011)</td>
<td>(0.035)</td>
<td>(0.012)</td>
</tr>
<tr>
<td>Low education</td>
<td>-0.056**</td>
<td>0.094</td>
<td>0.003</td>
<td>-0.019</td>
<td>0.0007</td>
<td>-0.012</td>
</tr>
<tr>
<td></td>
<td>(0.028)</td>
<td>(0.060)</td>
<td>(0.020)</td>
<td>(0.024)</td>
<td>(0.038)</td>
<td>(0.013)</td>
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<tr>
<td>High education</td>
<td>0.010</td>
<td>0.255***</td>
<td>0.019*</td>
<td>0.008</td>
<td>0.224***</td>
<td>0.000</td>
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<tr>
<td></td>
<td>(0.016)</td>
<td>(0.032)</td>
<td>(0.011)</td>
<td>(0.013)</td>
<td>(0.038)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>Children</td>
<td>0.004</td>
<td>-0.017***</td>
<td>-0.011***</td>
<td>-0.0007</td>
<td>-0.017**</td>
<td>-0.010***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.005)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.007)</td>
<td>(0.003)</td>
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<tr>
<td>Good health</td>
<td>0.015</td>
<td>0.004</td>
<td>-0.016*</td>
<td>0.006</td>
<td>0.032</td>
<td>-0.004</td>
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<tr>
<td></td>
<td>(0.009)</td>
<td>(0.017)</td>
<td>(0.008)</td>
<td>(0.008)</td>
<td>(0.022)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>Suppl. insurance</td>
<td>0.019</td>
<td>0.075***</td>
<td>0.012</td>
<td>0.019</td>
<td>0.070***</td>
<td>0.019</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.021)</td>
<td>(0.011)</td>
<td>(0.013)</td>
<td>(0.027)</td>
<td>(0.014)</td>
</tr>
<tr>
<td>Ln annual wage</td>
<td>0.037**</td>
<td>1.109***</td>
<td>0.010</td>
<td>0.026**</td>
<td>1.189***</td>
<td>0.015</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.037)</td>
<td>(0.010)</td>
<td>(0.012)</td>
<td>(0.034)</td>
<td>(0.013)</td>
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<tr>
<td>Non-default allocation</td>
<td>0.349***</td>
<td>1.285**</td>
<td>0.044**</td>
<td>0.009</td>
<td>0.515</td>
<td>0.007</td>
</tr>
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Table 3
(Continued)

<table>
<thead>
<tr>
<th>Variable</th>
<th>All</th>
<th>Default allocation</th>
<th>Non-default allocation</th>
</tr>
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<tr>
<td></td>
<td>DC participation (1)</td>
<td>Ln balance (2)</td>
<td>Voluntarily contributing (3)</td>
</tr>
<tr>
<td>Non-default alloc</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>× Log wage</td>
<td>−0.113**</td>
<td>(0.044)</td>
<td></td>
</tr>
<tr>
<td>Years of contribution</td>
<td>0.009***</td>
<td>(0.001)</td>
<td>0.007</td>
</tr>
<tr>
<td>Employers</td>
<td>−0.006</td>
<td>(0.005)</td>
<td>0.005</td>
</tr>
<tr>
<td>Wave 2</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Observations</td>
<td>10,421</td>
<td>10,417</td>
<td>10,421</td>
</tr>
<tr>
<td>Model fit</td>
<td>Ps R²: 23.6%</td>
<td>R²: 64.9%</td>
<td>Ps R²: 14.2%</td>
</tr>
</tbody>
</table>

Notes. All specifications are logit models (marginal effects reported), except for (2), (5) and (8), which are OLS. 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. Including Age² in specifications (2), (5) and (8) leaves results unchanged.
stay in DB), (ii) an OLS model on log of pension balance, and, (iii) a logit model on the decision to voluntarily contribute. The previous Section revealed systematic differences between default and non-default allocation members that might transfer to other pension decisions. We thus present estimation results for these two groups next to the estimation results for the whole sample. We do this for a baseline observation defined as a 45-year-old, married female with a Bachelor degree (or above), with 1.8 children on average, no supplementary insurance, 12 years of contributions and average wage, who opted for the default allocation.

For the decision to opt for a DC plan, wage appears to be an important element, both for the whole sample and for the two default/non-default investment subsamples. A unit increase in log wage (which roughly corresponds to 100% increase in wage relative to baseline) is significantly associated with a 3.7% increase in the DC plan participation probability for the whole sample. The effect is larger in the non-default investment subsample (7.0%) than in the default one (2.6%). Moreover, changing from the default to the non-default investment allocation is associated with 34.9% higher DC participation. This is not surprising given that making portfolio choices is particularly relevant for DC members. Married individuals are significantly more likely to opt for a DC plan, possibly because of intra-household risk-sharing or because of an added need for job-market mobility that may make the DB less attractive. The m.e. for the whole sample suggests that changing marital status from single to married is related with a significant 5.1% increase in the probability that an individual opts for DC. Interestingly, the years of contribution m.e. is small and negative for the default investment subsample but quite high and positive for non-default investment members. Here also note that there is a higher percentage of married men who opt for non-default investments than there are in the default category. For married people, the option of a ‘portable’ DC (i.e. the option to roll over the retirement savings into a different fund due to an added need for job-market mobility) might be quite valuable and with higher tenure years (and more experience with the system), more individuals will value the extra flexibility offered by a DC plan. This is consistent with the findings related to those that plan for retirement (and note that moving to the DC plan means assuming full control of retirement savings) being older, higher educated and with higher income (Clark et al., 2012). In contrast, those who rely on defaults will do so across decisions and age/tenure will not induce them to assume control of their retirement ‘pot’. Finally, age and education also matter: Going from medium to low education is significantly associated with a 5.6% lower chance of choosing DC in the full sample. As for age, because the DB/DC decision is made upon becoming a Unisuper member, the relevant age in ‘DC participation’ specifications is the enrolment age. And in all three such specifications, enrolment age appears positively correlated with opting out of the DB plan.

We now turn to the determinants of the accumulated pension balance. All specifications estimate linear regression models for the amount accumulated in the pension account, measured in terms of log pension balance. Results are in Table 3, columns (2), (5) and (8). As expected, older individuals with more years of contribution and more employers contributing will also accumulate more in their pension account. This is also the case for individuals taking out supplementary insurance. Compared to women, men appear to have a significantly higher balance.
(the associated m.e. is 7.2%). Being married and highly educated also matters for retirement savings, both in the whole sample and in the two subsamples. The coefficient on the number of children is significant and negative, which may reflect their role as an alternative form of retirement savings (Scholz and Seshadri, 2009a). Notably, all these effects hold for both the default and non-default investment subsamples. The elasticity of pension balances with respect to wages is roughly 1.11 for the whole sample, and 1.19 (1.14) for the subsamples of default (non-default) members. These high figures may at least partially be due to both employers and employees contributing and so, a wage increase will affect the pension balance via both these channels. Finally, opting for a non-default allocation is positively related with the log of the account balance (the m.e. is 1.17). This is the result of a positive (and sizeable) effect of choosing a non-default allocation and a negative effect of the interaction between opting for this non-default and log wage on account balance.

As for voluntary contributions, older people and women appear more likely to use this option to increase their retirement savings. Unsurprisingly, highly educated people are more likely to contribute than those with medium attainments, while having two children, for example, is associated with 2.2% lower chance of contributing. Once more, defaults appear sticky: compared to a non-default investment member, a default one has a 4.4% lower probability of opting out of the (0%) voluntary contribution default. While statistically insignificant for default allocation members, being healthy (and facing a higher work longevity) is related to a 3.1% decrease in the likelihood of voluntary contributions for non-default members, which may reflect the trade-off between working longer and saving at a higher rate.

