DISCUSSION PAPER PI-2003

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February 2020

ISSN 1367-580X

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Grouping Individual Investment Preferences in Retirement Savings: A Cluster Analysis of a USS Members Risk Attitude Survey

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Abstract

Cluster analysis is used to identify homogeneous groups of members of USS in terms of risk attitudes. There are two distinct clusters of members in their 40s and 50s. One had previously ‘engaged’ with USS by making additional voluntary contributions. It typically had higher pay, longer tenure, less interest in ethical investing, lower risk capacity, a higher percentage of males, and a higher percentage of academics than members of the ‘disengaged’ cluster. Conditioning only on the attitude to risk responses, there are 18 clusters, with similar but not identical membership, depending on which clustering method is used. The differences in risk aversion across the 18 clusters could be explained largely by differences in the percentage of females and the percentage of couples. Risk aversion increases as the percentage of females in the cluster increases, while it reduces as the percentage of couples increases because of greater risk sharing within the household. Characteristics that other studies have found important determinants of risk attitudes, such as age, income and (pension) wealth, do not turn out to be as significant for USS members. 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.

Key words: investment choices, cluster analysis, risk attitudes, risk capacity, defined contribution pension schemes

JEL: G11, G41

Executive summary

The Universities Superannuation Scheme (USS) launched a defined contribution (DC) section (USS Investment Builder) in October 2016. The introduction of the DC section meant USS became a hybrid scheme, offering its members both defined benefit (DB) and DC pensions. DB benefits were initially offered up to a salary threshold of £55,000, with contributions from pensionable salary above that threshold going into the DC section, and all active members, irrespective of salary, had the option to pay a 1% contribution and have that 'matched' by an additional 1% from the employer. As at 28 February 2019, 77,000 active members or 40% of the total were contributing to the DC section.

As part of its approach to designing the DC section, USS conducted a survey of risk attitudes of its members in September-October 2015. The survey was distributed to active members via their employer and members could participate whether their salary was above or below the salary threshold. A total of 9,755 active members responded to the survey, making it one of the largest studies of this kind in the UK.

A cluster analysis of the responses identified two clusters in the 40s and 50s age cohorts (the cohorts most likely to be eligible for the DC section based on salary and levels of interest in taking the 'match'). We found:

- A cohort with lower average pay, shorter average tenure, more interest in ethical investing, higher risk capacity,[1] a higher percentage of females, and a higher percentage of professional services staff. This cluster had not previously engaged with USS (in terms of previous additional voluntary contributions (AVCs) or added years contributions)
- A cohort 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 USS (in terms of previous AVCs or added years contributions).

There were only small (and statistically insignificant) differences between the two clusters in terms of the average degree of risk aversion and the propensity to match employer contributions: the first cluster was marginally more risk averse (since it contains a higher percentage of females, who typically have lower appetite for risk) and less likely to match than the second cluster.

Conditioning only on the attitude to risk responses, there are 18 clusters, with similar but not identical membership, depending on which clustering method is used. The differences in risk aversion across the 18 clusters could be explained largely by differences in the percentage of females and the percentage of couples. Risk aversion increases as the percentage of females in the cluster increases, while it reduces as the percentage of couples increases because of greater risk sharing within the household.

[1] Since the guaranteed DB pension will provide a higher percentage of the total pension for this cohort compared with the second cohort.

The similarity in risk aversion scores across both clusters in their 40s and 50s suggests that a single default fund will be suitable, so long as the default reflects the genuine risk tolerance – which takes account of both the risk appetite and risk capacity – of the USS membership. USS members can be characterised as having an overall risk tolerance which is broadly similar to that of the national population with salaries above £30,000, since their slightly greater risk aversion is offset by greater risk-bearing capacity due to the DB underpin. In short, under the current hybrid structure, there is no compelling evidence indicating the need for multiple defaults. In addition, the low level of heterogeneity across the membership suggests that to cater for variations in risk tolerance it might be acceptable to offer just a limited range of funds in addition to the default fund: At its minimum this could include just four funds: (1) a well-diversified fund with a higher level of risk than the default fund, (2) a well-diversified fund with a lower level of risk than the default fund, (3) an ethical fund (with a lifestyle option) and (4) a Shariah-compliant fund, the latter two catering to specific member investment beliefs. However, we acknowledge that self-select funds may be in place to meet the requirements of a small minority of members who would like more control over investment for a wide variety of reasons.

