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Smart defaults: Determining the number of default funds in a pension scheme☆

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ABSTRACT

We propose a new methodology for the smart design of the default investment fund(s) in occupational defined contribution pension schemes based on the observable characteristics of scheme members. Using a unique dataset of member risk attitudes and characteristics from a survey of a large UK pension scheme, we apply factor analysis to identify single factors for risk aversion, risk capacity and ethical investment preferences, and then apply cluster analysis to these factors to identify two distinct groups of members across age cohorts. We find membership of these clusters depends on a number of personal characteristics, with the principal differentiating feature being that one group had previously engaged with the pension scheme, while the other had not. These identified characteristics can be utilised in the design of smart default funds, including appropriate engagement strategies.

1. Introduction

Around the world, occupational pension schemes are shifting from defined benefit (DB) to defined contribution (DC) with implications for scheme governance (OECD, 2009). Under a DB arrangement, employers bear the investment risks of fund performance, whereas a DC scheme shifts investment risks to the individual member. Policy makers and regulators have recognised the need for a code of practice concerning the governance of DC schemes, and one of the central governance requirements is the provision of a default investment fund. The UK Pensions Commission's *Second Report* (2005, p. 378), recognised that there are two reasons for needing a default investment vehicle. First, some contributors may fail to inform the scheme of their asset allocation preferences, and second some members may "not feel well-equipped to make asset allocation decisions".

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Since the introduction of auto-enrolment in 2012, DC pension schemes in the UK have been required to offer a minimum of one default investment fund for members who do not wish to exercise an investment choice (under section 17(2)(b) of the Pensions Act 2008).[1] The design and suitability of these default funds have been enshrined in The Pension Regulator's (TPR) code of practice for DC schemes which came into force in July 2016 (TPR, 2016). TPR (2019) identifies five key governance requirements (KGRs) that DC schemes should satisfy, and, in particular, KGR5 states "Trustee boards must ensure the default investment strategy is suitably designed for their members" (p. 1). The design of a suitable investment strategy will depend on members' risk and returns preferences, which, in turn, will depend on the individual members' own preferences for risk and other personal attributes of the individual. An implication is that the greater the heterogeneity of the members' preferences, the greater the number of default funds that will be needed. The two extreme cases are one fund for each member and one-fund-for-all.

In this paper, we consider the UK's largest private sector occupational pension scheme, the Universities Superannuation Scheme (USS), with a view to establishing the appropriate number of default funds required to reflect the pension scheme members' attitudes to risk and other characteristics. We make use of a survey of USS members carried out during September–October 2015 in preparation for the introduction of a new DC section in addition to the existing DB pension scheme. This survey had 9755 respondents who provided information about their demographic profile, risk preferences and other characteristics. We apply both factor analysis and cluster analysis to these survey responses to identify similar groups of members with relatively homogeneous preferences and characteristics (Everitt et al., 2011).

Our literature survey points to member age as being a potentially important determinant of risk preferences, and we apply cluster analysis to the whole sample, as well as two specific age cohorts: 25–44 (denoted the "younger" cohort) and 45–64 (denoted the "older" cohort). Our cluster analysis identifies just two groups of members. In the case of the whole sample, one group displays higher pay, longer tenure, less interest in ethical investing, lower risk capacity, a higher percentage of males, and a higher percentage of academics than the members of the other group – and significantly, *all* of its members have previously taken the active decision of making additional contributions (in the form of additional voluntary contributions (AVCs) or added years contributions), whereas *none* of the members of the other cluster has previously engaged with the scheme in terms of additional contributions. We differentiate the two groups in terms of their degree of *engagement* with the scheme, with the first group classified as "engaged" and the second group classified as "disengaged". For the whole sample and also for the older cohort, the two groups form distinct clusters. For the younger cohort, the two groups are not distinct across the two clustering techniques that we use, although there is still a significant overlap and again the two groups largely separate according to their degree of prior engagement.

These findings support the strategy subsequently adopted by USS: a single age-dependent lifestyle default fund designed primarily for those members that have not previously engaged with USS and a range of self-select funds which are likely to be taken up by some of those scheme members who have previously engaged. This was combined with an engagement strategy aimed at guiding members who self-select a different fund from the default fund into adjusting their risk exposure over time to maximise their lifetime welfare.

Characteristics that other studies have found important determinants of risk attitudes, such as age, gender, income and (pension) wealth, do not turn out to be as significant for USS members. We put this down to the high degree of homogeneity across these characteristics in this particular pension scheme. Further, despite being on average more highly educated than the general population, USS members are marginally more risk averse than the general population, controlling for salary, although the difference is not significant. This is consistent with other evidence that public-sector workers – which university staff are generally classified as, despite working for what are legally private-sector organisations established by private subscription – are generally more risk averse than private-sector workers (Blake, Cannon, & Wright, 2019).

Our paper builds on studies by Goda and Manchester (2013), Sunstein (2013) and Fernandes et al. (2014) explaining the cost-benefit trade-offs of multiple defaults when the relevant population is heterogeneous and the conditions under which a single default will be adequate. The paper then develops the idea of smart default investment funds proposed by Smith et al. (2013) and Dahlquist et al. (2018) which construct default asset allocations conditioned on the observable characteristics or preferences of pension scheme members.

The key empirical contributions of our paper are to use cluster analysis to identify groups of USS scheme members with similar risk attitudes and risk capacities, to examine whether individuals in these groups exhibit particular demographic and personal characteristics, and then to determine whether the groups are sufficiently distinctive to justify having more than one default investment fund.

The outline of the paper is as follows. Section 2 describes the USS pension scheme. Section 3 provides the theoretical background, based on two-fund separation, for the analysis of multiple default investment funds and reviews the existing literature on how attitude to risk is influenced by personal characteristics and other factors. Section 4 summarises the survey data from a questionnaire undertaken by USS of its members. Section 5 explains the use of factor analysis and cluster analysis to identify similar groupings of

[1] Section 17(2)(b) of the Pensions Act 2008 states "no provision of the scheme requires [an active member of the scheme] to express a choice in relation to any matter, or to provide any information, in order to remain an active member" (http://www.legislation.gov.uk/ukpga/2008/30/section/17). This has been interpreted to mean that the scheme must operate on the basis of one or more defaults, in particular, with a default minimum contribution rate and a default investment fund for those who do not express a choice. One of the reasons for expressing the legal arrangements in this way is that it allowed both the government and the scheme sponsor to avoid any legal liability for a poor pension outcome – unlike the case in which the contribution rate and investment fund were mandated by either the government or scheme sponsor. The legislation requires an employee to be auto-enrolled by the employer into a scheme selected by the employer. But it also allows the member to opt out of the scheme altogether or change the member contribution rate (so long as it does not fall below the minimum) or the investment fund. This places the legal responsibility for the pension outcome on the member.

scheme members' responses to the survey, while section 6 presents the empirical findings. Section 7 concludes. The survey questionnaire emailed to USS members is reproduced as an Appendix.

2. The Universities Superannuation Scheme

The Universities Superannuation Scheme – which covers academic and professional services staff in UK universities – is one of the largest pension schemes in the UK, and, at March 31, 2015, had 322,779 members, comprising 147,137 active, 115,288 deferred, and 60,354 pensioner members.[2] On March 31, 2016, it closed its final salary section to future accrual and replaced this with a career average revalued earnings (CARE) section. The final salary section had already been closed to new members since March 31, 2011. This new DB section, named USS Retirement Income Builder, has an annual accrual rate of 1/75th, Consumer Price Index (CPI) partial uprating of the pension in payment, and a tax-free lump sum at retirement equal to three times the initial pension.

On October 1, 2016, a salary threshold was introduced, initially set at £55,000 per annum, above which member and employer contributions were paid into a new DC section, named USS Investment Builder, and USS became a hybrid scheme with some members building up both DB and DC benefits. In 2016, contribution rates were set at 18% of salary for the employer and 8% of salary for members up to £55,000.[3] Above £55,000, the employer contribution rate was 12% of the excess, while the member's contribution rate was 8% of the excess. Members at all salary levels could make AVCs into the DC section and initially this could be "matched" from the employer for additional contributions up to 1% of salary.[4]

To design the new DC section, USS undertook a programme of research in 2015 to understand member requirements within the hybrid scheme. This included comparative studies of other DC schemes and prevailing pension industry best practice, demographic analysis of the USS membership to understand risk capacity, member outcome analysis based on stochastic modelling of possible investment strategies and member impacts and focus groups.[5] As part of this programme, during September–October 2015, USS worked with A2Risk[6] to design and execute a risk attitude survey of USS members. The primary purpose of the survey was to inform USS's understanding of active member risk attitude and investment beliefs in order to support the design of the USS Investment Builder investment fund range.

As explained above, there was a legal requirement to put a suitable default investment fund in place for the start of the hybrid scheme on October 1, 2016. USS reviewed the international evidence on the design of investment fund defaults. One example that it examined was the Australian pension scheme, QSuper, which designed its default funds by segmenting its members according to age and size of the accumulated fund.[7] QSuper has eight gender-neutral lifetime groups based on age and fund size. Members are first allocated to the group most suitable for them and then are automatically moved as they age: they are moved from higher risk to lower risk assets, consistent with an age-dependent investment strategy called "lifestyling" or "lifecycling" (Blake et al., 2014). USS's aims were to (1) design the default lifestyle fund(s) so it (or they) was (were) aligned with the objectives and preferences of the majority of USS members saving in USS Investment Builder and (2) assess whether there are identifiable groups of members within the USS membership with heterogeneous objectives and preferences that may need to be actively supported or guided towards an investment fund (default or self-select) that is best suited to meeting their long-term objectives.

3. Two-fund separation, the optimal number of default funds and factors influencing risk attitudes

3.1. Two-fund separation

Tobin (1958) demonstrated that Markowitz's mean-variance portfolio selection framework leads to two-fund separation whereby all investors hold a combination of the same portfolio of risky assets and the risk-free asset. It is possible to use this framework to assess the optimality of the default fund asset allocation in a pension scheme. Although some scheme members may choose themselves where to locate on the risk-return frontier, others who believe they are not sufficiently well-informed to make this decision will rely on the default fund asset allocation in the pension scheme to make this decision on their behalf.

Fig. 1 shows the location of a particular default fund on the capital market line which combines a portfolio of risky assets with the safe asset. In addition, we include the risk-return preferences of three pension scheme members (A, B, C). This default fund matches the optimal preferences of B, but the constraint of a single default means that scheme members A and C suffer a welfare loss. The risk-

[2] USS Report and Accounts 2015.

[3] This salary threshold is automatically revalued each April in line with USS pension increases, which equals the annual increase in the CPI up to the previous September, subject to a 10% cap (see *Your Guide to the Universities Superannuation Scheme*).