3. The Model

In this Section, we develop a life-cycle model of consumption and pension choices consistent with the facts presented in Section 2. We consider the problem of an individual who plans to retire at age \( R = 65 \), faces a stochastic time of death and lives to a maximum age \( T = 100 \). For simplicity, the retirement age \( R \) is assumed to be exogenous and deterministic. Let \( t \) denote adult age and \( s_t \) denote the probability that the individual is alive at time \( t + 1 \), conditional on being alive at time \( t \).

3.1. Preferences

While alive, in each period, the individual derives utility from the consumption of a single good, according to

\[
u(c_t) = \frac{c_t^{1-\gamma} - 1}{1 - \gamma_i},
\]

where \( c_t \) is the level of time \( t \) consumption, and \( 1/\gamma_i \) (with \( i \in \{1, \ldots, N_c\} \)) is the intertemporal elasticity of substitution. This specification allows us to introduce persistent preference heterogeneity that captures unobservable differences across individuals (der Klaauw and Wolpin, 2008; French and Jones, 2011). Specifically, we
assume that each individual can belong to a finite number of preference types, with the probability of being a certain type depending on an individual’s initial state variables (i.e. age $t_0$, wage $w_{t_0}$ and non-pension wealth $a_{t_0}$).\textsuperscript{12} To simplify notation, in what follows we denote risk aversion by $\gamma$.

When an individual dies, he values his total bequeathable wealth $A_t$ according to a bequest function

$$b(A_t) = \theta \frac{(a_{t}^{DB} + a_{t}^{DC} + a_{t} + k)^{1-\gamma}}{1 - \gamma},$$

(2)

where $\theta$ is the bequest weight and $k$ determines the curvature of the bequest function (De Nardi et al., 2010). Bequeathable wealth $A_t$, on the other hand, includes all pension wealth (both DB accumulated $a_{t}^{DB}$ and DC accumulated $a_{t}^{DC}$), as well as non-pension wealth $a_t$. Below we describe in detail the wealth accumulation processes for $a_{t}^{DB}$ and $a_{t}^{DC}$.

3.2. Employment

We assume individuals start working at age $t_0$ and while working they earn annual wage $w_t$. We use a traditional Mincer (1958) specification for the wage equation, with time-$t$ wage $w_t$ depending on age $t$ and years of contribution (or service) $s$,\textsuperscript{13}

$$\ln w_t = \lambda_0 + \sum_{k=1}^{4} \lambda_k t^k + \sum_{k=1}^{2} \lambda_{4+k} t^k + \xi_t,$$

(3)

$$\xi_t = \phi w \xi_{t-1} + \epsilon_{t}^w, \epsilon_{t}^w \sim \mathcal{N}(0, \sigma_{w}^2).$$

(4)

Note that we also include an autoregressive term $\xi_t$ with innovation $\epsilon_{t}^w$, which follows an i.i.d normal distribution. This AR(1) process allows us to capture some level of wage persistence among individuals and is denoted by a discrete Markov process with $N_\xi$ discrete state points.

3.3. Choices and Defaults

Following the UniSuper choice architecture, we assume that individuals choose the pension plan type (DB or DC), the voluntary contribution rates and the investment allocation option. As mentioned, upon becoming a UniSuper member, one is automatically enrolled into DB (the default plan). However, within the first year of UniSuper membership, the member can irrevocably switch to the DC plan by submitting an application form. (If the member does not switch within the first year, the default (DB) plan enrolment becomes permanent). In the model, we assume that if the member decides to switch to a DC plan, a fixed utility cost $u_p$ must be paid. This

\textsuperscript{12} In the estimation, we assume there are two preference types $i \in \{H, L\}$, and $\text{Prob}(\gamma_i = \gamma_L) = \logit(\lambda_0 + \lambda_1 t_0 + \lambda_2 \ln w_{t_0} + \lambda_3 a_{t_0}) \times \{\lambda_i\}_{i=0}^3$ are estimated together with our other structural parameters.

\textsuperscript{13} We use tenure to proxy for labour experience; using a quadratic in $t$ yields almost identical results.

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cost captures the effort of researching, comparing and filing the forms and varies with enrolment age $t_0$ (Steel, 2007; Agarwal et al., 2009),

$$u_p = \psi_i + \exp(v_0^i + v_1^i t_0 + v_2^i t_0^2),$$

while $\psi_i$ is a ‘default preference’ parameter. To keep things computationally feasible, we assume there are two preference types $i \in \{H, L\}$, with $\Pr(\psi_i = \psi_L) = 1/2$.\(^\text{14}\)

After choosing the plan type, the employer and the employee start making their contributions,\(^\text{15}\) which we model as a function of the employee’s wage. Specifically, in each period, the employer’s mandatory contribution $v_E$ and the standard employee contribution $v_S$ are set to certain fixed shares of employee’s gross income $w_t$. What is not fixed (but the individual can decide upon each period) are the voluntary contributions $v_t \in \{v_i, i = 1, 2 \ldots N_v\}$, which we model as a discrete choice among a number $N_v$ of different contribution levels. The default choice for these contributions is 0\% and so, if individuals decide to make positive voluntary contributions, they would need to apply and set up online transfers or mail cheques. In the model, if one chooses to make positive voluntary contributions, a switching cost $u_v$ needs to be paid. This cost captures the liquidity value of savings outside the pension plan, which we do not explicitly account for in the model but are especially important for young employees and those with low non-pension wealth. Hence, we model $u_v$ as a function of age $t$ and non-pension wealth $a_t$ and interpret it in terms of utility lost, as follows

$$u_v = \psi_i + \exp \left[ v_0^i + v_2^i (t - v_1^i)^2 + v_3^i \max\{0, \ln(a_t)\} \right].$$

Finally, each period, individuals can choose whether to leave the balance accumulated in their DC component to be invested into the default (balanced) investment allocation, or to switch actively to a more (or less) risky option. These investment options differ by expected return and risk – see below. If the member chooses a non-default investment option, either via an online request or by mailing the relevant form to UniSuper, a fixed switching cost (in terms of utility lost) $u_r$ needs to be paid. Similar to $u_v$, this cost captures the extra effort of gathering information and completing paperwork. Consistent with the data profiles on (i) the share of people with default investments (overall and among DB/DC members), and (ii) the share of DC balance invested in this default option, we assume $u_r$ depends on age $t$, on the pension amount at stake (i.e. the DC balance) $a_t^{DC}$,\(^\text{16}\) and on plan switching costs $u_p$,

$$u_r = \psi_i + \exp \left[ v_0^i + v_1^i t + v_2^i t^2 + v_3^i \max\{0, \ln(a_t^{DC})\} + v_4^i u_p \right].$$

\(^\text{14}\) We note that this random draw assumption is reasonable given our setup: since $\psi_i$ – the preference for a UniSuper default – becomes active only upon enrolment into UniSuper, individuals arrive at $t_0$ with $i = H$ or $i = L$, independent of initial wage $w_{t_0}$ and non-pension wealth $a_{t_0}$.

\(^\text{15}\) We differentiate between employer and employee contributions because the way in which the benefits from these two sources accumulate differ with the type of plan selected by the employee. We assume all contributions are pre-tax and subject to 15\% concessional tax rate, for the first $25,000$ (concessional contribution cap). Any exceeding amount is subject to 46.5\% tax rate.