USS Investment Builder members can currently choose from two 'Do it for me' and 10 'Let Me Do It' funds. This choice architecture is designed to encourage members to engage to the level they feel comfortable – for example, those with strong ethical beliefs are not expected to manage their own investment risk in the run up to retirement and so there is also an ethical lifestyle fund alongside the default lifestyle fund. The appropriate communication and engagement strategy involves informing all members that the trustee has designed the investment fund range with their needs in mind, the investment options and additional contribution options available to them and how they can make their choices (via My USS), and the objectives and risk factors they need to consider, particularly as they get closer to retirement.

USS Investment Builder sees markedly higher levels of active engagement compared to USS's previous Additional Voluntary Contribution (AVC) arrangements and many other multi-employer DC schemes. This is likely to be driven, in part, by the underlying characteristics, appetite and aptitude of the members to engage with their pension choices, and, in part, by the design and communication of the scheme by the trustee and employers.

Further phases of research could consider the revealed preferences (i.e., observed behaviour) of members over time compared to their stated preferences based on a set of underlying member characteristics.

Grouping Individual Investment Preferences in Retirement Savings: A Cluster Analysis of a USS Members Risk Attitude Survey

1. Introduction

The Universities Superannuation Scheme (USS)[2] – which covers academic and professional services staff in UK universities – is one of the largest pension schemes in the UK, with 420,000 members, comprising 200,000 active, 69,000 deferred, and 151,000 pensioner members.[3]

On 31 March 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 31 March 2011. This new defined benefit (DB) section, named USS Retirement Income Builder, has an annual accrual rate of 1/75th, Consumer Price Index (CPI) uprating of the pension,[4] and a tax-free lump sum at retirement equal to three times the initial pension.

On 1 October 2016, a salary threshold was introduced, initially set at £55,000 per annum, above which member and employers contributions were paid into a new defined contribution (DC) section, named USS Investment Builder, and USS became a hybrid scheme with some members building up both DB and DC benefits.

Contribution rates were set at 18% of salary for employers and 8% of salary for members up to £55,000. Above £55,000, the employer's contribution rate was 12% of the excess, while the member's contribution rate was 8% of the excess. Members at all salary levels could initially make additional voluntary contributions (AVCs) into the DC section and will receive a 1% 'match' from the employer if they make additional contributions of at least 1% of salary.[5]

To design the new DC section, USS undertook a programme of research in 2015 to understand member needs 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.[6] As part of this programme, in October 2015, USS worked with A2Risk[7] to design a risk attitudes survey of USS members. The primary purpose of the survey was to inform USS's understanding of risk appetite and investment beliefs in order to support the design of the USS Investment Builder investment fund range.

[2] https://www.uss.co.uk/

[3] USS Report and Accounts 2018.

[4] USS will match increases in CPI for the first 5% plus half of the difference above 5% up to a maximum increase of 10%. So, if official pensions increased by 15%, USS increases would be 10%. (https://www.uss.co.uk/members/members-home/retiring/pensions-in-payment)

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

[6] A summary of this research can be found at https://www.uss.co.uk/~/media/document-libraries/uss/scheme/uss-investment-builder-a-summary-of-research.pdf?la=en

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

To design the default investment fund and the appropriate range of other funds, USS required information on four aspects of financial planning from the survey: (1) personal circumstances,[8] (2) attitude to risk (ATR), (3) capacity to bear risk as measured by capacity for loss (CFL),[9] and (4) investment beliefs, including ethical considerations. An online questionnaire was distributed to members by participating employers in the scheme. A total of 9,755 responses were collected,[10] making it one of the largest surveys of risk attitudes in the UK. Members were requested to answer 12 ATR questions and the results can be compared against a survey of the UK national population conducted by A2Risk via YouGov at the same time.

There was a requirement to put a suitable default investment fund in place for the start of the hybrid scheme in October 2016.[11] To do this, alongside the risk survey, USS conducted a 'bottom up' quantitative analysis, which involved heatmapping members according to some common sense priors, including their age, tenure within the scheme, DB benefits built up, and salary, and then identifying a suite of 11 member types or 'personas' that represented both the concentrations within, and diversity (including outliers) of, the USS active membership.

An example of some of the personas is shown in Table 1. The last two will be eligible for the USS Investment Builder, while the others will only participate in the DC section if they selected the match.