[4] USS member presentation, July 2016. The 1% employer match was removed in April 2019.

[5] USS produces regular updates of its member research in *FocUSS on Members*; https://www.uss.co.uk/-/media/project/ussmainsite/files/about-us/report-and-accounts/focuss-on-members.pdf (accessed 18 June 2021).

[6] http://www.a2risk.com/.

[7] https://qsuper.qld.gov.au/our-products/investment-options/lifetime/.

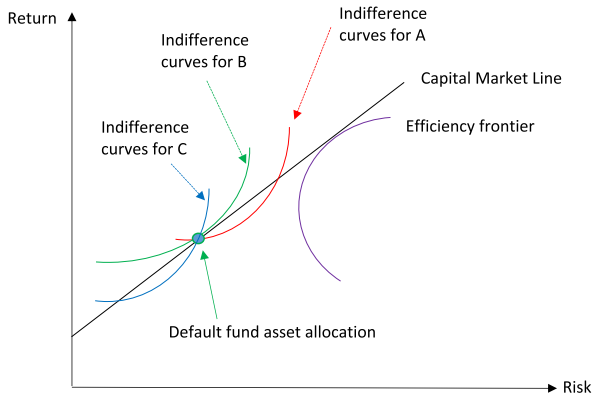

Fig. 1. Potential welfare losses from a single default fund with heterogeneous scheme member preferences.

return combination for the default fund is too low for A and too high for C.[8]

3.2. *The optimal number of default funds*

Goda and Manchester (2013) point out the welfare benefits of multiple defaults when there is significant individual-level heterogeneity. Sunstein (2013) argues that it would be possible to set up a default fund for each member, although recognising that this may be costly. Alternatively, if the scheme could segment the membership into a number of distinct groups based on similar risk-return characteristics, this would reduce the number of default funds required. If the entire scheme membership were sufficiently homogeneous, then just a single default fund would be sufficient (Fernandes et al., 2014). It is arguable whether there can ever be more than a *single* default fund in any given scheme, given the meaning of the term default. However, when scheme membership segments into mutually exclusive groupings – as, for example, when some members are interested in ethical or Shariah-compliant investing – then more than one default fund might be optimal.

Smith et al. (2013) recommend the use of "smart" (or "conditional") defaults which are default asset allocations, conditioned on the observable characteristics or preferences of pension scheme members. Members may also be "guided" using an appropriate choice architecture, such as checklists (Appelt et al., 2016), to determine whether they have an interest in, say, ethical or Shariah-compliant investing (Butt et al., 2020).

Dahlquist et al. (2018) identify the additional conditioning variables that could be used in the design of default funds using a longitudinal administrative dataset from 300,000 Swedish households. They find that there are three identifiable personal characteristics that affect an individual's optimal asset allocation: age, current value of pension wealth and stock market participation status outside the pension plan. They argue that these three sets of characteristics could be used effectively to enhance investor welfare to design multiple default pension schemes. In a calibrated life-cycle portfolio choice model, they calculate that implementing the optimal asset allocation based on these three characteristics results in a 1.5% average ex ante welfare gain during the retirement phase.

Dobrescu et al. (2018) consider the impact of multi-default provisions (related to scheme type, voluntary contributions and investment allocations) on retirement savings in UniSuper, covering all higher education and research sector employees in Australia with 460,000 members. They emphasise the importance of selecting the optimal choice architecture and estimate that changing the default scheme for permanent staff from defined benefit to defined contribution leads to a 10.13% and 18.34% net increase in total pension wealth for males and females, respectively.

With reference to Fig. 1, the empirical questions are (1) whether there are distinct groups of scheme members with similar sets of preferences, (2) how close these group preferences are to each other, and (3) how close the risk attitudes of USS members are to those of the national population. Our aim in this paper is to identify groups of sufficiently homogeneous pension scheme members to assess the minimum number of default funds required.

We explained in footnote 1 that the legislation in the UK requires DC pension funds to establish at least one default fund into which compulsory contributions are allocated when members do not record any choice. Although members may not wish to make explicit choices, they may have identifiable characteristics which the pension scheme can utilise to design the optimal default fund. Individual risk-return preferences may depend on a range of demographic (including gender and age), socio-economic, health and personality factors, and we now summarise the existing evidence from the academic literature for these as potential conditioning variables.

[8] Bernstein (1992) provides an alternative perspective. He calls this risk-return approach the "interior decorator fallacy", namely that portfolios should reflect attitudes to risk in the same way that interior decorators attempt to reflect the personal taste of their clients. If the aim is to achieve a target pension fund (or retirement income) with a specified degree of probability, then that is a technical exercise largely independent of a scheme member's risk preferences. Of course, this view is not incompatible with having a default fund investment strategy with the same aim.

3.3. Factors influencing risk attitudes

3.3.1. Gender

Early evidence such as Schubert et al. (1999) and a number of studies summarised in Croson and Gneezy (2009) indicated that, on average, women are more risk averse than men and this had consequences for financial decision-making contexts, such as asset allocation, trading patterns and ethical choices. However, later work began to accumulate evidence that was more nuanced. For example, Eckel and Grossman (2008) show that studies with contextual frames exhibit less consistent differences in risk aversion between men and women. Cupples et al. (2013) report that women exhibit a more risk-averse profile, but with education mediating and explaining these gender differences. Similarly, Fisher and Yao (2017) found that gender differences in financial risk tolerance can be explained by gender differences in the determinants of risk tolerance and that these differences are moderated by income uncertainty and net worth. Other recent studies go so far as to conclude there is little evidence for gender differences controlling for other factors. Nelson (2017) argues that many previous studies were contaminated with confirmation bias or gender stereotyping. Similarly, Filippin and Crosetto (2016)'s survey of the literature reports that gender differences are the exception rather than the rule.

With respect to pension schemes, Bajtelsmit & VanDerhei (1997), Hinz, McCarthy, & Turner (1997) and Sundén and Surette (1998) report gender differences in participant-directed pension investments, with women selecting more conservative investments. Watson and McNaughton (2007) examined the impact of gender on the pension fund risk preferences of staff in the Australian university sector. They also find that women choose more conservative investment strategies than men and that, combined with lower contributions (as a result of lower salaries), explains why women have lower projected retirement benefits than men in Australian universities. According to recent data from the Association of Superannuation Funds Australia, men retire with an average account balance of A$154,453, while for women it is A$122,848.[9]

More recent evidence is again more nuanced. For example, Arano et al. (2010) found no gender difference in the proportion of stocks held in retirement accounts among a group of university faculty in Kansas. A study of risk attitudes in the Turkish Pension Fund System found that women were more risk averse than men in some experiments (self-reported willingness to take risks and hypothetical lotteries), but not in others (Gürdal at al, 2017). Similarly, Bouchouicha et al. (2019), using four definitions of loss aversion, found women to be more loss averse than men according to one definition, less loss averse than men on the basis of two others, while the fourth definition resulted in no gender differences.

Overconfidence is another apparent difference between men and women, as reported in the early literature. Gervais and Odean (2001) find that men are generally more confident about their own abilities than women. Further, over-optimistic investors tend to make poorer investment decisions (Hunt et al., 2015). Barber and Odean (2001) document that men transact their common stock investments 45% more frequently than women, and this excessive trading reduces men's net investment returns compared with women. Recent evidence is again more mixed. Deaves et al. (2009) found little evidence that gender influences trading activity, while Hardies et al. (2012) found no evidence for a gender difference in overconfidence within a population of auditors.

Ethical behaviour differs by gender, with women generally behaving more ethically than men (Boulouta, 2013; Dollar et al., 2001). Beams et al. (2003) report that the social stigma of trading on inside information was a more important deterrent for female respondents than male respondents. A caveat to all these risk aversion and trading studies is that they are often undertaken in relation to particular samples of participants, such as business school students, and the results may not be directly applicable to other groups.

3.3.2. Age

Life-style investment strategies, as frequently advocated by financial advisers, state that young people should invest in risky assets and shift gradually to safer assets as they age. Such a strategy was originally criticised by Samuelson (1989) on the grounds that, for a given degree of risk aversion, the optimal asset allocation should be independent of age. However, if it is the case that risk aversion does indeed decline with either age or the length of the financial planning horizon, then this provides a justification for life-styling (Schooley & Worden, 1999).

Most studies investigating whether risk aversion changes with age show that very young people and very old people tend to be risk averse. Between these ages, risk aversion initially falls before rising again following a U-shaped pattern (e.g., Blake et al., 2019; Cohen & Einav, 2007; Hallahan et al., 2004; Riley & Chow, 1992). Brooks et al. (2018), while confirming that risk aversion falls with age (which they call the "pure age effect"), find evidence that falling risk aversion is associated with a reduced ability to bear losses and a declining investment horizon. There is also evidence of a specific cohort effect with different generations having different risk attitudes at the same age – possibly influenced by experience when young. Gilliam et al. (2010) report that leading baby boomers are less risk tolerant than trailing baby boomers.

Korniotis and Kumar (2011) identify two effects of age on financial investments. First, older experienced investors make better investment decisions, because they follow rules of thumb that reflect greater investment knowledge. However, there is a second effect that investment skill deteriorates with age due to the adverse effects of cognitive aging. Older investors are less effective in applying their investment knowledge and exhibit worse investment skill, especially if they are less educated, earn lower income, and belong to ethnic minority groups. Overall, the adverse effects of aging appear to dominate the positive effects of experience. Dohmen et al. (2010) confirm that lower cognitive ability in otherwise healthy people is associated with greater risk aversion. Kim et al. (2016) conclude that older investors should delegate their investment decisions to experts.

[9] *Pension Policy*, 26 April 2021; https://www.pensionpolicy.net/australia-women-retire-with-over-30000-lower-balance-in-super-than-men/.

3.3.3. Socio-economic, health and personality factors

Many studies find that risk aversion decreases with higher salary and wealth, controlling for other factors such as gender, age, education and financial knowledge (Riley & Chow, 1992; Campbell, 2006). However, individuals who are more likely to face salary uncertainty or to become liquidity constrained exhibit a higher degree of risk aversion (Guiso & Paiella, 2008). Similarly, individuals become more risk averse after a negative shock to wealth, such as a reduction in the value of their home (Paravisini et al., 2017). Individuals with higher levels of general educational attainment or higher IQs tend to be more risk tolerant (Grinblatt et al., 2011). This is strongly reinforced if individuals also have a high degree of financial literacy (Behrman et al., 2012; Lusardi & Mitchell, 2014). Financial literacy tends to be lower amongst the young, women, the less educated, and ethnic minorities (Lusardi & Mitchell, 2011). Using data from the Rand American Life Panel, Fonseca et al. (2010) was able to determine that the gender gap in financial literacy results from the role of household marital specialisation and division of labour among couples. The degree of risk aversion is also influenced by marital status. Yao and Hanna (2005) demonstrate that risk aversion is highest amongst married women, followed by single women, followed by single men, and lowest among married men. Having children tends to increase risk aversion amongst both men and women according to Hallahan et al. (2004) and Gilliam et al. (2010). Another way of differentiating between individuals is through the types of jobs they choose. Studies show that entrepreneurs are more risk tolerant than employees, private-sector employees are more risk tolerant than public-sector employees, and professionals are more risk tolerant than employees without a professional qualification (Roszkowski & Grable, 2009).