\(^\text{16}\) See Besedes et al. (2012), Agarwal et al. (2009), Ebersbach and Wilkening (2007).
3.4. Pension Plans: DB Versus DC

The defining characteristic of a DB plan is that the employer pays the employee a nominal benefit based on a formula related to the individual’s age, service years, level of contributions and average wage over the last three years of continuous employment. However, the UniSuper DB plan includes both a genuine DB component and a separate DC component. Hence, there is substantial heterogeneity in the replacement rates under this type of contract. All the employee’s voluntary contributions \( v_t \) will be made in the DC component, while his standard contributions \( v_S \) will be made into the DB component. As for the employer’s contribution, a share \( a_v \) will be made in the DB component, and the remaining \( (1 - a_v) \) will be transferred to the DC component. Hence, the amount of DB benefit is calculated according to

\[
da_{DB}^t = f_{ACF}^t (v_S) \times f_{LSF}^t (t) \times f_{ASF}^t \times \tau \times \bar{w}_t,
\]

where \( f_{ACF} \) is the Average Contribution Factor (ACF) over the entire service time span, and \( f_{LSF} \) is the Lump Sum Factor (LSF) with

\[
f_{LSF}(t) = \max\{18, \min\{23, 23 - 0.2(65 - t)\}\}/100.
\]

Thus, for a member who is 65-years or older \( f_{LSF}(t \geq 65) = 23\% \), while for someone 40-years or younger \( f_{LSF}(t \leq 40) = 18\% \). We also assume permanent workers always work full-time and so, the Average Service Fraction (ASF) \( f_{ASF} = 100\% \). Finally, the average wage over the last three years of continuous employment, \( \bar{w}_t \), is calculated as

\[
\bar{w}_t = \frac{1}{3} [w_t + g(w_{t-1}) + g(w_{t-2})],
\]

where \( w_{t-1}, w_{t-2} \) are replaced by imputations in the computational solution (Appendix B).

The DC account balance, on the other hand, is accumulated according to

\[
da_{DC}^{t+1} = \begin{cases} (1 + r^d_t) \times \{a_{DC}^t + [v_t + (1 - x)v_E]w_t\}, & \text{if in DB} \\ (1 + r^h_t) \times \{a_{DC}^t + (v_t + v_S + v_E)w_t\}, & \text{if in DC} \end{cases}
\]

where \( r^d_t, r^h_t, r^l_t \) is the rate of return corresponding to the selected allocation. There are three allocation options available, namely:

(i) a balanced option (which is the default, yielding \( r^d_t \)),
(ii) a higher-risk/higher-return option (yielding \( r^h_t \)), and
(iii) a lower-risk/lower-return option (yielding \( r^l_t \)).

This choice will have a significant impact on the sequence of returns individuals face. However, it will only affect the amount accumulated in the DC component (if they are in a DB plan) or in their DC account (if in a DC plan).

If an individual opts for the default allocation, we assume that their investment will yield log-normally distributed returns, with log gross return \( \ln r^d_t \) given as the sum of a constant mean and a normal shock.

Conversely, if the higher risk allocation is chosen, investments yields a return rate $r_t^h$, with
\[
\ln r_t^h = r^h + h\varepsilon_t^d, \quad \text{with } \varepsilon_t^d \sim N(0, \sigma_{\varepsilon_t^d}^2),
\]
where $r^h > r^d$ is the mean return for the high risk asset and $h > 1$ is a scaling factor that amplifies asset market shocks. Similarly, we define a relatively low risk investment as a re-scaling of the balanced portfolio,
\[
\ln r_t^l = r^l + l\varepsilon_t^d, \quad \text{with } \varepsilon_t^d \sim N(0, \sigma_{\varepsilon_t^d}^2),
\]
where $r^l < r^d$ is the mean return for the low risk asset and $l < 1$ is a scaling factor that dampens asset market shocks.

3.5. Budget Constraint

To close the model we derive the budget constraint. We assume all workers cash out their pension as a lump-sum upon retirement at age $R = 65$ and there is only one risk-free asset in which individuals can invest (outside their pension wealth) and that yields a constant gross interest rate $r$. Thus, the intertemporal budget constraint is
\[
a_{t+1} = \begin{cases} 
(1 + r)a_t + (1 - v_t - v_S)w_t - c_t, & \text{if } t < R \\
(1 + r)a_t + a_t^{DB} + a_t^{DC} - c_t, & \text{if } t = R \\
(1 + r)a_t - c_t, & \text{if } t > R
\end{cases}
\]
Finally, we assume there is no borrowing and so, $a_{t+1} \geq 0$.

3.6. Timing of Events and Bellman Equation

The dynamic problem can be viewed as a two-stage optimisation. At the beginning of the first period, each individual with assets $a_0$ and labour income shock $\xi_t$ irrevocably chooses the pension plan type. The associated Bellman equation for period $t_0$ is therefore
\[
V_t(X_t) = \max_{\{DB, DC\}} \left\{ V_t(X_t|DB) + \zeta_{DB}, V_t(X_t|DC) - u_p + \zeta_{DC} \right\},
\]
where $X_t = (a_t, a_t^{DC}, \xi_t, \tau, \{DB, DC\})$ is the vector of state variables, $\{DB, DC\}$ denotes the plan type, and $u_p$ is the utility cost of choosing the (non-default) DC plan. We further assume there is an unobservable utility component in each option $\zeta_{DB, DC}$, which follows a type I extreme value distribution with scale parameter $\sigma_p$. This term captures the idea that the econometrician might not observe everything that affects each individual’s decision. So, the probability of choosing DC is (McFadden, 1974; Rust, 1987)
\[
\Pr(\text{DC}) = \frac{\exp\left\{ V_t(X_t|DC) - u_p / \sigma_p \right\}}{\exp\left\{ V_t(X_t|DB) / \sigma_p \right\} + \exp\left\{ V_t(X_t|DC) - u_p / \sigma_p \right\}}.
\]

The variance of the distribution of $\zeta_{DB, DC}$ is therefore $(\pi^2/6)\sigma_p^2$, and note that in our framework, is it more convenient to select the scale of the shock than to multiply the value functions by scaling parameters.
After this stage, in each period, the individual sequentially chooses voluntary contribution \(v_t\) (from the set \(\{v_i, i = 1, 2 \ldots N_v\}\)), investment allocation \(r_t\) (from the set \(\{r^d, r^h, r^l\}\)), and optimal consumption \(c_t\) (before observing the interest rate realisation) to maximise the discounted present value of life-time utility. Formally, the value of each discrete \(v_t\) level is

\[
\hat{V}_t(X_t, v_t) = V_t(X_t, v_t) + \zeta_{v_t},
\]

where \(\zeta_{v_t}\) is the unobservable utility of the \(v_t\) choice. The deterministic value \(V_t(X_t, v_t)\) is

\[
V_t(X_t, v_t) = \mathbb{E}\left\{ \max_{r_t \in \{r^d, r^h, r^l\}} \tilde{V}_t(X_t, v_t, r_t) \right\} - u_v \times 1\{v_t \neq 0\},
\]

where \(\tilde{V}_t(X_t, v_t, r_t)\) is the value of investment \(r_t\) for each discrete level of \(v_t\), defined as

\[
\tilde{V}_t(X_t, v_t, r_t) = V_t(X_t, v_t, r_t) + \zeta_r,
\]

with \(\zeta_r\) being the unobservable utility component for the \(r_t\) choice. The observable part

\[
V_t(X_t, v_t, r_t) = \max_{c_t} u(c_t) - u_r \times 1\{r_t \neq r^d\} + \beta \mathbb{E}_t[s_t V_{t+1}(X_{t+1}) + (1 - s_t) b(A_{t+1})],
\]

subject to the budget constraint (15), where \(\beta\) is the time discount factor and

\[
V_{t+1}(X_{t+1}) = \mathbb{E}\left\{ \max_{v_{t+1} \in \{v_{t+1}\}_{v_{t+1}}^N} \tilde{V}_{t+1}(X_{t+1}, v_{t+1}) \right\}.
\]