The purpose of this study is to conduct a more comprehensive quantitative analysis of the survey responses and to assess whether there are alternative 'personas' or clusters of members with shared characteristics or preferences which emerge based on the USS/A2Risk survey compared with the analysis of demographic characteristics. This would then allow USS to (1) consider the suitability of the design of the default lifestyle fund and whether it is 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 towards an investment fund (default or self-select) that is better suited to meeting their long-term objectives.

[8] Information was collected on: institution, age, gender, annual salary, expected retirement age, years of membership of USS, whether the member's role was predominantly academic or professional services, whether AVCs were being made, whether the member could reasonably expect to live a long and healthy retirement, and whether the USS pension was likely to be the main household income in retirement.
[9] CFL is defined as the ability to sustain losses on an investment portfolio and this will be influenced by factors such as the number of dependants, existing financial commitments, etc.
[10] Equal to 6.6% of active members. The sample was assessed 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.
[11] Since 2012, UK DC pension schemes have been required to offer a default investment fund for members who do not wish to exercise an investment choice (under section 17(2) of the Pensions Act 2008).

Table 1 – Example USS member personas				
Name	Age	Salary (£)	Family status	Key aspirations
Anthony	28	28,000	Single with no children	To work hard and play hard, and put down roots, but not just yet
Mae	32	39,000	Joint earner with no children	To buy a house and start a family
Mahmood	49	46,000	Main earner with children and a mortgage	A comfortable and long retirement
Gerry	55	59,000	Married with no children	To retire at 65 on a good pension and travel extensively
Isabel	62	83,000	Married with grown-up children	To retire at 66, with full service and work part-time to fund her lifestyle
Source: USS				

An *a priori* example of this is women, who tend to be more risk-averse investors than men and would therefore be more comfortable investing in lower-risk funds. Over a long investment horizon, such as that involved in building up a pension pot, this behaviour has been described as 'reckless conservatism' – women with the same career salary profile as men would, on average, have lower pensions as a result. To avoid this, ways may need to be found of guiding or nudging women away from their comfort zone. One common way to do this is to have a gender-neutral default fund that involves a more aggressive investment strategy at young ages than women would normally choose. An additional justification for this strategy is that all USS members – whether male or female – will have the security of a DB pension on salaries up to £55,000 p.a., as well as a state pension, and this potentially allows for greater risk bearing in the DC section than might otherwise be the case.

Men, on the other hand, tend to suffer from investment overconfidence which can lead to 'reckless adventurism'. This is not necessarily desirable at older ages close to retirement, since there is less time to recover from a severe fall in equity markets. To avoid this, ways need to be found of guiding or nudging men away from this type of behaviour. Again, one way to do this is to design the gender-neutral default fund to involve a less aggressive investment strategy at older ages than men may otherwise choose.[12]

This is the approach taken by the Australian pension fund, QSuper, which segments its members according to age and size of accumulated fund, but not by gender. Its

[12] Both men and women can, of course, choose from one of the 10 other funds on offer, but then have to accept the consequences of that decision.

default investment fund is called ‘QSuper Lifetime – The hands-off investment option that automatically changes when you do’:[13]

> *Lifetime is based on a simple philosophy – your super investment strategy should change as you get older, and as you accumulate more money.*
>
> *What's great about Lifetime is that everything's automated, so you don't need to make adjustments to your super as things change.*
>
> *It works like this. We'll place you in one of our investment groups (there are eight in total), which has an investment strategy linked to your age and Lifetime balance. Twice a year (May and November) we'll reassess your situation, and move you into another group if things have changed.*
>
> *When you're younger, we'll put more emphasis on growth. When you're nearing retirement, we'll switch to a more stable strategy that protects your savings.*
>
> *It's a clever way to make sure you get the most out of your super, at every stage in your life.*

The eight gender-neutral lifetime groups are listed in Table 2. Members are first allocated to the group most suitable for them and then are automatically moved (not guided or nudged) as they age: they are moved from higher risk to lower risk assets, consistent with the age-dependent investment strategy called lifestyling or lifecycling (Blake et al. (2014)). They are also moved if their lifetime balance changes sufficiently, through investment returns, contributions or transfers.