Individuals who score higher on the financial literacy questions are much more likely to plan for retirement. Financial planning can explain the differences in levels of retirement savings and why some people reach retirement with very little or no wealth (Lusardi & Mitchell, 2011). Education and financial literacy levels can influence investment preferences, as well as risk attitudes. Rossi et al. (2019), using responses to a Dutch representative household panel questionnaire, found that highly educated individuals had a strong demand (both actual and latent) for socially responsible (SR) investments and were willing to accept a return penalty compared with traditional investments. On the other hand, keeping education constant, individuals who consider themselves financially literate were less interested in SR products than others.

Health is another factor that can influence risk aversion. A typical finding is that financial risk tolerance is positively associated with both health and life expectancy (Hammitt et al., 2009; Love & Smith, 2010). But particular diseases can change people's risk attitudes. Tison and Hammitt (2018), using data from the US Health and Retirement Study, find that people suffering from cancer and arthritis can become less risk averse, while people with diabetes can become more risk averse.

None of the above factors can fully explain an individual's risk aversion. There are numerous other factors that influence risk attitude – typically given the name background risks – such as the weather, emotional factors, the environment in which an individual lives, and recent financial events (Hirshleifer and Shumway, 2003, Grable and Roszkowski (2008); Guiso & Paiella, 2008; Grable and Roszkowski (2008); Guiso et al., 2018). Grable and Roszkowski (2008) found that being in a happy mood was positively associated with having a higher level of financial risk tolerance, holding biopsychosocial and environmental factors constant. Similarly, Gusio et al. (2018) found that risk aversion is time varying and changed following the 2008 global financial crisis. The Covid-19 pandemic might have a similar effect, suggesting that risk attitudes should be assessed on a regular basis to determine their stability over time.

In summary, we have identified a number of factors that might affect pension scheme members attitudes risks and willingness to take risks in a defined contribution pension plan. USS members typically have high levels of general educational attainment and many may also have a high degree of financial literacy. In terms of other identifiable characteristics, the USS questionnaire asked questions on gender, salary, job type, health and marital status.

4. Data: survey questionnaire

In 2015, USS announced that it would introduce a DC section to the pension scheme, named USS Investment Builder, from October 2016. During September–October 2015, USS undertook a survey of all active members asking questions about member risk attitudes and investment beliefs and the operation of the proposed DC scheme. USS required information on four aspects of financial planning from the survey: (1) personal circumstances,[10] (2) attitude to risk (ATR), (3) capacity to bear risk as measured by capacity for loss (CFL),[11] and (4) investment beliefs, including ethical considerations. An online questionnaire was distributed to all active members by participating employers in the scheme, since these were the scheme members who would be affected by the new DC scheme.

USS received 9755 responses to this questionnaire, making it one of the largest surveys of risk attitudes in the UK, with a response rate of 6.6% of active members.[12] The survey was designed to be completed in 15 min and included 11 questions on self-reported personal circumstances (Section A of the Appendix) including: age (within five-year bands), gender, marital status, current annual salary (within £10,000 bands), expected retirement age, length of USS membership, job-type (academic or professional services), previous additional voluntary contributions to USS (in terms of AVC contributions or buying additional years of service in the DB

[10] Information was collected on: institution, age, gender, annual salary, expected retirement age, membership tenure in USS, academic or professional services role, self-reported life expectancy, prior AVCs, and likely importance of USS pension in household income.

[11] CFL is defined as the ability to sustain losses on an investment portfolio which may be influenced by factors such as the number of dependants, and existing financial commitments.

[12] The survey was only sent to the active members because deferred and pensioner members were not eligible for the new DC scheme. The sample was assessed by USS as being broadly representative of the active membership of USS in terms of the age and salary distributions, the gender balance and the balance between academic and professional services staff.

section), whether the member could reasonably expect to live a long and healthy retirement, and whether the USS pension was expected to be the main source of income in retirement.

Participants then answered additional questions on a range of themes establishing: (1) their attitude to risk (Appendix Section B, with 14 questions), (2) their capacity to bear risk (Appendix Section C, with 6 questions), (3) investment beliefs, including attitudes to ethical investing and whether there was interest in investing in a Shariah-compliant fund (Appendix Section D, with 7 questions), and (4) participants' intentions in the new DC section, such as the likelihood of taking up the additional 1% employer matching contribution and the importance of having flexibility in the way benefits are drawn (Appendix Section E, with 2 questions). These survey responses form the basis of our study with an anonymous code for each individual.

Table 1 provides descriptive statistics on the sample of participants. Panels A and B show that the median respondent is a 47-year-old married male academic who has been a member of USS for 7 years with a salary of £50,000. This person intends to retire at 65 and expects to have a long healthy retirement during which the USS pension will be the household's main source of income. Further, this person has not previously made additional contributions to USS via AVCs or additional years of service. Recall that the DB section continues to operate as the main pension scheme for individuals earning up to £55,000 (through USS Retirement Income Builder), so that many individuals completing the USS survey might not be expected to immediately participate in the new additional DC scheme (USS Investment Builder), unless they make AVCs which attract matching contributions from the employer up to 1% of salary (the "match").[13] Panel C of Table 1 shows the age distribution of the sample of respondents, and most of the 9755 respondents to the survey were in the age range 25–65 (98.4%). Because of the relatively small number of respondents below 25 (32 observations) and above 65 (125), we concentrate much of our subsequent analysis on the remaining 9598 members divided into two age cohorts. As well as applying cluster analysis to the whole sample, we also form two cohorts of 4217 "younger" members aged 25–44 and 5381 "older" members aged 45–64 and apply cluster analysis to each age cohort separately.

Not all the questions in the survey are relevant for designing the default investment fund, e.g., questions on the flexibility of benefits in retirement. Of the questions that are relevant, we arranged these into five themes: (1) attitude to risk, (2) risk capacity, (3) investment beliefs, including ethical considerations, (4) the intention to make matching contributions (the "match"), and (5) previous AVCs. To reduce the dimensionality of the problem, we apply factor analysis in the case of the first three themes in order to identify a smaller number of common factors. For example, there are six questions in the questionnaire inviting responses on the individual's capacity for bearing risk (Appendix Section C). We apply factor analysis to the responses to these six questions to identify if there are one or more common factors that can account for the patterns of observed correlations. Table 2 shows the results of the factor analysis across the five themes. In order to determine the appropriate number of factors for each theme, we applied the Kaiser-criterion that factors be retained with eigenvalues greater that unity, coupled with a visual inspection of the eigenvalues via a Cattell scree test. These criteria suggest that for the risk aversion, risk capacity, and ethical investment themes a single factor in each case is appropriate.

The final column in Table 2 reports the Kaiser–Meyer–Olkin measure of sampling adequacy as an additional assessment of the factor structure for each theme, with a value above 0.6 normally indicating sampling adequacy.

The set of responses in Appendix B were around the theme of attitude to risk. Each response was aligned on a 1-to-5 point Likert-scale to represent a risk attitude and we averaged these responses across the 12 attitude to risk questions to provide an average risk aversion score (av_ATRQ). We found that there was an almost perfect correlation between the single factor identified in the risk-aversion theme in Table 2, and av_ATRQ with a correlation coefficient of 0.993. In all our subsequent analysis, we used av_ATRQ as our measure of the risk-aversion theme, since av_ATRQ has been computed for other datasets and this enabled a comparison to be made between the measure of attitudes to risk in our USS sample with other samples, in particular, the national population.

In Fig. 2, we plot the distribution of av_ATRQ by age, with higher values representing greater risk aversion. While the distributions look similar across ages, Fig. 3 plots the average value of av_ATRQ within each of the eight 5-year age groups in our data set (age range 25–29 centred on age 27, up to age range 60–64 centred on age 62). This shows the broadly U-shaped pattern previously identified in the literature. A Bartlett test for equal variances rejects the hypothesis that the distributions in Fig. 2 are the same ($\chi^2(7) = 27.38$). Pairwise tests of the difference in means of adjacent distributions indicates that only the 35–39 and the 40–49 age groups have statistically significantly different means. We conclude that the U-shaped distribution of risk-aversion and age illustrated in Fig. 3 means that it is appropriate to ensure that the default asset allocation is age-dependent.

On the basis of the factor analysis and the average risk aversion scores, we now have, for each individual in the sample, one or more estimated values for the responses to five sets of themed questions: (1) attitude to risk (av_ATRQ), (2) risk capacity (a single factor), (3) interest in ethical investing (a single factor), (4) match intentions (on a Likert scale 1–5 indicating the likelihood of making additional matching contributions), and (5) and previous AVCs/added years (a dummy variable taking the value unity if previous additional USS contributions have been made, and zero otherwise). We denote these five variables "investment characteristics" to differentiate them from variables, such as gender, age and salary etc, which we denote as "personal characteristics". We now examine the research methodology and questions before examining the cluster analysis results.

5. Research methodology and research questions

We apply cluster analysis to the 9755 responses to the USS survey questionnaire in order to assess whether it is possible to identify groups of scheme members with similar preferences and characteristics. Cluster analysis is an exploratory data analysis technique used

[13] While it was operating prior to April 2019.

Table 1
Summary demographics and personal characteristics of the respondents to the USS questionnaire.

Panel A (Values)							
	Mean	Std. dev.	10%	25%	Median	75%	90%
Age (years)	46	0.87	32	37	47	52	57
Annual salary (£, based on bands)	£50,010	£22,830	£30,000	£40,000	£50,000	£60,000	£80,000
Expected retirement age (years)	65.01	3.39	58	65	65	67	69
USS tenure (years)	11.92	9.14	2	4	7	17	30

Panel B (Categories)			
Gender	Male	Female	
	5377 (55%)	4378 (45%)	
Marital status	Married (incl. civil part.)	Single (incl. sep., div., wid.)	
	6360 (68%)	2941 (32%)	
Job-type	Academic	Prof. services/Other	
	5768 (59%)	3987 (41%)	
Expect long, healthy retirement	Agree	Neither agree nor disagree	Disagree
	7177 (74%)	2071 (21%)	507 (5%)
USS pension as main income	6745 (69%)	1682 (17%)	1328 (14%)
Additional contributions to USS (AVCs/added years)	No	Yes	
	7395 (76%)	2360 (24%)	

Panel C (Age distribution)		
Age range	Number of members	Percent
<25	32	0.33
25–29	394	4.04
30–34	1038	10.64
35–39	1374	14.09
40–44	1411	14.46
45–49	1630	16.71
50–54	1667	17.09
55–59	1468	15.05
60–64	616	6.31
65–69	108	1.11
>70	17	0.17
Total	9755	100

Table presents summary information on demographic and personal characteristics of 9755 members of USS who responded to the questionnaire. Numbers may not sum to 9755 because of no-responses to some questions. In Panel A, salary information is based on mid-points of £10,000 bands. Similarly Panel C reports ages in bands, and subsequent analysis of the age variable uses mid-points of these age bands.