We assume both unobservable utilities \(\zeta_{v_t}\) and \(\zeta_r\) follow type I extreme value distributions independently. The scale parameters of \(\zeta_{v_t}\) are allowed to differ across plan types, so we must estimate \(\sigma_{v_j}, j \in \{DB, DC\}\). Similarly, the scale parameter of \(\zeta_r\) is assumed to be \(\sigma_{r_j}, j \in \{DB, DC\}\). Therefore, the calculation can be simplified as follows\(^{19}\)

\[
V_t(X_t) = \sigma_{v}^{\dagger} \log \left\{ \sum_{v_b \in \{v_t\}_{b=1}^{N_v}} \exp \left[ \frac{V_t(X_t, v_b)}{\sigma_{v}} \right] \right\},
\]

\[
V_t(X_t, v_t) = \sigma_{r}^{\dagger} \log \left\{ \sum_{r_b \in \{r^d, r^h, r^l\}} \exp \left[ \frac{V_t(X_t, v_t, r_b)}{\sigma_{r}} \right] \right\} - u_v \times 1\{v_t \neq 0\}.
\]

The discrete choice probabilities are

\[
Pr(v_t = v_i) = \frac{\exp[V_t(X_t, v_i)/\sigma_{v}^{\dagger}]}{\sum_{v_b \in \{v_t\}_{b=1}^{N_v}} \exp[V_t(X_t, v_b)/\sigma_{v}^{\dagger}]},
\]

\(^{19}\) The position parameters of \(\zeta_{v_t}\) and \(\zeta_r\) are assumed to be \(-\sigma_{v}^{\dagger} \gamma_E\) and \(-\sigma_{r}^{\dagger} \gamma_E\), where \(\gamma_E = 0.57721\) is the Euler constant. Since voluntary contribution and investment choices are not relevant at ages beyond 65, we estimate the scale parameters directly (instead of normalising them to 1 and multiplying the corresponding deterministic value functions by \(1/\sigma_{v}\) or \(1/\sigma_{r}\), respectively, for ages below 65). This is essentially a nested logit model (Berkovec and Rust, 1985).
\[ \Pr(r_t = r_j) = \frac{\exp[V_t(X_t, v_t, r_j)]}{\sum_{r_h \in \{r^*, r^1, r^2\}} \exp[V_t(X_t, v_t, r_h)]}, \]  

(26)

where \( j \in \{DB, DC\}. \)

3.7. Solving the Model Numerically

Because there is no analytic solution, the model is solved numerically. First, each of the continuous state variables \((a_t, d_{t}^{DB}, \xi_t)\) is discretised into a certain number of grid points. The value function and policy functions are then solved, using backward induction: in period \( t \), given that at \((t + 1)\) the value function and the policy functions are solved for every combination of points in the state space grid of \( X_t = (a_t, d_{t}^{DB}, \xi_t, \tau, \{DB, DC\}) \), we calculate the values and choice probabilities of (22)–(26) for each contribution level \( v_t \) and each corresponding investment choice \( r_t \), with optimal consumption computed via the Euler equation

\[ c_t^{-\gamma} = \beta(1 + r_t)E_t[s_t c_{t+1}^{-\gamma} + (1 - s_t)\theta(a_{t+1} + k)^{-\gamma}]. \]  

(27)

Note that due to discrete plan choices and switching, the value function in our model need not be globally concave for \( t < 65 \). To find optimal decision rules we thus use our discretised state space and employ grid search techniques (French, 2005; French and Jones, 2011). Finally, the choice probabilities are calculated from (25) and (26). This mechanism starts from the last period where the terminal value is given by the bequest function. (For more details, see Appendix B.)

4. Calibrations and Estimation Method

Since it would be computationally too burdensome to estimate all parameters simultaneously, we use a two-step strategy (Gourinchas and Parker, 2002; Cagetti, 2003; French and Jones, 2011). In the first step, we estimate or calibrate some parameters to fix the data-generating process for the state variables. In the second step, we use these estimated data-generating processes to simulate life-cycle profiles for a large number of hypothetical individuals. The goal is to find the set of parameters that generates simulated profiles that match the data.

To this effect, we first calibrate the parameters that determine survival probabilities, annual wages, standard employee and employer contribution rates, the pension factors, as well as the investment returns. Specifically, survival probability \( s_t \) is calibrated to match the Human Mortality Database average survival probability between age \( t \) and \( t + 1 \) in Australia. The wage equation parameters are determined using an OLS model with AR1 standard errors that associates the log of estimated wages to a quartic in age and a quadratic in years of service. The shock \( \xi_t \) is discretised and represented with \( N_\xi = 5 \) grid points. For employee contributions, we set the standard rate \( v_S \) to 2.35% (with a corresponding \( f_t^{AE} \) of 86.0% that approximates the mean and median observed in the data). For employer contributions, we set \( v_E \) to 17% for both DC and

\[ 20 \] Since the state space \( X_t \) includes the plan type \( \{DB, DC\} \), \( V_t(X_t) \) in (23) differs across plan types.

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DB members (hence \(x = 100\%\) as \(v_i = 2.35\%\)). We assume a constant interest rate for non-pension wealth equal to 2.4\%, which is the average real return for long-term (indexed) treasury bonds for the period 1982–2012.\(^{21}\) For pension wealth, we set the interest rate parameters for the default and the two non-default options to match the risk and return targets stated in the UniSuper product disclosure statements: we set \(r^d_t\) to 2.88\%, \(r^l\) and \(r^h\) to 1.93\% and 4.76\% respectively, \(\sigma^d\) to 0.064, \(l\) and \(h\) to 0.54 and 1.68 respectively. Finally, we set the bequest shifter parameter \(k\) equal to the weighted average of the marital status-specific parameters (Ding, 2012).

We use Simulated Method of Moments (SMM) (McFadden, 1989; Pakes and Pollard, 1989) to estimate the following parameters\(^{27}\):

\[
\phi = \left\{ \{\gamma_j\}^2_{j=1}, \{\lambda_j\}^3_{j=0}, \beta, \theta, \{\psi_j\}^2_{j=1}, \{\nu^p_j\}^3_{j=0}, \{v^r_j\}^4_{j=0}, \{v^r_{j=0}\}, \sigma_p, \{\sigma_v^i, \sigma^i\}_{i \in \{DB, DC\}} \right\} \in \mathbb{R}^{27}.
\]

The SMM matches the distributions related to pension plan, voluntary contributions and investment allocations to the corresponding moments of the same variables in the simulated sample. The objective is to find the vector of preferences \(\hat{\phi}\) that simulates the distributions such that they fit the data best. To this end, we match the

(i) first order moments related to pension and non-pension wealth, and voluntary contributions;
(ii) second order moments of non-pension wealth;
(iii) plan-specific second order moments of pension wealth and voluntary contributions;
(iv) proportion of members opting for DC, voluntarily contributing and having non-default allocation;
(v) plan-specific correlations between pension wealth and making voluntary contributions, as well as between pension wealth and having non-default allocation; and
(vi) correlation between opting for non-default allocation and choosing DC, all conditional on age cohort and gender.

Finally, we also match the share of first tenure year staff voluntarily contributing and with non-default allocations and the shares of pension wealth invested in the default and risky options. We discuss our identification strategy in Appendix C.

For efficiency reasons, the models for males and females are estimated separately. We use data from two different UniSuper waves, corresponding to May and September 2012. For each model, we calculate the age-specific empirical moments in three steps. First, we select the appropriate subsample (i.e. males or females). Second, we assign the individuals in our data set into five-year age cohorts as follows: the first cohort consists of individuals with ages below 25 in May 2012, the second cohort contains ages 25–29 in May 2012, and so on.\(^{22}\) Third, we take cell means by cohort\(^{23}\) for the balanced panel, in each wave. For the share of total pension wealth accumulated via the default

\(^{21}\)

\(^{22}\) The last cohort, labelled ‘60–64’, also contains a few observations on individuals 65+. Their data (i.e. on wealth and consumption, contributions and investments) is, however, not very different from the ‘60–64’ cohort data, so, including the 65+ in the last cohort does not significantly alter the empirical moments.