QSuper used quantitative heatmapping to identify groups of members according to their age and pot size, which formed the basis for their decision to introduce multiple defaults. They did not undertake risk appetite research in the way that USS did, but did test member understanding through a series of focus groups. The priority was to identify groups which were materially different and therefore would benefit from default strategies with different risk levels. It was also important to make sure their approach was operationally viable and simple to communicate.

The QSuper approach is designed to work with how the Australian state pension, called the ‘age pension’, operates. The age pension is means tested, so it tapers as the member's Qsuper fund grows. The default structure segments by age and pot size, making an allowance for the age pension. If members have a lot saved in a DC scheme, this is likely to be because they are on higher salaries and hence will receive a reduced age pension. By contrast, members with a smaller DC pot are likely to be below or just above the threshold for means testing, which means they are likely to have a larger guaranteed age pension so can afford to be more aggressive. This explains why members with bigger pots at age 58 and over are in a lower risk strategy than members of the same age with smaller pots.

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

Table 2 – QSuper Lifetime groups

Group name	Your age	Lifetime balance	Objective *	Risk #
Outlook	Under 40	Any balance	CPI + 4.5%	Medium to high
Aspire 1	40-49	Less than $50,000	CPI + 4.5%	Medium to high
Aspire 2	40-49	$50,000 or more	CPI + 4.0%	Medium to high
Focus 1	50-57	Less than $100,000	CPI + 4.0%	Medium
Focus 2	50-57	$100,000 - $250,000	CPI + 3.75%	Medium
Focus 3	50-57	$250,000 or more	CPI + 3.5%	Medium
Sustain 1	58 or over	Less than $300,000	CPI + 2.5%	Low
Sustain 2	58 or over	$300,000 or more	CPI + 2.0%	Very low

* All objectives are after fees and tax, measured over rolling 10-year periods.
# Standard risk measure
Source: https://qsuper.qld.gov.au/our-products/investment-options/lifetime/

Our study therefore has a number of aims:

1. To test the basis for the identification and definition of current USS member personas
2. To additionally identify any particular groups that may have materially different characteristics, attitudes and needs
3. To assess the implications for the default fund investment strategy and for the other funds offered
4. To assess the implications for member communication and engagement.

Our principal technique for meeting these aims is cluster (or classification) analysis which can be used to segment or partition the USS membership into a number of different investor groups (e.g., Everitt et al (2011)). Market researchers, for example, use the technique to divide a population into different market segments in order to understand the relationship between the groups and to test and promote new products (e.g., Punj and Stewart (1983)).

The outline of the paper is as follows. Section 2 reviews the existing literature on attitudes and personal characteristics. Section 3 discusses the research methodology needed to address these aims. The empirical findings are examined in section 4, while the implications for the USS Investment Builder fund range are considered in section 5. Section 6 concludes. The questionnaire sent to USS members is reproduced in the Appendix.

2. Factors influencing risk attitudes – A review of the literature

In this section, we review the literature on the demographic, socio-economic, health and personality factors that influence risk attitudes.

2.1 Gender

The vast majority of studies show that, on average, women are more risk averse than men and this has consequences for behaviour in a number of financial decision making contexts, such as asset allocation, trading patterns and ethical decision making (e.g., Bajtelsmit and Bernasek (1996), Powell and Ansic (1997), Jianakoplos and Bernasek (1998), Schubert et al. (1999), Finucane et al. (2000), Croson and Gneezy (2009) and Dohmen et al. (2011)). However, Nelson (2017) reviewed the literature on gender differences in risk aversion and concluded that there was little evidence for a difference, claiming instead that existing studies were contaminated with conformation bias or gender stereotyping.

With respect to pension schemes, Bajtelsmit and VanDerhei (1997), Hinz et al. (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.

Overconfidence is another recognised difference between men and women. Lenny (1977), Meehan and Overton (1986), and Gervais and Odean (2001) find that men are generally more confident about their own abilities than women. Barber and Odean (2001) test the overconfidence model using accounting data from a large discount brokerage to analyse the common stock investments of men and women. They document that men transact 45% more frequently than women. They also find that this excessive trading reduces men's net investment returns by 2.65 percentage points a year, compared with 1.72 percentage points for women. Over-optimistic investors also tend to make poorer investment decisions (Hunt et al. (2015)).