Table 2
Factor analysis of responses to all questions by theme.

Theme	Eigenvalues		Kaiser–Meyer–Olkin sampling adequacy
	Factor 1	Factor 2	
Risk aversion	4.762	0.623	0.917
Risk capacity	1.190	0.189	0.678
Ethical investment beliefs	4.181	0.401	0.868

We adopt the Kaiser criterion and retain factors with eigenvalues greater than unity. The Kaiser-Meyer-Olkin statistic lies between (0,1) and higher values indicate that a factor model is appropriate with a cut-off of 0.6 as being adequate. The risk aversion theme includes responses to questions Q12-Q25. The risk capacity theme includes responses to Q26-Q31. The ethical investment beliefs theme includes responses to Q32-Q36.

to identify patterns in a data sample (Everitt et al., 2011), using some type of distance measure for determining the similarity or dissimilarity between observations. There are two main methods of cluster analysis: partition clustering and hierarchical clustering. A commonly used partition clustering method is "*k*-means cluster analysis", where the number of clusters, *k*, is specified in advance and an iterative algorithm is used to determine which observation should be included in each group. Each observation in the sample is assigned to one of the *k* groups based on the closeness of the value of the observation to the mean value of the *k*th group. For each group, the group mean is computed, and an observation is reassigned to another group if it is closer to the other group's mean. New group means are determined, and these steps continue until no observation changes groups. Following Everitt et al. (2011, p. 114), the *k*-means partition method specifies in advance *k* groups, and then assigns observations to these groups by minimising the error sum-of-squares (*SSE*) between observations and their group mean:

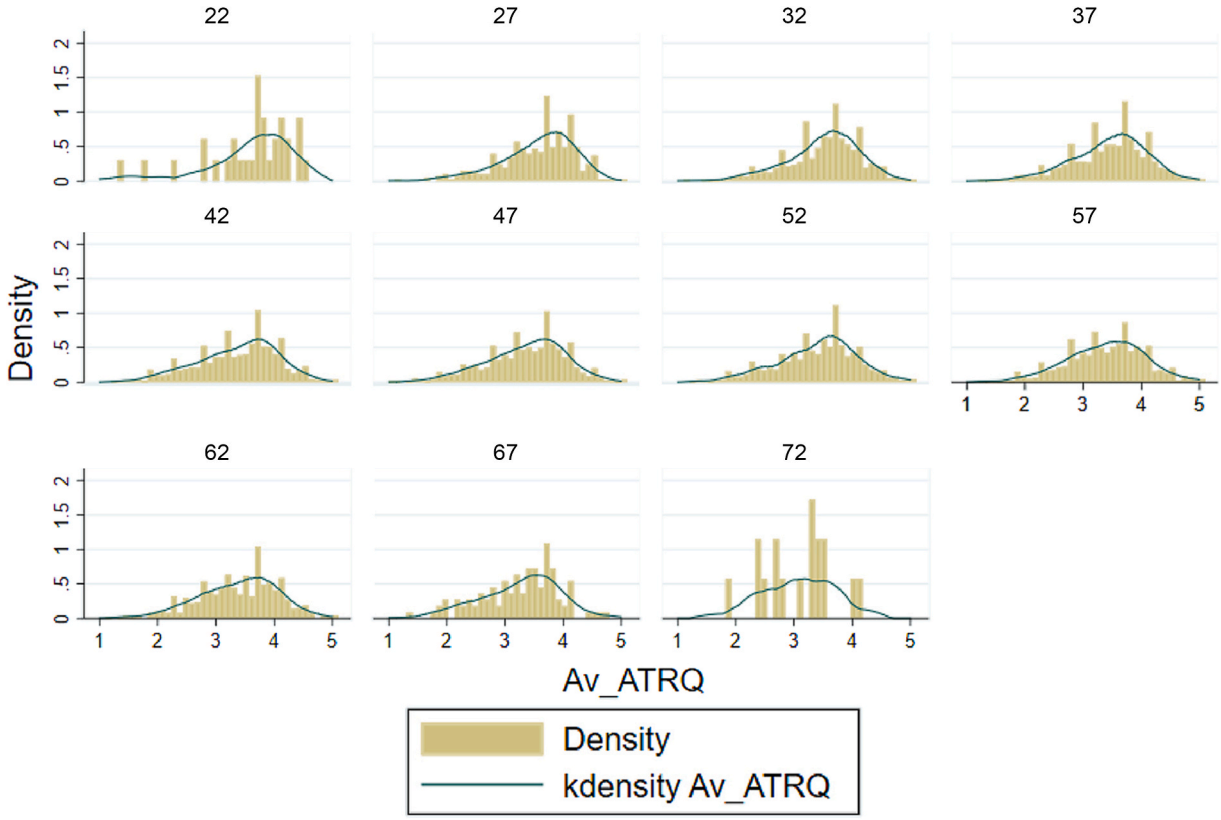

Fig. 2. Distribution of the average risk aversion questions scores by age
Note: Figure shows distribution of attitude to risk questions score (Av_ATRQ) by age, both in the form of a histogram and a kernel density.

$$\min SSE = \sum_{m=1}^{k} \sum_{i=1}^{n_m} d_{mi,m}^2$$

where n_m is the number of members of the mth group and $d_{mi,m}$ is the Euclidean distance between the ith observation in the mth group and the mean of mth group.[14]

An alternative to partition clustering is hierarchical clustering, which creates hierarchically related sets of clusters. Agglomerative hierarchical clustering methods start with each observation in the sample of N observations being in a separate group (N groups each of size 1). The closest two groups are combined (giving N-1 groups: one of size 2 and the rest of size 1), and this process continues until all observations belong to the same group. This process creates a hierarchy of clusters. The simplest hierarchical method is single-linkage, which computes the similarity between two groups as the similarity between the closest pair of observations in the two groups. In our analysis, to measure the closeness between groups, we apply Ward's clustering method in which the criterion for joining groups is based on a within-cluster error sum-of-squares. Following Everitt et al. (2011), let SSE be the total within-cluster error sum-of-squares, then Ward's method is to

$$\min SSE = \sum_{m=1}^{k} E_m$$

where $E_m = \sum_{i=1}^{n_m} \sum_{j=1}^{p} (x_{mi,j} - \overline{x}_{m,j})^2$ and where $\overline{x}_{m,j} = (1/n_m) \sum_{i=1}^{n_m} x_{mi,j}$, with $x_{mi,j}$ being the value of the jth variable ($j = 1, \ldots, p$) for the ith observation ($i = 1, \ldots, n_m$) in the mth group ($m = 1, \ldots, k$). There are two methods for judging the appropriate number of clusters in a dataset: the Calinski-Harabasz pseudo-F statistic and visual inspection of a dendrogram. Calinski-Harabasz pseudo-F statistic is based on the ratio of the (between-clusters sum-of-squares)/(k-1) and the (within-cluster sum-of-squares)/(N-k), where k is number of clusters and N is number of observations. The appropriate number of clusters is where the Calinski-Harabasz statistic is maximised.

[14] In this case, the method simply minimises the sum across the k groups of the sum of squared differences between each observation in each group and the mean of that group.

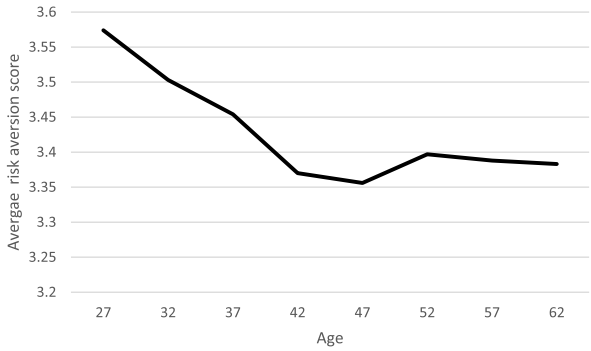

Fig. 3. The average risk aversion questions score by age.

This criterion can be used for both *k*-means partitions and for hierarchical approaches. The second method, relevant for hierarchical approaches only, is visual inspection of a dendrogram.

Cluster analysis has previously been applied to research questions in pensions. Gough and Sozou (2005) identify the attitudes of UK consumers to pension savings, and analyse 540 respondents that had made inquiries about pensions, and identify 6 groups based on age, income and DB membership. Deetlefs et al. (2015) examine a sample of UniSuper members and use cluster analysis to identify groups of similar members, and then use these clusters to predict the likelihood of these groups choosing default options and levels of engagement with the pension scheme.

The objective of using cluster analysis in our case is two-fold: (1) to identify groups of individuals with similar risk attitudes and risk capacities; and (2) having done this, to examine whether individuals in these groups exhibit particular demographic and personal characteristics. Finally, a decision can be made as to whether the groups are sufficiently distinctive to justify having more than one default fund.

Based on the literature review of the possible candidate characteristics used in the design of smart default funds, we will be able to answer the following questions for our data sample: (1) Do risk aversion, risk capacity, ethical investment considerations, match intentions and whether participants have previously engaged with USS by making AVCs vary by gender, age, tenure, salary/wealth and job type (academic vs professional services), and if so, do they help in determining whether USS members fall into distinct clusters and hence justify having more than one default fund? (2) Are USS members more or less risk averse than members of the national population, and if so, should they be offered a more or less conservative default investment fund than the national population?

6. Empirical findings

We wish to identify whether there are patterns or clusters in our five standardised variables across the individuals in the sample: (1) av_ATRQ (higher value denoting greater risk aversion), (2) a single risk capacity factor (higher value denoting lower risk-bearing capacity), (3) a single ethical investment factor (higher value denoting a greater interest in ethical investing), (4) match intention (higher value indicating a stronger intention to match the employer contribution), and (5) members' previous engagement with the pension scheme through additional contributions (0–1 dummy).[15] We are also interested in applying cluster analysis to sub-samples of younger and older age cohorts, in addition to the whole sample.

Table 3 reports the Calinski-Harabasz pseudo-*F* statistics for both Ward's hierarchical and the *k*-means partition methods for the full sample and for each age cohort. The *F*-statistic takes its highest value for groupings of two clusters for all ages and in both the younger and older age cohorts.