\(^{23}\) For pension and non-pension wealth, as well as for consumption, we deal with outliers by excluding the 1st and the 99th percentile of each data series.

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and risky investment options, we use the figures from the 2012 UniSuper Annual Report.24

To compute the simulated moments, we first simulate \( N = 10,000 \) paths of individual choices, collecting the simulated values of each variable for each path.25 The initial conditions, including non-pension wealth and age in the first service year, are jointly imputed from the data;26 first service year pension wealth is zero. Next, we generate the \( N \) sets of simulated moments, conditional on the initial values of the state variables \( X_t^0 \) and on the parameters \( \hat{\phi} \). Finally, the SMM estimator \( \hat{\phi}_{SMM} \) minimises the distance between the set of empirical moments \( m_T \) and the average of the \( N \) sets of simulated moments \( \frac{1}{N} \sum_{n=1}^{N} m_n(X_n, \hat{\phi}) \),

\[
\hat{\phi}_{SMM} = \arg \min_{\phi} \left[ m_T - \frac{1}{N} \sum_{n=1}^{N} m_n(X_n, \hat{\phi}) \right] W_T \left[ m_T - \frac{1}{N} \sum_{n=1}^{N} m_n(X_n, \hat{\phi}) \right],
\]

where \( W_T \) is the weighting or distance matrix that almost surely converges to \( W_T = S^{-1} \), where \( S \) is the limit, as \( NT \to \infty \), constant full-rank matrix of the covariance of the estimation errors.27

For a given \( N \), as \( T \to \infty \), if the weighting matrix is chosen optimally,

\[
T(1 + 1/\tau) \left[ m_T - \frac{1}{N} \sum_{n=1}^{N} m_n(X_n, \hat{\phi}) \right] W \left[ m_T - \frac{1}{N} \sum_{n=1}^{N} m_n(X_n, \hat{\phi}) \right] \to \chi^2(j - k),
\]

where \( \tau \) is the ratio of the simulated sample size to the empirical one, \( j \) is the number of moments and \( k \) is the number of estimated parameters.

5. Results from the Structural Model

This Section presents the SMM results and discusses our model’s ability to recreate the data patterns. Table 4 shows the parameter estimates, while Figures 1–5 below plot selected moments by cohort. In all Figures, the lines labelled data1 and data2 correspond to Wave 1 and 2 of UniSuper data, whereas lines sim1 and sim2 denote their simulated counterparts.

5.1. Data Patterns and Model Fit

A quick glance at Figures 1–5 (and Appendix D) reveals that the models fit quite well overall, for both male and females. In particular, we have successfully replicated both (i) the high prevalence of default plan type and default investment allocation, and (ii)
the increasing incidence and level of voluntary contributions with age, that we observe in the data. The goodness of fit between the simulated and the empirical (data) moments is assessed via a $\chi^2$-test (or corresponding $p$-value). In both cases, the model easily passes the $\chi^2$-test of goodness of fit, with $\chi^2$-values well below the 5% critical value. Thus, we cannot reject the null that the simulated and empirical moments are the same at standard significance levels.

Let us now take a closer look at the data profiles. Figures 1 and 2 show the level of non-pension and pension wealth by cohort, respectively. As expected, both types of wealth increase with age but women appear to accumulate less in their pension account than men. As explained before, this gradient might be due to women working fewer hours and being more likely to face career interruptions, due to maternity leave and carer responsibilities.28 With fewer years of service and potentially a slower rate of wage growth, they will also have lower pension balances. Additionally, women are less

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likely to opt for the DC plan: on average, only 18% of women switch out of the default (DB plan), compared to 27% of the men (see Figure 3). These differences further deepen the wealth gradient between sexes due to missed opportunities for high return investments.

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One possible way to supplement pension wealth is by making voluntary contributions. Surprisingly, women do not rely significantly more than men on this option to insure their retirement savings against negative labour events. Indeed, Figure 4 shows that, across cohorts, women are slightly more likely to contribute than men, which confirms our empirical results in Section 2. But when looking at the amounts

Fig. 2. Mean Pension Wealth (DB + DC) by Cohort (Thousands of $)

Note. Colour figure can be viewed at wileyonlinelibrary.com.
effectively contributed, the gender gap appears much more severe, with men voluntarily contributing significantly more than women over the entire life span. This difference in contributions decreases though as individuals become older (see Figure 5), with women contributing on average only 8.5% less at age 55 or older.

Fig. 3. Proportion of Individuals Choosing Non-default (DC) Plan by Cohort

Note. Colour figure can be viewed at wileyonlinelibrary.com.
Finally, we note that our estimation procedure did not include fitting consumption. In Figure 6, we show our model’s performance in fitting this variable, effectively presenting an informal over-identification test. Remarkably, we find that both models were able to generate cohort-specific consumption patterns endogenously with trends resembling the empirical ones. In terms of level, however, we note some discrepancy between simulations and data. The reason for this gap might be that we are under-

Fig. 4. Proportion of Individuals Making Voluntary Contributions by Cohort

Note. Colour figure can be viewed at wileyonlinelibrary.com.
estimating real consumption by limiting it to non-durables, effectively excluding some substantial expenses, such as mortgage downpayments or durable goods. In fact, the gap is less accentuated for women, who have been shown to spend a greater share of their budget than men on non-durables (i.e. fuel and power, clothing, toys, household goods and services) or personal care (Blow et al., 2004; Bradbury, 2004).

Fig. 5. Mean Voluntary Contributions by Cohort (Thousands of $)

Note. Colour figure can be viewed at wileyonlinelibrary.com.
5.2. Switching Costs

Our model features three different types of switching costs, all measured in terms of discounted life-time utility. Pension plan switching costs are paid only once during the first UniSuper enrolment year, while voluntary contributions and investment switching costs are charged at each annuity purchase decision.
costs are paid each period. To ease the interpretation, we expressed these costs in monetary terms, as the DC pension balance (at retirement) required compensating for the utility loss associated with them. Figure 7 plots these rough monetary equivalents by age. (The sharp drop in $u_p$ is due to no men in our sample enrolling into UniSuper after the age of 53.)
Our calculations show a median estimated cost of switching away from the default (DB) plan of roughly $32,000 for both males and females, in line with the figures obtained by Yang (2005) for a similar plan choice setup. These figures might seem high but note first that this does not mean that the median participant would not switch for this amount in cash but that they would not switch for this amount in their average DC balance upon retirement. Finally, note that these are costs associated with an irreversible switch and so, we would expect them to be higher than those associated with opting out of the other (reversible) defaults. Indeed, compared to DC switching, opting out of the default investment is roughly 34% cheaper for women and 78% for men. This gender gradient appears reversed when looking at the switching cost of making positive contributions, which confirms our results in Section 2 on men being less likely to contribute voluntarily.

Another way of interpreting the switching costs is to consider how pension wealth would have changed over time had the switching been costless. The last three rows in Panel (a) and (b) of Table 5 in the next Section present these results.