There is also evidence that women behave more ethically than men (Dollar et al. (2001). Betz et al. (1989) use data from a sample of 213 business school students and find that men are more than twice as likely as women to engage in actions regarded as unethical. For example, they find that 50% of the males were willing to buy stock with insider information (which is illegal in most countries). Beams et al. (2003) use student subjects to test the relationship between the likelihood of trading based on insider information and subjective probabilities of deterrents and motivations for insider trading. Expected gain, loss avoidance, guilt, cynicism, and fairness of laws were the determinants that had a significant relationship with the intent to transact based on insider information. With respect to gender differences, the study finds that social stigma was a more important deterrent for female respondents than male respondents. Borkowski and Ugras (1998) conclude from a meta-analysis of previous empirical studies that females behave more ethically than males on average.

However, an important caveat to these risk aversion and trading studies is that they are undertaken in relation to the general population or particular sub-samples, such as business school students, and the results may not be directly applicable to a different group, such as university staff. Johnson and Powell (1994) compare the decision making characteristics of males and females in ‘non-managerial’ positions with those in ‘managerial’ positions and find that for those in managerial positions of both genders display similar risk attitudes and make decisions of comparable quality. Atkinson et al. (2003) and Niessen and Ruenzi (2006) compare the performance of male and female mutual fund managers. Both studies find that male and female managed funds do not differ significantly in terms of performance, risk, and other fund characteristics.

Eckel and Grossman (2008) show that studies with contextual frames show less consistent differences in risk aversion between men and women. Perceptions are also important. Siegrist et al. (2002) show that both men and women overestimated male risk preferences, but accurately predicted female risk preferences, suggesting that predictions were influenced by knowledge about risk preferences incorporated in gender stereotypes and by their own feelings.

2.2 Age

Lifestyle investment strategies, as frequently advocated by financial advisors, state that young people should invest in risky assets and shift gradually to safer assets as they age. This strategy has been criticised by Samuelson (1989a) on the grounds that, for a given degree of risk aversion, the optimal asset allocation should be independent of age (see also Poterba et al. (2006)). 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 lifestyling (Samuelson (1989b) and Schooley and Worden (1999)).

There is an extensive literature identifying whether risk aversion changes with age, and whether this affects portfolio allocations. Most studies 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., Riley and Chow (1992), Bakshi and Chen (1994), and Pålsson (1996)). A study by Wang and Hanna (1996), on the other hand, shows that risk aversion falls with age when other variables are controlled for. The bulk of the evidence, however, suggests that, for most people, risk aversion increases from some time during middle age and, as a consequence, such people would optimally choose more conservative investment portfolios than younger people. 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 might also be a cohort effect with different generations having different risk attitudes at the same age – possibly influenced by experience when young. Gilliam et al. (2010) find that leading baby boomers are less risk tolerant than trailing baby boomers.

Korniotis and Kumar (2011) find that older experienced investors make better investment decisions, because they follow rules of thumb that reflect greater investment knowledge. On the other hand, they also find that, for most people, 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, in particular, should delegate their investment decisions to experts.

2.3 Socio-economic, health and personality factors

Most studies suggest that risk aversion decreases with higher salary and wealth, controlling for other factors such as gender, age, education and financial knowledge (e.g., Riley and Chow (1992), Grable (2000), Hartog et al. (2002), Campbell (2006), Guiso and Paiella (2008), and Grinblatt et al. (2011)). However, individuals who are more likely to face salary uncertainty or to become liquidity constrained exhibit a higher degree of risk aversion (Guiso and 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 (e.g., Grable (2000) and Grinblatt et al. (2011)). This is strongly reinforced if individuals also have a high degree of financial literacy (Behrman et al. (2012), Lusardi and Mitchell (2014)). Financial literacy tends to be lower amongst the young, women, the less educated, and ethnic minorities (Lusardi and Mitchell (2011)). 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 and Mitchell (2007, 2011)). Bluethgen et al. (2008) find that financial advice can also help to overcome risk aversion, especially for women, and lead to more diversified portfolios that are better targeted to achieving an investor's goals.

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)). But particular diseases can change people's risk attitudes. For example, Tison and Hammitt (undated), 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.