Fig. 4 reports the dendrogram from applying Ward's method to the whole sample, and suggests that, across the five standardised variables, there are just two clusters in the dataset. The vertical axis shows how the L2squared dissimilarity measure[16] between groups increases as more members are added to existing groups. A large jump in the dissimilarity measure suggests a cut-off for the number of clusters – at two groups in this case.

We may examine the observations identified by the clusters from both the hierarchical and *k*-means partitions to assess whether the two methods classify the observations into the same two sets of clusters. The results of these cross-tabulations are reported in Table 4. The two methods produce identical groupings for all ages and almost identical groupings for the older age cohort. We can therefore be very confident that the clusters formed for these groups are robust to the clustering method used. On the other hand, for the younger age cohort, the two clustering methods produce different groupings, so that, although there is substantial overlap with two main clusters, clear and robust clusters do not exist for this age cohort. For example, there are 2450 observations that overlap in the first

[15] Because cluster analysis minimises a weighted sum of error-sum-of-squares, the results will be influenced by the size of a particular variable. Therefore, each of the five variables of interest is standardised to have zero mean and unit variance.

[16] The Stata name for the minimised squared Euclidean distance between groups.

Table 3
Identifying the number of clusters for all ages and by selected age cohorts (25–44 and 45–64).

Number of clusters	Ward's hierarchical method			*k*-means partition		
	All ages	25–44	45–64	All ages	25–44	45–64
2	2619.78	748.90	1665.29	2619.78	1013.09	1688.59
3	2053.63	730.32	1201.15	2488.58	904.06	1420.27
4	1841.48	700.13	1083.33	2220.83	813.95	1207.24
5	1695.15	662.22	998.16	2099.16	771.99	1168.24
6	1602.73	633.74	921.57	1938.14	847.36	1116.72

The numbers in the table are values of the Calinski-Harabasz pseudo-*F* statistic for each potential cluster. Unreported analysis of a further 7 to 10 clusters revealed the continuing monotonic decline in the Calinski-Harabasz pseudo-*F* statistic as the number of clusters increased.

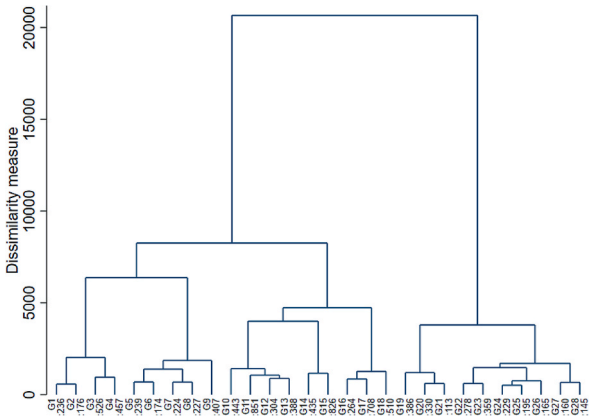

Fig. 4. Dendrogram from the hierarchical clustering method for the full sample of members
Note: This dendrogram only reports groups with cut-off value of L2squared dissimilarity measure >500. There are 28 groups with cut-off > 500, and numbers in each group are shown below (e.g., 236 members in G1). There are many more groupings with cut-off < 500, until the bottom row (not shown), will have 9755 groups: one for each member, and a dissimilarity measure of zero. The large reduction in the dissimilarity measure when moving to more than two groups confirm the findings in Table 3 that there are two distinct clusters.

Table 4
Cross-tabulation of clusters from the *k*-means partition and Ward's hierarchical method for all ages and by age-cohort (25–44 and 45–65).

	All ages			25–44			45–65		
	Clusters from *k*-means partition			Clusters from *k*-means partition			Clusters from *k*-means partition		
Clusters from Ward's hierarchical method	k1	k2	Total	k1	k2	Total	k1	k2	Total
W1	7395	0	7395	2450	583	3033	3534	17	3551
W2	0	2360	2360	188	996	1184	0	1830	1830
Total	7395	2360	9755	2638	1579	4217	3534	1847	5381

Each panel shows the cross-tabulations of the number of observations by age-cohort of the two clusters formed by Ward's hierarchical method (W1 and W2) and two clusters formed by a *k*-means partition (k1 and k2).

cluster defined by Ward's method with the first cluster defined by the *k*-means partition. However, there are a further 583 observations in the first cluster defined by Ward's method but are in the second cluster defined by the *k*-means partition method. This means that any inferences that we draw for the younger cohort needs to be tempered by the more ambiguous set of clusters. But this is not a serious problem when it comes to designing a set of default funds for the new DC scheme, since most members in younger age cohort have salaries below the £55,000 threshold necessary for automatic participation in the DC segment of USS.

We next examine the distribution of the demographic and personal characteristics of individuals allocated to each of these pairs of clusters. The results, reported in Table 5, show the mean value of the distribution of variables across members of the two sets of clusters for all ages and by age cohort.

Examining the columns for all ages first, it can be seen that there are distinct differences between the two clusters, with Cluster 2 containing older members, with higher pay, longer tenure, greater pension wealth, more engagement, less interest in ethical investing, lower risk capacity, a higher percentage of males, and a higher percentage of academics than the members of Cluster 1. We might have expected that a cluster with higher pay would also have higher risk capacity, but the higher concentration of males (who are likely to be the main source of pension income in the household) and longer tenure (implying greater reliance on the USS DB pension) suggests that this higher-pay cluster may also be associated with lower risk capacity. There are only small differences between the two clusters in terms of the degree of risk aversion and the intention to make matching contributions.

Table 5
Characteristics by clusters for all ages and by age cohort (25–44 and 45–64).

	All ages		25–44		45–65	
	Cluster 1 (k1,W1)	Cluster 2 (k2,W2)	Cluster 1 (k1,W1)	Cluster 2 (k2,W2)	Cluster 1 (k1,W1)	Cluster 2 (k2,W2)
Variable						
Av_ATRQ	3.44	3.30	3.79	2.75	3.42	3.33
Risk_capacity_fact1	−0.046	0.145	0.15	−0.37	−0.04	0.17
Ethics_fact1	0.009	−0.029	0.22	−0.28	−0.04	−0.03
Match	3.46	3.91	3.15	4.30	3.48	3.92
Previous AVCs (Engage)	0.0	1.00	0.00	0.29	0.0	1.00
Age	44.2	51.2	36.1	37.4	52.5	53.9
Pay	£47,433	£58,114	£39,891	£48,860	£53,043	£60,729
Tenure	10.2	17.2	6.5	7.2	14.2	19.2
Pens_wealth	£242,587	£422,000	£159,038	£207,750	£325,588	£464,887
Exp_retire	65.3	64.4	66.0	65.3	64.7	64.1
Observations	7395	2360	2450	996	3534	1830
%female	46.4%	39.1%	55.2%	30.8%	45.1%	38.1%
%couple	67.1%	72.4%	58.8%	66.7%	73.5%	73.8%
%academic	57.6%	69.4%	57.1%	56.9%	59.%	70.5%
F(8, 9234)	184.57***					
F(8, 3976)			50.46***			
F(8,5098)					55.19***	

The table shows the average (mean) characteristics for pairs of clusters formed for all ages and split by age: for the 25–44 and 45–64 age cohorts. Av_ATRQ is the member's average ATRQ score (a higher value denotes greater risk aversion). Risk-capacity_fact1 is the single factor indicating the member's risk capacity (a higher value denotes lower risk-bearing capacity). Ethics_fact1 is the single factor indicating the degree of member interest in making ethical investments (a higher value denotes a greater interest in ethical investing). Match indicates the likelihood of the member matching the available 1% employer contribution (a higher value indicates a stronger intention to match the employer contribution). Engage is a 0–1 dummy indicating if the member has previously made additional contributions into the scheme by making AVCs or buying added years (taking a value of 1 in this case, 0 otherwise). Age is the member's age. Pay is the member's salary. Tenure measures the number of years the member has been an active member of USS. Pens_wealth is the member's pension wealth measured as 23*(1/80) x Tenure x Pay x (1.041/1.015)^(65-Age); this incorporates the following assumptions (from the USS 2015 Actuarial Valuation with data at March 31, 2015): a capitalisation factor for the pension at retirement of 20, a lump sum of 3 x the pension at retirement, pay growth of CPI/RPI + 1%, with CPI = 2.25% and RPI = 3.05%, expected return on assets = 3.75% and 15-year gilt yield = 2.25%. Note that this measure of pension wealth was valid at the time of the survey and does not take into account subsequent scheme rule changes from April 1, 2016. Exp_retire is member's expected retirement age; %female measures percentage of cluster that is female; %couple measures percentage of cluster that is married/in civil partnership; %academic measures percentage of cluster in academic rather than professional services role. The *F*-statistic for a multivariate analysis-of-variance is reported for Roy's largest root test for joint significant differences between pairs of clusters for eight common characteristics (Age, Pay, Exp_retire, Tenure, Pens_wealth, %female, %couple, %academic); *** indicates statistical significance at the 1% level. Note the *F*-statistic excludes the first five variables in the table, since these were used to form the two clusters.

The engagement variable represented by previous additional contributions (in the form of AVC or added years contributions) to USS is particularly noteworthy, since *all* members of the second cluster have made these contributions, but, in contrast, *none* of the members of the first cluster have made additional contributions. An *F*-statistic for a multivariate analysis-of-variance for jointly significant differences between the two clusters for eight common characteristics (Age, Pay, Exp_retire, Tenure, Pens_wealth, %female, %couple, %academic) indicates that we can reject the null of same values.

Turning to the results for the older age cohort, there are similar differences between the two clusters for most of the variables, with the exception that ethical investment beliefs are the same across the two clusters. As with the full sample, *all* members of the second cluster have previously engaged with USS making additional contributions whereas *none* of the members of the first cohort have. Again, the reported *F*-statistic rejects the null hypothesis of no differences between pairs of mean values suggesting that there are significant differences between the observable characteristics of the two groups.

When we compare the two clusters in the younger age cohort (formed from the overlaps between the two clustering methods), we again observe that members in Cluster 1 with no previous engagement are slightly younger, with lower pay, lower tenure, lower pension wealth, a larger percentage of females, and a lower percentage of couples. In Cluster 2, only 29% of the cluster have previously engaged with USS rather than 100% in the older sub-sample. The second cluster again has a lower level of risk aversion, a higher intention to match and a lower interest in ethical investing. The *F* statistics again indicates that there is a significant difference between the mean values of the personal characteristics between the two clusters. As we anticipated, the average pay in both clusters in this younger cohort is well below the £55,000 threshold to automatically be enrolled in the new DC segment. In fact, over 90% of the members in Cluster 1 and over 70% of members in Cluster 2 have pay below the salary threshold. So, the relevance of the new DC segment for this younger cohort is moot.