6. Counterfactual Simulations

This Section shows results from counterfactual experiments focusing on evaluating the role of different default settings in shaping retirement savings. Specifically, we considered how pension wealth would have changed over time (i) had the default pension plan been a DC plan, instead of a DB one (referred to as ‘Default: DC plan’

<table>
<thead>
<tr>
<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel (a): males</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Data</td>
<td>0.291</td>
<td>0.196</td>
<td>0.557</td>
<td>0.226</td>
<td>0.217</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Baseline</td>
<td>0.273</td>
<td>0.100</td>
<td>0.410</td>
<td>0.363</td>
<td>0.227</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Default: DC plan</td>
<td>0.932</td>
<td>0.086</td>
<td>0.704</td>
<td>0.182</td>
<td>0.114</td>
<td>10.129</td>
<td>2.635</td>
</tr>
<tr>
<td>Default: low risk invest.</td>
<td>0.273</td>
<td>0.100</td>
<td>0.267</td>
<td>0.368</td>
<td>0.365</td>
<td>–0.498</td>
<td>–0.133</td>
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<tr>
<td>Default: high risk invest.</td>
<td>0.277</td>
<td>0.101</td>
<td>0.252</td>
<td>0.529</td>
<td>0.219</td>
<td>2.029</td>
<td>0.454</td>
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<tr>
<td>Invest. SC = 0</td>
<td>0.306</td>
<td>0.101</td>
<td>0.312</td>
<td>0.427</td>
<td>0.262</td>
<td>1.628</td>
<td>0.377</td>
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<tr>
<td>DC/DB SC = 0</td>
<td>0.614</td>
<td>0.092</td>
<td>0.626</td>
<td>0.231</td>
<td>0.143</td>
<td>5.809</td>
<td>1.501</td>
</tr>
<tr>
<td>Invest &amp; DC/DB SC = 0</td>
<td>0.814</td>
<td>0.092</td>
<td>0.312</td>
<td>0.423</td>
<td>0.265</td>
<td>16.332</td>
<td>3.481</td>
</tr>
</tbody>
</table>

Panel (b): females

<table>
<thead>
<tr>
<th></th>
<th></th>
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<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Data</td>
<td>0.211</td>
<td>0.162</td>
<td>0.603</td>
<td>0.203</td>
<td>0.194</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Baseline</td>
<td>0.178</td>
<td>0.134</td>
<td>0.560</td>
<td>0.233</td>
<td>0.207</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Default: DC plan</td>
<td>0.687</td>
<td>0.125</td>
<td>0.631</td>
<td>0.198</td>
<td>0.171</td>
<td>18.344</td>
<td>3.692</td>
</tr>
<tr>
<td>Default: low risk invest.</td>
<td>0.168</td>
<td>0.130</td>
<td>0.194</td>
<td>0.237</td>
<td>0.570</td>
<td>–1.652</td>
<td>–0.348</td>
</tr>
<tr>
<td>Default: high risk invest.</td>
<td>0.208</td>
<td>0.144</td>
<td>0.175</td>
<td>0.638</td>
<td>0.187</td>
<td>6.863</td>
<td>1.350</td>
</tr>
<tr>
<td>Invest. SC = 0</td>
<td>0.354</td>
<td>0.201</td>
<td>0.31</td>
<td>0.360</td>
<td>0.330</td>
<td>15.249</td>
<td>2.240</td>
</tr>
<tr>
<td>DC/DB SC = 0</td>
<td>0.418</td>
<td>0.130</td>
<td>0.615</td>
<td>0.202</td>
<td>0.184</td>
<td>8.399</td>
<td>1.707</td>
</tr>
<tr>
<td>Invest &amp; DC/DB SC = 0</td>
<td>0.647</td>
<td>0.185</td>
<td>0.314</td>
<td>0.362</td>
<td>0.323</td>
<td>27.156</td>
<td>4.666</td>
</tr>
</tbody>
</table>

Note. Pension wealth refers to UniSuper balance right before retirement (conditional on surviving), excluding non-pension wealth.
scenario), (ii) had the default investment allocation been either a low risk or a high risk investment option, instead of balanced (labelled ‘Default: Low risk invest’. and ‘Default: High risk invest’. scenarios), and (iii) had switching away from the default investment and/or plan type been costless (captured via the ‘SC = 0’ labelled scenarios). Every simulation modifies certain parameters, solves the model numerically and generates the corresponding wealth patterns. The issue is how wealth in each scenario compares with the wealth generated by the baseline model (‘Baseline’ scenario). Results are presented in Table 5.

First, we find that when the default pension type is changed from DB to DC, the proportion of DC members among permanent staff more than triples for both sexes. On average, this stickiness leads to a considerable 10.13% and 18.34% net increase in total pension wealth for males and females, respectively. These results are not surprising: Given the risk and returns performance reported by UniSuper, replacing the formula-based DB benefit with a market-contingent DC benefit is clearly beneficial, especially for women who have on average shorter job tenure and so, also lower wages than men towards the end of their careers.

In the second and third experiment, we change the default investment from a balanced allocation to a safer and a riskier option, respectively. At lower (higher) levels of risk, pension assets are invested at lower (higher) rates of return, which diminishes (augments) the amount accumulated as pension wealth. We find both default settings to be highly sticky, with high proportions of men and women generally choosing not to switch away. These results confirm Beshears et al. (2009) finding on default allocations being able to completely change the prevalence of certain investment options. But the overall drop in wealth due to the new low-risk default is rather small (below 1.65%) for both men and women. Similarly, changing the default from a balanced option to a riskier one will increase pension wealth on average by 2.03% (6.86%) for men (women) due to the higher returns, as expected.

Given the high level of defaulting shown by our first three experiments, we also wanted to check what happens if we reduce default stickiness by setting switching costs to zero. The penultimate row of Panel (a) and (b) in Table 5 shows that being able to costlessly switch between DB and DC plans yields a pension wealth gain of about 5.81% for men and 8.40% for women). With no cost of researching and comparing the plans and no bureaucratic costs of preparing the application, roughly double the baseline shares of men and women would have opted for the DC plan. Even in the absence of switching costs individuals still choose the DB plan, which might be related to the slightly low discount factor that we estimate: being less future oriented, they are less interested in actively accumulating in their pension accounts, even if the DC plan generates more retirement savings over time than the DB plan.

If only the cost of opting out of the default investment option is eliminated, the wealth increase is more modest (1.63%) for men, but about 15.25% for women (due to their lower risk aversion). But if both plan and investment switching could happen at no cost, pension wealth gain would rise to values comparable with a high risk-DC default scenario. The difference with respect to removing only the plan switching cost
is due to more people taking advantage of the non-default investment options and, with a high prevalence of DC plan adoption, this will affect the overall pension wealth.

Finally, we conduct two additional experiments considering scenarios that represent bigger departures from the current UniSuper plan architecture but yield very interesting insights into the timing and irreversibility of plan choices. First, we ask what would have happened with pension wealth had an individual been able to irreversibly switch plans in any period. We find that this change is beneficial for pension wealth, with men (women) accumulating 1.48% (11.66%) more. With women’s switching costs declining as they delay DB-DC transitions, it is not surprising that their pension boost is significantly higher than for men. Second, allowing individuals to switch back and forth between DB and DC would generate a 10.47% (for men) and 5.91% (for women) difference in pension wealth. This sizeable amount directly reflects the severe effects of irreversibility and one-off decisions on retirement savings.

Overall, our results show that the default structure influences wealth accumulation in important ways. We also find that defaults tend to be quite sticky and so, if such settings are not carefully chosen, retirement savings can be severely affected.

7. Conclusions

With financial decisions becoming increasingly complex and people being called upon to take charge of their economic well-being after retirement, many delay making choices or rely on defaults. But remaining passive may lead to substantial reductions in retirement wealth.

This article investigates the factors behind the high prevalence of defaults in pension choices and evaluates the impact of multi-default provisions (related to plan type, voluntary contributions and investment allocations) on retirement savings. Our novel setting, where (i) we observe automatic enrolment into a sector-wide employer sponsored plan, (ii) enrolled members confront decisions about plan type, contribution rates and investment strategy, and (iii) opting out of defaults for each of these decisions ranges from trivially easy to very difficult (or impossible), implies broadly generalisable results. Specifically, we use administrative data on an industry-wide Australian pension fund and present two new sets of findings.

First, our empirical results show that risk, demographic and labour characteristics matter greatly for plan choices and influence the overall level of savings. For instance, the likelihood of opting for the non-default (DC) plan increases with age, wage and years of contribution. Females, who are more likely to face career interruptions, have lower pension balances, but are also slightly more likely to voluntarily contribute. And finally, having a non-default investment allocation is associated with higher pension balance.

Second, we use a structural dynamic life-cycle model to assess how these factors affect retirement savings patterns. We do so by (i) providing a quantitative framework to solve for the optimal choice of pension plan type, contribution and investment allocation, and (ii) assessing the welfare gains (or losses) from changing the default structure and increasing choice flexibility. As a novelty, our setup focuses on defaults related to

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29 Detailed estimates are available from the authors upon request.

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multiple decisions, while combining automatic enrolment with an irreversible time-limited plan choice and an active decision regime (on both contributions and investment allocation).

Our structural results show that defaults are highly persistent – both over time and across various decisions, with estimated costs of switching to DC roughly $32,000 at the median, and opting out of balanced investments 34% cheaper for women and almost twice that for men. Additionally, we find both an increasing incidence and level of voluntary contributions with age. Finally, since the choice of default settings affects retirement savings, we perform several counterfactual experiments to study what would have happened to retirement wealth had the default structure been different. We find several interesting results: first, changing the default plan for permanent staff from DB to DC leads to a substantial 10.13% and 18.34% net increase in total pension wealth for males and females, respectively. Second, defaults remain sticky when the standard investment option becomes either the low or high risk (instead of balanced) allocation, although the wealth loss or gain is significantly smaller. Third, the possibility of switching freely between DB and DC has a positive effect for both men and women (5.81% and 8.40%, respectively). Fourth, eliminating the cost of opting out of the default investment would bring a gain of 1.63% (15.25%) for men (women).

These results provide strong evidence of the central role that complex default settings (with both reversible and irreversible choices, with(out) strict opt-out deadlines) play in ensuring savings adequacy and, ultimately, financial security in retirement. If policy-makers are to implement social security programmes that protect the well-being of retirees, sustainability will require them to also support institutions and products that provide sufficient retirement income to reduce other welfare programmes’ needs. The recent rapid shift from DB to DC plans, combined with the potential of defaults to significantly impact retirement savings in these types of schemes, highlight the need to carefully assess what default settings public policy and plan architects should encourage, especially given people’s diverse savings needs.

Appendix A. UniSuper Features

Table A1

| Mandatory, Default and Choice Features of the UniSuper Pension Scheme |

<table>
<thead>
<tr>
<th>Permanent employees</th>
<th>Mandatory</th>
<th>Default</th>
<th>Choice to</th>
</tr>
</thead>
<tbody>
<tr>
<td>Enrolment</td>
<td>✔</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Plan type</td>
<td>–</td>
<td>DB*</td>
<td>DC (within one year)</td>
</tr>
<tr>
<td>Employer contributions</td>
<td>17%</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Employee contributions: **</td>
<td>(Irreversible)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard</td>
<td>–</td>
<td>7%</td>
<td>Choice to reduce</td>
</tr>
<tr>
<td>Voluntary</td>
<td>–</td>
<td>0%</td>
<td>Choice to increase</td>
</tr>
<tr>
<td>Investment option</td>
<td>–</td>
<td>Balanced</td>
<td>Choice of 15 options</td>
</tr>
<tr>
<td>Insurance</td>
<td>–</td>
<td>Life and TPD</td>
<td>Choice to change cover</td>
</tr>
</tbody>
</table>

Notes. * DB has a small DC component and any voluntary member contributions are to the DC component. ** An additional choice dimension here (that we do not model) is that employee contributions can be made pre- or post-tax.

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Appendix B. Computational Details

B.1. Model

In the expression of the average wage over the last three years of continuous employment $w_t$,

$$g(w_{t-j}) = \frac{1}{Pr(\xi)} \sum_{i=1}^{N} Pr(\xi_i) \times P(\xi_i, \xi_j) \times \exp \left[ \lambda_0 + \sum_{k=1}^{4} \lambda_k (t-j)^k + \sum_{k=1}^{3} \lambda_{4+k} (t-j)^k + \xi_j \right].$$

This is derived from the reverse of the Markov process (4) (Chung and Walsh, 1969), with $N$ discrete state points, distribution $Pr(\cdot)$ and transition matrix $P(\cdot, \cdot)$ and allows us to reduce computational burden and not carry $(\xi_{t-2}, \xi_{t-1})$ in the state space.

B.2. Solving the Model

To solve the model, we discretise the asset space and the DC balance space into 35 gridpoints each. The wage autoregressive term $\xi_j$ is discretised into a 5-state Markov process following Kopecky and Suen (2010). The space of service years $\tau$ is integer and ranges from 0 to 49 ($=65 - 16$). With a binary pension type (DB/DC) and 50 gridpoints for $\tau$, the dimension of $X_t$ mounts from 12,250 gridpoints for $t = 16$ to 612,500 for $t = 65$. For ages 66+, $X_t$ has only 35 gridpoints each period since there is only one state variable, $a_t$. Finally, we consider six different levels of voluntary contribution rates, including 0%, and three different investment choices ($r^d$, $r^h$, $r^l$). Experiments with the grid’s fineness suggested that the ones we used produce reasonable approximations.

Appendix C. Identification

To address the question of which moments identify certain parameters, we proceed in two stages. Given that providing analytic proof is not possible, we first present some intuitive arguments as to why each parameter might significantly affect only a subset of moments. Second, to validate these
We also establish identification in a local neighbourhood of a selected subset of parameters via simulation.\footnote{To do so, we compute the moments and fit the value function at and around estimated parameter values. We then check to what extent the resulting simulated profiles fit the empirical ones as we vary the value of selected parameter and verify the fitted function shape in a neighbourhood of the selected parameter value.}

Altering one of the target data moments, however, changes more than one parameter. The parameters denoting risk aversion, bequest weight and discount factor, for instance, are jointly identified by cohort-specific first order wealth moments: high estimates of the relative risk aversion coefficients for consumption makes individuals accumulate more. Similarly, a higher discount factor means they are more future orientated and dissave more slowly than with a lower $\beta$. And having a strong bequest motive (high values of $\theta$) also generates higher savings. We identify these parameters better by requiring the model also to match the first order moments of pension wealth by cohort. To see this, note first that the Euler equation can give some intuition for the identification of $\gamma$’s, $\beta$ and $\theta$. Ignoring bequests, the Euler equation shapes the savings profiles (i.e. the non-pension wealth profiles, at least before retiring and cashing out the pension benefits). So, these wealth profiles are largely dictated by a combination of time discounting ($\beta$) and taste for smoothing ($\gamma$’s). This equation however identifies the product $\beta_\gamma(1 + r)$ but not its individual elements. Therefore, lower values of $r$ and/or $\gamma$ can lead to higher $\beta$ estimates. To check whether the interest rate can be separately identified, we set its value to the maximum rate observed for the high risk-high return investment option and re-estimate the models. As expected, the realised returns are on average higher than our benchmark assumption of 2.4% and our $\beta$’s are accordingly lower. We therefore conclude that we can only identify $\beta(1 + r)$ but not each term separately.

Going back to the Euler equation, we note that bequest motives are related to the total amount of resources that could be passed on as bequeathable wealth. Thus, the bequest weight $\theta$ will apply to both non-pension and pension wealth, and we additionally identify this parameter via the age-profile of the mean pension account balance.