A strong result from Table 5 is that a key differentiator between the two clusters for all ages and both sub-samples is whether or not members have previously engaged with USS through making AVCs or added years contributions. We decided to investigate this relationship further by undertaking a probit analysis of the variables that determine the probability of the pension scheme member engaging with USS. The common characteristics across scheme members were: age, pay, tenure, pension wealth, the member's expected retirement age, gender, marital status, job-type, life expectancy and type of university employing the scheme member. Table 6

Table 6
Probit model of determinants of engagement variable for all-ages and by age cohort.

	All ages		25–44		45–65	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Age	0.030***	_	0.041***	_	0.0201***	_
	(0.002)		(0.007)		(0.004)	
Pay	2.64×10^{-6}***	_	2.27×10^{-6}	_	2.67×10^{-6} ***	_
	(7.22×10^{-7})	_	(1.69×10^{-6})	_	(8.22×10^{-7})	_
Tenure	0.028***	_	0.028***	_	0.026***	_
	(0.002)		(0.006)		(0.002)	
Pens_wealth	_	1.19×10^{-6} ***		1.26×10^{-6}***	_	7.42×10^{-7} ***
		(5.47×10^{-8})		(1.47×10^{-6})		(6.47×10^{-8})
Exp_retire	−0.033***	−0.040***	−0.025***	−0.026***	−0.033***	−0.035***
	(0.005)	(0.004)	(0.008)	(0.008)	(0.006)	(0.006)
Gender_dum	0.032	0.019	0.038	0.012	0.042	0.056
	(0.032)	(0.031)	(0.057)	(0.055)	(0.040)	(0.039)
Mstat_dum	−0.044	0.018	−0.023	0.034	−0.064	−0.063
	(0.033)	(0.032)	(0.057)	(0.056)	(0.042)	(0.041)
Job_dum	0.120***	0.132***	0.097*	0.080	0.143***	0.180***
	(0.034)	(0.032)	(0.057)	(0.056)	(0.042)	(0.042)
Life_exp	0.058***	0.034**	0.070**	0.057*	0.052**	0.047**
	(0.018)	(0.017)	(0.032)	(0.031)	(0.022)	(0.022)
Uni_alliance	−0.036	0.068	0.168*	0.206**	−0.114*	−0.103*
	(0.0507)	(0.049)	(0.097)	(0.095)	(0.060)	(0.059)
Constant	−0.453	1.456***	−1.385**	0.218	0.111	1.566***
	(0.308)	(0.285)	(0.590)	(0.523)	(0.408)	(0.363)
Observations	9311	9311	4033	4033	5131	5131
Pseudo-R^2	0.129	0.0752	0.058	0.039	0.061	0.044
LR $\chi^2(9)$	1326.76***		159.25***		405.77***	
LR $\chi^2(7)$		775.93***		107.84***		289.25***

Probit model of engagement with USS on ten common characteristics (age, pay, tenure, pension wealth, expected retirement age, gender, marital status, job-type, life expectancy and university type). Model 1 includes age, pay and tenure; Model 2 includes pension wealth calculated from age, pay and tenure. Standard errors are reported below coefficients, and *** indicates statistical significance at the 1%, ** at 5% and * at 10% levels. For definition of first five variables (including pensions wealth), see Table 5; gender is dummy variable with Gender_dum = 1 denoting male; marital status is dummy variable with Mstat_dum = 1 denoting married/civil partnership; job type is dummy variable with job_dum = 1 denoting academic role; Life_exp is self-reported life expectancy on 1–5 Likert scale with higher values denoting a longer life expectancy; Uni_alliance is a dummy variable denoting member is employee at University Alliance group of professional and technical universities. A higher or more positive value of an estimated coefficient indicates a higher probability of the member engaging with USS, while a lower or more negative value indicates a lower probability of the member engaging with USS in terms previously making additional voluntary contributions (AVCs) or added years contributions. LR is the likelihood ratio test of the included variables.

presents the estimates from this probit model for all-ages and for both the younger and older cohorts. A higher or more positive value of an estimated coefficient indicates a higher probability of engaging, and vice versa. In each case, we present the results for two different models. In Model 1, we include age, pay and tenure as separate variables, but in Model 2 we combine these three variables in calculating pension wealth. Since pension wealth is calculated from these three variables, we cannot include them together in the same model. The probability of engaging with the scheme is strongly positively correlated with age, pay and tenure, or with pension wealth, and with being an academic. It is weakly positively correlated with being a member of University Alliance group of professional and technical universities. The probability of engaging with the scheme is positively correlated with life expectancy: members who expect to live a long healthy retirement are more likely to make additional contributions to the pension scheme. It is negatively correlated with the member's expected retirement age, implying that members with a shorter time to retirement are more likely to make AVCs or added years purchases presumably in order to make good any pension shortfall below a desired level, while members who intend to retire later recognise that they will be drawing their pension for a shorter period.

Finally, we examine how USS member ATRQ scores compare with the UK adult population as a whole. A2Risk conducted a YouGov survey of risk attitudes of the UK adult population at around the same time as the USS survey. Average earnings for USS members were £38,000 and over 90% of respondents reported an income above £30,000. Since at the time, average UK earnings were around £26,000, it is clear that USS members' salaries above the national average. USS members are slightly less risk averse than the UK adult population (an av_ATRQ of 3.41 compared with 3.56). However, when we compare the USS risk aversion scores with those of the UK adult population with an income above £30,000, USS members are marginally more risk averse (3.41 compared with 3.34). We find a higher percentage of USS members who are labelled "cautious" by A2Risk: 16% of USS members compared to 10% of UK adults earning £30,000 or more. Slightly fewer USS members are "moderately adventurous" or "balanced". Male respondents in the USS survey tended, on average, to be less risk averse than female respondents, and this finding is consistent with the UK population when controlled for age and salary. For both USS and UK samples, ATRQ scores tend to be weakly correlated with income, but do not vary greatly by age. We also found for USS members that ATRQ scores were negatively related to the intention to make matching contributions, indicating that the lower risk aversion, the higher the likely match.

7. Conclusions

Our aim in this study was to investigate the number of default funds appropriate for a large occupational pension scheme with a defined contribution segment where the investment risk – and hence the uncertainty concerning the pension outcome – is borne by the scheme members. We examined a survey of member characteristics and risk attitudes, applying cluster analysis (both hierarchical and partitioning) to segment the members into a small number of distinct groups or clusters. We tested whether these clusters are sufficiently distinctive to justify more than one default investment fund.

For USS pension scheme members, we were able to identify two distinct clusters across the whole sample. The first cluster included members with lower average pay, shorter average tenure, more interest in ethical investing, higher risk capacity, a higher percentage of females, and a higher percentage of professional services staff. This cluster had not previously engaged with the scheme by making additional contributions (in terms of previous AVCs or added years contributions). The second identifiable cluster contained members with higher average pay, longer average tenure, less interest in ethical investing, lower risk capacity, a higher percentage of males, and a higher percentage of academics. This cluster had previously engaged with the scheme by making additional contributions.

When we divided scheme members into two age cohorts, the older 45–64 cohort formed into two clusters that had very similar characteristics as the whole scheme. The younger 25–44 cohort also formed into two clusters that were broadly similar to the older cohort, but there was more ambiguity in the membership of these clusters and the engagement variable was a weaker determinant of cluster membership (none of the first cluster and only 29% of the second cluster had previously engaged).

Across the two age cohorts, there were only small differences between the two clusters in terms of the average degree of risk aversion, but there was some weak evidence that risk aversion is age-related. The survey also showed that, despite being on average more highly educated than the national population, USS members as a whole are marginally more risk averse than the national population, controlling for salary, although the difference is not significant.

All this suggests that a single default fund with an age-related risk profile might be suitable, so long as it reflects the genuine risk tolerance – which takes account of both the risk attitude and risk capacity – of the USS membership. Such a default fund could be similar to that offered to members of any typical UK scheme, given the closeness of USS member risk attitudes to those of the national population. We found no evidence of a requirement for multiple defaults in the case of USS, given the high degree of homogeneity of its members.

This simplified matters considerably. USS decided on the basis of this research to introduce a single default lifestyle fund which would de-risk gradually in the 10 years prior to retirement.[17] This was designed to be optimal for the majority of scheme members who are classified as B-type members in Fig. 1. It also introduced an ethical default lifestyle fund, although a member making no choice would be allocated to the standard lifestyle fund. In addition, USS offered 10 other (non-lifestyle) funds for self-selectors, including a Shariah-compliant fund, to satisfy the preferences of A- and C-type members.[18]

The appropriate communication and engagement strategy follows on naturally from our empirical findings concerning the segmentation of the membership into two groups depending on whether they have previously engaged (just 24% of the total) or not (a large majority at 76%). This involves informing all members at joining about the default lifestyle fund in place for those who are not interested in engaging with the scheme – as well as the lifestyle ethical fund. Self-selectors, by contrast, need to be guided at key ages (e.g., 30, 40, 50 and 60) into adjusting the risk exposure of their pension fund. USS should be particularly concerned about self-selectors who had never engaged with the scheme as younger members. When it comes to the appropriate time to begin de-risking, they are unlikely to be motivated to do so without suitable USS information and guidance.

We believe we have identified a powerful method for understanding the characteristics of pension scheme members, for assessing how many clusters they fall into, and for influencing the design of the "smart" default investment fund(s) that are typically required for modern DC pension schemes,[19] and finally for determining the optimal career-long engagement strategy needed to ensure that members who self-select a different fund from the default fund are guided at key ages into adjusting the risk exposure of their pension fund in order to maximise their lifetime welfare.

Appendix. USS Questionnaire

This short questionnaire has been designed to take less than 15 min.

The anonymised information you and your colleagues provide will be used by the trustee of USS to inform the requirements for the defined contribution (DC) section of the new USS. The changes to USS will be introduced on a phased basis, starting from April 2016.

The new USS will continue to offer DB (career-revalued) benefits up to an initial salary threshold of £55,000 per year. Above that salary threshold, the employer will contribute 12% of pensionable earnings into a new DC section, alongside an 8% contribution from the member. Further details of the new USS can be found here.

The new DC section will be relevant to all active members of USS, either because they have (or will have) a pensionable salary over the initial salary threshold of £55,000 per year, or because they may wish to take up the additional 1% matching contribution from the employer available to all active members. Some members may also wish to make additional contributions.

[17] This therefore has similarities with Australia's QSuper approach in having a lifestyle fund that de-risks over 10 years. However, USS decided not to have multiple age-related default funds, unlike QSuper.

[18] The full list of funds is available at: https://www.uss.co.uk/how-uss-invests/the-fund/investments/uss-equity-holdings (accessed 20 January 2017).