We now turn to the unobservable utility components associated with our three choices. First, we identify the scale parameter $\sigma_p$ that determines the variance of $\zeta_{DB}$ and $\zeta_{DC}$ using the variability in pension wealth by plan type. Second, as we mentioned, people choosing DB or DC might value liquidity differently or have different attitudes towards risk, which are not captured by observables. To account for this, we allow the relative weight of $\zeta_{vt}$ to differ across plan types and identify its parameter $\sigma_v$ using the plan-specific variance of voluntary contributions. For the $\zeta_{vt}$, we unfortunately do not have detailed investment allocation data (except if one has a default allocation or not) and so we are not able to separately identify the scale parameters for each contribution category. However, we note that whatever individuals contribute translates into pension wealth via the allocation they choose, so we can identify $\sigma_v$ by some plan-specific measures of correlation between pension wealth and contributions, as well as between pension wealth and having a non-default allocation. (Note that due to the risky option yielding higher returns in the log run, we expect a higher positive correlation between wealth and contributions as risky asset exposure increases.)

Our last identification task is to try to separately identify switching costs from the preference (risk) heterogeneity $\gamma$’s. Previous studies have been unable to disentangle switching from persistent risk preferences elements cleanly largely because (i) the setup did not allow for ‘passive’ and then ‘active’ choices from one period to the next, and (ii) these choices were separated enough to prevent persistent preference heterogeneity having cross-decisions effects. Thus, one can identify preference heterogeneity based on the initial choices, with switching costs being captured by the dynamics of these choices.\footnote{Thus, if switching costs were zero, the subsequent choices with a changed plan structure for instance would reflect the preferences existent at the beginning.} In our case, to pin down the risk preferences...
parameters we use the share of people making active decisions (regarding contributing and investing) in their first tenure year. Intuitively, this might bias our estimates of risk, downwards as we identify them based only on the ‘active’ sample when presumably the people remaining in defaults have certain attitudes towards risk too. To acquire additional identification, we use the direct relation between risk aversion and savings and require the model to also match non-pension wealth variance.

Turning to switching costs, we note that their identification comes from the observations where individuals actually switched away from defaults. For instance, to identify the age parameters of the cost associated with opting out of the DB plan, we match the age-specific proportion of people that switched to a DC plan. To capture the cost of making voluntary contributions, we match the mean level of voluntary contributions by age to identify \( v_r^m \) and the age-specific proportion of people contributing to identify the age coefficients. For the investment switching costs, the parameter \( v_r^l \) of \( \ln(\alpha_{it}^{DC}) \) is identified by the shares of DC wealth invested in the balanced and risky investment options, \( v_4^l \) is captured by the correlation between opting for non-default allocations and opting for DC, while \( v_1^l \) and \( v_2^l \) are once again identified by the proportion of people with default allocations by age. Also, the latent factors \( \psi \)'s are identified via plan-specific correlations involving non-default choices.

Finally, note that we did not directly fit consumption. Section 5 discusses in more detail the model’s performance in fitting this variable, effectively presenting an informal over-identification test. There we show that the model manages to endogenously replicate the relationship between consumption and age observed in the data. And, for females, it also generates a closer fit than for men, supporting previous findings on gender patterns in non-durable spending (Blow et al., 2004).

### Appendix D. Tables and Figures

#### Table D1

**Moment Fit**

<table>
<thead>
<tr>
<th></th>
<th>Male moments</th>
<th>Female moments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percentage of wealth in default allocations</td>
<td>0.45</td>
<td>0.45</td>
</tr>
<tr>
<td>Percentage of wealth in high risk allocations</td>
<td>0.28</td>
<td>0.36</td>
</tr>
<tr>
<td>Staff in 1st year tenure with ( r_t \neq r_d )</td>
<td>0.31</td>
<td>0.29</td>
</tr>
<tr>
<td>Staff in 1st year tenure with ( v_t &gt; 0 )</td>
<td>0.00</td>
<td>0.02</td>
</tr>
</tbody>
</table>

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Fig. D1. Standard Deviation of Non-pension Wealth by Cohort (Thousands of $)

Note. Colour figure can be viewed at wileyonlinelibrary.com.
Fig. D2. Standard Deviation of Pension Wealth by Cohort, DB Staff (Thousands of $)

Note. Colour figure can be viewed at wileyonlinelibrary.com.
Fig. D3. Standard Deviation of Pension Wealth by Cohort, DC Staff (Thousands of $)

Note. Colour figure can be viewed at wileyonlinelibrary.com.
Fig. D4. Standard Deviation of Contributions by Cohort, DB Staff (Thousands of $)

Note. Colour figure can be viewed at wileyonlinelibrary.com.
Fig. D5. Standard Deviation of Contributions by Cohort, DC Staff (Thousands of $)

Note. Colour figure can be viewed at wileyonlinelibrary.com.
Fig. D6. Correlation (Pension Wealth, Making Contributions) by Cohort, DB Staff

Note. Colour figure can be viewed at wileyonlinelibrary.com.
Fig. D7. Correlation (Pension Wealth, Making Contributions) by Cohort, DC Staff
Note. Colour figure can be viewed at wileyonlinelibrary.com.
Fig. D8. Correlation (Pension Wealth, Non-default Investments) by Cohort, DB Staff

Note. Colour figure can be viewed at wileyonlinelibrary.com.
Fig. D9. Correlation (Pension Wealth, Non-default Investments) by Cohort, DC Staff
Note. Colour figure can be viewed at wileyonlinelibrary.com.
Fig. D10. Correlation (DC, Non-default Investments) by Cohort

Note. Colour figure can be viewed at wileyonlinelibrary.com.
Appendix E. A Comment on Preferences Estimates

Table 4 shows that the estimates are economically reasonable across both sexes. For instance, the relative risk aversion coefficients in the literature vary from 1 to 6, or higher depending on the context (Mehra and Prescott, 1985; Kocherlakota, 1996; Chetty, 2006). Our average estimate of $\gamma$ is roughly 4.52 for males and 3.69 for females. These relatively high coefficients of risk aversion (greater than 3) are in line with the estimates in Cagetti (2003) for U.S. college graduates. Previous work has also suggested that, ceteris paribus, risk aversion increases with age and decreases with wealth (Riley and Chow, 1992; Morin and Suarez, 1983). With lower wages, retirement income and wealth in general, it is not surprising that women appear less risk averse than men. Our discount factor estimate $\beta$, however, is 0.90 for both males and females. Combined with risk aversion being lower on average for women than for men, it suggests that not only different time preferences but also different attitudes towards risk can explain the heterogeneous savings behaviours across groups.

The term $\theta$ denotes the intensity of the bequest motive. It indirectly captures the marginal propensity to bequeath $\phi$ in a one-period problem where individuals are allocating wealth between consumption and immediate bequest (for people rich enough to consume at least $\theta^{1/2} k$), since $\theta = [\phi/(1 - \phi)]^\gamma \in [0, 1]$. Our point estimates of $\theta$ imply a $\phi$ close to one and so a bequest motive that approaches a linear one with a constant marginal utility of bequests $\theta k^{-\gamma}$. Interestingly, bequest motives seem slightly stronger for women than for men, which may reflect women’s stronger intergenerational altruism bonds and thus greater incentive to save for their heirs (Seguino and Floro, 2003).

We make one additional remark on bequests and their role in investment allocation decisions. We note that the presence of bequest motives acts toward making an investor’s horizon longer, potentially generating a higher allocation in risky investments (with higher return rates). For those with stronger bequest motives, however, this effect is counteracted by their attempt to ‘protect’ their wealth by opting for more balanced portfolios in the accumulation phase. So, the tendency to increase investment risk over time exists, but the portfolio might remain balanced up until retirement if bequest motives are strong. This confirms Cocco et al.’s (2005) findings on the role of bequests in generating balanced portfolios.

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Additional Supporting Information may be found in the online version of this article:

Data S1.

References


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