[19] As evidence of this, our methodology is being actively considered in other countries, such as Australia (see, e.g., Lung et al., 2021).

The DC section will offer members a range of investment options, chosen by the trustee. The fund range will include an investment option designed to suit the needs of the majority of members, that will also be the default if members do not make an active choice. It is important that any investment funds members choose reflect (1) their personal circumstances, (2) their attitude to risk and (3) their capacity to take risk. It is also important that the investment option developed by the trustee to suit the majority of members reflects the attitude to risk and capacity to take risk of members across the DC section.

Investment options that have higher anticipated returns also generally have a higher level of risk, as measured by the extent to which the actual return in a given year can fluctuate or fall short of what was expected. There is an unavoidable risk-return trade-off that members will need to make if they are choosing an investment option and the trustee will want to make sure that members have a sufficient range investment choices, and supporting information, to be able to select an appropriate option for their circumstances. By answering the questions in this survey you will be helping the trustee do this as well as informing the design of the new DC section and the investment options it offers.

The questionnaire has five sections. Section A is about you. Section B relates to your attitude to risk, which is largely psychological. Section C covers your capacity to take risk, which is mostly defined by your personal circumstances. Section D deals with your investment beliefs concerning the DC scheme. Section E asks about your intentions concerning the DC section of the new USS.

A. Your circumstances

The key details requested in this section will help us to analyse your responses. Please remember that all the information is anonymous.

1. Institution (drop down)
2. Age (under 25, 25–29, 30–34, …65–69, 70 or over)
3. Gender
4. Marital status (standard response grid as advised)
5. Annual salary with USS employer/s (up to £24,999, £25,000-£29,999 … (5k bands), £95,000-£99,999, £100,000-£124,999, … (25k bands), £250,000 or above)
6. Expected retirement age (up to age 55, 56–60, 61, 62, …69, 70 or over) [can't be earlier than age 55]
7. Approximately how many years have you been a member of USS? (up to 1 year, 2–3 years, 3–4 years, 5–9 years, 10–14 years, 15–19 years, 20–24 years, 25 years or more)
8. Would you describe your role, broadly speaking, as one which is wholly or predominantly: (Academic or academic-related; Professional services; Other)
9. Are you currently, or have you previously made, additional voluntary contributions (AVCs) to USS? Please tick all that apply.
   * I have been making AVCs to USS through the Prudential MPAVC arrangement. (I am currently making AVCs, I have previously made AVCs)
   * I am purchasing, or have purchased, additional defined benefits within the USS (either through purchasing added years of service or career revalued benefits) (I am currently purchasing additional defined benefits, I have previously purchased additional defined benefits)
   * No, I have not made additional contributions to USS
10. I can reasonably expect to live a long, healthy retirement. (Please remember that your responses are anonymous. The information you provide will help us generally to understand USS member needs.) (Strongly agree; agree; neither agree nor disagree; disagree; strongly disagree)
11. My USS pension is likely to be the main household income in my retirement (Strongly agree; agree; neither agree nor disagree; disagree; strongly disagree)

B. Your attitude to risk

The following statements focus on issues related to your attitude to investment risk. Please respond to each statement as accurately as you can. Do not spend too long thinking about each statement. If you do not have experience of the issue discussed, try to think about how you would feel or behave. (Response grid for 12–24 is: Strongly agree; agree; neither agree nor disagree; disagree; strongly disagree).

12. People who know me would describe me as a cautious person.
13. I feel comfortable about investing in the stock market.
14. I generally look for safer investments, even if that means lower returns.
15. Usually it takes me a long time to make up my mind on investment matters.
16. I associate the word "risk" with the idea of "opportunity".
17. I generally prefer bank deposits to riskier investments.
18. I find investment matters easy to understand.
19. I'm willing to take substantial investment risk to earn substantial returns.
20. I've little experience of investing in stocks and shares.
21. I tend to be anxious about the investment decisions I've made.
22. I'd rather take my chances with higher risk investments than increase the amount I'm saving.

23. I'm concerned by the volatility of stock market investments.
24. I'm not prepared to take any investment risk with my DC pension fund.
25. At what level of fall in value of your investments would you begin to feel very uncomfortable? (zero, 5% fall, 10% fall, 20% fall, more than 20% fall, don't know)

C. Your capacity to take risk

We are interested in your responses even if you are not yet close to retirement and have not considered your pension options. Please respond to each statement as accurately as you can. Please consider your own situation even if you have a partner or dependants.

26. I expect the income from sources other than my USS pension (continued work, other pensions excluding my USS pension, etc) to cover most or all of my spending needs for the duration of my retirement. (Strongly agree; agree; neither agree nor disagree; disagree; strongly disagree)
27. I expect a significant proportion of my retirement spending needs to be met from assets other than my pension fund (e.g., investments or home equity). (Strongly agree; agree; neither agree nor disagree; disagree; strongly disagree)
28. I do NOT expect to have significant outstanding debts (e.g., mortgage or credit cards) by the time I retire. (Strongly agree; agree; neither agree nor disagree; disagree; strongly disagree)
29. How much paid work do you expect to do after your formal retirement? (A substantial amount; a little; none)
30. My spouse or partner (or another family member) is likely to be able and willing to support me financially throughout my retirement if circumstances require. (Strongly agree; agree; neither agree nor disagree; disagree; strongly disagree)
31. It would be relatively easy for me to cut my spending in retirement if circumstances require. (Strongly agree; agree; neither agree nor disagree; disagree; strongly disagree)

D. Your investment beliefs concerning the DC section

32. How would you rate your level of interest in ethical investment? (1 = no interest to 9 = very high interest)
33. Would you opt for an ethical investment fund within the DC section if one was offered? (1 = certainly not to 9 = definitely)
34. If your answer to question 33 was >5, would you still consider opting for this fund if it meant the possibility of higher charges, or lower investment returns? (Y/N/Not Sure)
35. To what extent would you like USS to adopt the following approaches for a specific DC ethical investment option (from 1 not at all to 9 very much)
    a. Negative screening/divestment (not investing in certain companies or sectors based on Environmental, Social and Governance (ESG) criteria)
    b. Positive screening (investing in certain companies or sectors based on ESG criteria)
    c. Voting and engagement (encouraging better management of ESG and ethical issues at companies)
    d. ESG integration (incorporating how companies are managing ESG and ethical issues into investment decision making)
36. If score >5 on 35a, on what issues would you like to see screening out if suitable DC ethical investment options were available (i.e. level of concern from 1 not concerned to 9 extremely concerned)
    * Gambling, Tobacco, Alcohol, Weapons, Nuclear power, Climate change impact, Pornography, Animal welfare, Child labour, Human rights
37. Do you have any interest in investing in a Shariah-compliant fund? (Y/N/Not Sure)

Suggested definition of a Shariah-compliant fund to be shown underneath:

A Shariah-compliant fund is an investment fund which meets all of the requirements of Shariah law and the principles articulated for 'Islamic finance'. Shariah-compliant funds must follow a variety of rules, including investing only in Shariah-compliant companies, appointing a Shariah board, carrying out an annual Shariah audit and purifying certain prohibited types of income, such as interest, by donating them to a charity.

38. How would you rank the most important attributes of a DC investment fund:
    * Size of the DC investment fund at retirement
    * Investment in companies that operate responsibly
    * Clear communications and information from the DC investment fund
    * Level of risk in the DC investment fund
    * Level of charges within the DC investment fund

E. Your intentions concerning the DC section

39. How likely are you to take up the additional 1% employer matching contribution in the USS DC section? (I will definitely not match, I am unlikely to match, I am undecided, I am likely to match, I will definitely match)
40. Thinking about the features you would be looking for from your USS DC pension after you retire, and bearing in mind that you will also have accrued DB benefits within USS which will provide secure benefits (including income for life), how would you

rate the following in terms of importance to you (high importance, medium importance, low importance. Response grid to be rotated)

* The ability to change the amount of income I receive at different stages of my retirement.
* The potential to increase my income in my retirement if stock markets increase.
* The ability to pass on lump sums to my dependants.
* An income throughout my retirement that grows in line with a rising cost of living (i.e., inflation).
* Protection from falls in the value of my fund due to stock market movements.
* The ability to access lump sums when I want to.
* An income throughout my retirement that remains constant over time.
* To maximise my pension income after tax.

These questions were created by A2Risk, a specialist research company that provides risk profiling and personality tools to help financial services firms assess the risk attitudes of their clients for the purpose of meeting their clients' investment objectives. A2Risk's attitude to risk questionnaires (ATRQs) have been used by UK financial services firms since 2006 and have now been translated and tested in other markets. Long-standing clients include Vanguard, Royal London and Moody's Analytics. In recent years, the company has also provided ATRQs and related services to two large European banks. The original questionnaires were developed by Dr Alistair Byrne and Professor David Blake.

Thank you for taking the time to complete this survey. USS values your input and will use it to inform the design of the new DC section.

Questions 12–25 in Appendix B have been copyrighted by A2Risk Ltd

References

Appelt, K. C., Knoll, M. A., Johnson, E. J., & Westfall, J. E. (2016). Preference checklists: An effective, selective choice architecture. In *Working paper*. New York: Columbia University.

Arano, K., Parker, C., & Terry, R. (2010). Gender-based risk aversion and retirement asset allocation. *Economic Inquiry, 48*, 147–155.

Bajtelsmit, V. L., & VanDerhei, J. L. (1997). Risk aversion and pension investment choices. In M. S. Gordon, O. S. Mitchell, & M. M. Twinney (Eds.), *Positioning Pensions for the Twenty-first Century* (pp. 45–66). Philadelphia: University of Pennsylvania Press.

Barber, B. M., & Odean, T. (2001). Boys will be boys: Gender, overconfidence, and common stock investment. *Quarterly Journal of Economics, 116*(1), 261–292.

Beams, J. D., Brown, R. M., & Killough, L. N. (2003). An experiment testing the determinants of non-compliance with insider trading laws. *Journal of Business Ethics, 45*(4), 309–323.

Behrman, J. R., Mitchell, O. S., Soo, C. K., & Bravo, D. (2012). How financial literacy affects household wealth accumulation. *The American Economic Review: Papers and Proceedings, 102*(3), 300–304.

Bernstein, P. (1992). *Capital Ideas*. New York: Free Press.

Blake, D., Cannon, E., & Wright, D. (2019). *Quantifying loss aversion: Evidence from a UK population survey. Working paper*. London: Pensions Institute. http://www.pensions-institute.org/wp-content/uploads/wp1912.pdf (Forthcoming in the Journal of Risk and Uncertainty.).

Blake, D., Wright, D., & Zhang, Y. (2014). Age-dependent investing: Optimal funding and investment strategies in defined contribution pension plans when members are rational life cycle financial planners. *Journal of Economic Dynamics and Control, 38*(1), 105–124.

Bouchouicha, R., Deer, L., Eid, A. G., McGee, P., Schoch, D., Stojic, H., Ygosse-Battisti, J., & Vieider, F. M. (2019). Gender effects for loss aversion: Yes, no, maybe? *Journal of Risk and Uncertainty, 59*, 171–184.

Boulouta, I. (2013). Hidden connections: The link between board gender diversity and corporate social performance. *Journal of Business Ethics, 113*, 185–197.

Brooks, C., Sangiorgi, I., Hillenbrand, C., & Money, K. (2018). Why are older investors less willing to take financial risks? *International Review of Financial Analysis, 56*, 52–72.

Butt, A., Donald, M. S., Foster, F. D., Thorp, S., & Warren, G. J. (2018). One size fits all? Tailoring retirement plan defaults. *Journal of Economic Behavior & Organization, 145*, 546–566.

Campbell, J. Y. (2006). Household finance. *The Journal of Finance, 61*(4), 1553–1604.

Cohen, A., & Einav, L. (2007). Estimating risk preferences from deductible choice. *The American Economic Review, 97*(3), 745–788.

Croson, R., & Gneezy, U. (2009). Gender differences in preferences. *Journal of Economic Literature, 47*(2), 448–474.

Cupples, S., Rasure, E., & Grable, J. E. (2013). Educational achievement as a mediator between gender and financial risk tolerance: An exploratory study. *Ewha Journal of Social Sciences, 6*, 151–180.

Dahlquist, M., Setty, O., & Vestman, R. (2018). On the asset allocation of a default pension fund. *The Journal of Finance, 73*(4), 1893–1936.

Deaves, R., Lüders, E., & Ying, L. G. (2009). An experimental test of the impact of overconfidence and gender on trading activity. *Review of Finance, 13*(3), 555–575.

Deetlefs, J., Bateman, H., Dobrescu, L., Newell, B., Ortmann, A., & Thorp, S. (2015). *Suspicious minds (can be a good thing when saving for retirement). Working paper*. Sydney: University of New South Wales.

Dobrescu, L., Fan, X., Bateman, H., Newell, B., Ortmann, A., & Thorp, S. (2018). Retirement savings: A tale of decisions and defaults. *The Economic Journal, 128*(610), 1047–1094.

Dohmen, T., Falk, A., Huffman, D., & Sunde, U. (2010). Are risk aversion and impatience related to cognitive ability? *The American Economic Review, 100*(3), 1238–1260.

Dollar, D., Fisman, R., & Gatti, R. (2001). Are women really the 'fairer' sex? Corruption and women in government. *Journal of Economic Behavior & Organization, 46*(4), 423–429.

Eckel, C. C., & Grossman, P. J. (2008). Men, women and risk aversion: Experimental evidence. *Handbook of Experimental Economics Results, 1*, 1061–1073.

Everitt, B. S., Landau, S., Leese, M., & Stahl, D. (2011). *Cluster Analysis* (5th ed.). Chichester, UK: Wiley.

Fernandes, D., Lynch, J. G., Jr., & Netemeyer, R. G. (2014). Financial literacy, financial education, and downstream financial behaviors. *Management Science, 60*(8), 1861–1883.

Filippin, A., & Crosetto, P. (2016). A reconsideration of gender differences in risk attitudes. *Management Science, 62*(11), 3138–3160.

Fisher, P. J., & Yao, R. (2017). Gender differences in financial risk tolerance. *Journal of Economic Psychology, 61*, 191–202.

Fonseca, R., Mullen, K., Zamarro, G., & Zissimopoulos, J. (2010). *What explains the gender gap in financial literacy? The role of household decision-making*. Rand Labor and Population Working Paper Series. WR-762.

Gervais, S., & Odean, T. (2001). Learning to be overconfident. *Review of Financial Studies, 14*(1), 1–27.

Gilliam, J. E., Chatterjee, S., & Zhu, D. (2010). Determinants of risk tolerance in the baby boomer cohort. *Journal of Business & Economics Research, 8*(5), 79–87.
Goda, G. S., & Manchester, C. F. (2013). Incorporating employee heterogeneity into default rules for retirement plan selection. *Journal of Human Resources, 48*(1), 198–235.
Gough, O., & Sozou, P. D. (2005). Pensions and retirement savings: Cluster analysis of consumer behaviour and attitudes. *International Journal of Bank Marketing, 23*, 558–570.
Grable, J. E., & Roszkowski, M. J. (2008). The influence of mood on the willingness to take financial risks. *Journal of Risk Research, 11*(7), 905–923.
Grinblatt, M., Keloharju, M., & Linnainmaa, J. (2011). IQ and stock market participation. *The Journal of Finance, 66*(6), 2121–2164.
Guiso, L., & Paiella, M. (2008). Risk aversion, wealth, and background risk. *Journal of the European Economic Association, 6*(6), 1109–1150.
Guiso, L., Sapienza, P., & Zingales, L. (2018). Time varying risk aversion. *Journal of Financial Economics, 128*(3), 403–421.
Gürdal, M. Y., Kuzubaş, T. U., & Saltoğlu, B. (2017). Measures of individual risk attitudes and portfolio choice: Evidence from pension participants. *Journal of Economic Psychology, 62*, 186–203.
Hallahan, T. A., Faff, R. W., & McKenzie, M. D. (2004). An empirical investigation of personal financial risk tolerance. *Financial Services Review, 13*(1), 57–78.
Hammitt, J. K., Haninger, K., & Treich, N. (2009). Effects of health and longevity on financial risk tolerance. *The Geneva Risk and Insurance Review, 34*(2), 117–139.
Hardies, K., Breesch, D., & Branson, J. (2012). Male and female auditors' overconfidence. *Managerial Auditing Journal, 27*(1), 105–118.
Hinz, R. P., McCarthy, D. D., & Turner, J. A. (1997). Are women conservative investors? Gender differences in participant-directed pension investments. In M. S. Gordon, O. S. Mitchell, & M. M. Twinney (Eds.), *Positioning Pensions for the Twenty-first Century* (pp. 91–103). Philadelphia: University of Pennsylvania Press.
Hirshleifer, D., & Shumway, T. (2003). Good day sunshine: Stock returns and the weather. *The Journal of Finance, 58*(3), 1009–1032.
Hunt, S., Stewart, N., & Zaliauskas, R. (2015). Two plus two makes five? Survey evidence that investors overvalue structured deposits. In *Occasional paper No. 9*. London: Financial Conduct Authority.
Kim, H. H., Maurer, R., & Mitchell, O. S. (2016). Time is money: Rational life cycle inertia and the delegation of investment management. *Journal of Financial Economics, 121*(2), 427–447.
Korniotis, G. M., & Kumar, A. (2011). Do older investors make better investment decisions? *The Review of Economics and Statistics, 93*(1), 244–265.
Love, D. A., & Smith, P. A. (2010). Does health affect portfolio choice? *Health Economics, 19*, 1441–1460.
Lung, E., Roodt, C., Ryan, L., Warren, G. J., & Wymer, K. (2021). A framework for designing investment strategies for default retirement plans. *Journal of Retirement, 8*(3), 40–60.
Lusardi, A., & Mitchell, O. S. (2011). Financial literacy around the world: An overview. *Journal of Pension Economics and Finance, 10*(4), 497–508.
Lusardi, A., & Mitchell, O. S. (2014). The economic importance of financial literacy: Theory and evidence. *Journal of Economic Literature, 52*(1), 5–44.
Nelson, J. (2017). *Gender and risk-taking: Economics, evidence and why the answer matters*. London: Routledge.
OECD. (2009). *Guidelines for pension fund governance*. Paris: Organisation for Economic Cooperation and Development, 5 June http://www.oecd.org/pensions/private-pensions/34799965.pdf.
Paravisini, D., Rappoport, V., & Ravina, E. (2017). Risk aversion and wealth: Evidence from person-to-person lending portfolios. *Management Science, 63*(2), 279–585.
Pensions Commission. (2005). *A New Pension Settlement for the Twenty-First Century: The Second Report of the Pensions Commission. The Stationery Office*. https://webarchive.nationalarchives.gov.uk/+/http:/www.dwp.gov.uk/publications/dwp/2005/pensionscommreport/main-report.pdf.
Riley, W. B., & Chow, K. V. (1992). Asset allocation and individual risk aversion. *Financial Analysts Journal, 48*(6), 32–37.
Rossi, M., Sansone, D., van Soest, A., & Torricelli, C. (2019). Household preferences for socially responsible investments. *Journal of Banking & Finance, 105*(C), 107–120.
Roszkowski, M. J., & Grable, J. E. (2009). Evidence of lower risk tolerance among public sector employees in their personal financial matters. *Journal of Occupational and Organizational Psychology, 82*(2), 453–463.
Samuelson, P. A. (1989). The judgment of economic science on rational portfolio management: Indexing, timing, and long-horizon effects. *Journal of Portfolio Management, 16*(1), 4–12.
Schooley, D. K., & Worden, D. D. (1999). Investors' asset allocations versus life-cycle funds. *Financial Analysts Journal, 55*(5), 37–43.
Schubert, R., Brown, M., Gysler, M., & Brachinger, H. W. (1999). Financial decision-making: Are women really more risk-averse? *The American Economic Review, 89*(2), 381–385.
Smith, N. C., Goldstein, D. G., & Johnson, E. J. (2013). Choice without awareness: Ethical and policy implications of defaults? *Journal of Public Policy and Marketing, 32*(2), 159–172.
Sundén, A. E., & Surette, B. J. (1998). Gender differences in the allocation of assets in retirement savings plans. *The American Economic Review, 88*(2), 207–211.
Sunstein, C. R. (2013). Deciding by default. *University of Pennsylvania Law Review, 162*(1), 1–57.
Tison, A., & Hammitt, J. K. (2018). How do health shocks influence financial risk aversion? A theoretical and empirical investigation. In *Working paper*. Marseille: Aix Marseille University.
Tobin, J. (1958). Liquidity preference as behaviour towards risk. *The Review of Economic Studies, 25*, 65–86.
TPR. (2016). *Code of practice no. 13: Governance and administration of occupational trust-based schemes providing money purchase benefits* (July). The Pensions Regulator.
TPR. (2019). *Defined contribution trust-based pension schemes research: Report of findings on the 2019 survey*. Prepared for The Pensions Regulator by OMB Research (May).
Watson, J., & McNaughton, M. (2007). Gender differences in risk aversion and expected retirement benefits. *Financial Analysts Journal, 63*(4), 52–62.
Yao, R., & Hanna, S. D. (2005). The effect of gender and marital status on financial risk tolerance. *Journal of Personal Finance, 4*(1), 66–85.