Alzheimer's disease (AD) can also alter risk attitudes. In line with the predictions of prospect theory (Kahneman and Tversky (1979)), most individuals are risk averse for decisions framed as gains – they want to lower risk exposure to lock in gains – but risk taking for decisions framed as losses – they are prepared to take risks to avoid losses. Ha et al. (2012) show that this framing effect is attenuated in individuals with AD. The authors conclude that 'AD patients making high-risk choices is associated with attenuated sensitivity to the emotional frames that highlight rewards or punishments, possibly reflecting altered evaluations of prospective gains and losses'. Similarly, Sinz et al. (2008) find that individuals with mild AD gambled more often in situations with low-winning probabilities and less frequently in situations with high-winning probabilities than healthy participants in a controlled experiment. Delazer et al. (2007) concluded from their study that people with mild AD made such frequent changes between strategies that decisions were being made randomly, that no advantageous strategy was established and that no consistent response pattern was developed over time.

Depression is frequently associated with the avoidance of potentially rewarding outcomes. Smoski et al. (2008), in a controlled experiment, found that depressive participants would learn to avoid risky responses faster than control participants. They also demonstrated better performance than controls, scoring higher than controls overall and showing a trend toward earning more money overall. The authors conclude that depressive individuals tend to have enhanced feedback-based decision-making abilities, but are more risk averse than non-depressive individuals.

Attitude to risk can also be influenced by personality type. Psychologists distinguish between Type A personalities – who are categorised as being competitive, outgoing, ambitious, impatient and/or aggressive – and Type B personalities – who are more laid back. Type A individuals tend to take greater financial risks than Type B individuals according to a study by Carducci and Wong (1998). 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 (Grable (2000) and Hartog et al. (2002)).

The degree of risk aversion is also influenced by marital status. Sung and Hanna (1996) and Yao and Hanna (2005) show that single women are more risk averse than single men or married couples. However, when married couples are analysed separately, single women are more risk averse than married men, but less risk averse than married women. Having children tends to increase risk aversion amongst both men and women according to Chaulk et al. (2003), Hallahan et al. (2004) and Gilliam et al. (2010).

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, and the environment in which an individual lives (Hirshleifer and Shumway (2003), Kamstra et al. (2003), Guiso and Paiella (2008)).

3. Research methodology

The methodology that we use is a cluster analysis of the 9,755 responses to the USS/A2Risk member risk attitudes and investment beliefs survey conducted in September-October 2015. We also considered potential alternatives, such as principal component analysis and network analysis. We rejected these on the grounds that, in the first case, it is difficult if not impossible to identify the underlying components, and, in the second case, we do not believe that academics use their networks to discuss personal investment matters to any significant extent.

Cluster analysis is an exploratory data analysis technique to identify patterns in a data sample. According to Everitt et al. (2011), 'The term exploratory is important here because it explains the largely absent "p-value", ubiquitous in many other areas of statistics. Clustering methods are intended largely for generating rather than testing hypotheses' (2011, p. 10). Most cluster analysis methods use some type of distance measure, such as Euclidean distance, for determining the similarity or dissimilarity between observations. We also apply data transformations through factor analysis before applying the cluster analysis.

Cluster analysis has been used extensively in market research – to identify distinct homogeneous groups based on purchasing patterns – and we follow the best-practice approach outlined in Tuma et al. (2011) and Tuma and Decker (2013). It has also been used in other fields, such as biology – to derive plant and animal taxonomies – and geography – to identify groups of houses in a city according to house type, value, and location. A number of academic papers have applied cluster analysis to research questions in pensions. Speelman et al. (2013) undertake a cluster analysis of groups of savers in Australia, and report that gender differences dominate outcomes. It has also been used to identify the attitudes of UK consumers to pension savings by Gough and Sozou (2005) who 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,[14] 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.

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 we specify in advance the number of clusters, *k*, 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

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

where n_m is the number of members of the m^{th} group and $d_{mi,m}$ is the Euclidean distance between the i^{th} observation in the m^{th} group and the mean of m^{th} group.[15]

[14] UniSuper is the one of Australia's largest pension schemes with 460,000 members and is open to all employees in the higher education and research sectors (Dobrescu et al. (2017)).

[15] 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.

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 (Ward (1963)) 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 $E_m = \sum_{i=1}^{n_m} \sum_{j=1}^{p} \left(x_{mi,j} - \bar{x}_{m,j}\right)^2$ and where $\bar{x}_{m,j} = (1/n_m) \sum_{i=1}^{n_m} x_{mi,j}$, $x_{mi,j}$ is the value of the j^{th} variable ($j = 1, \ldots, p$) for the i^{th} observation ($i = 1, \ldots, n_m$) in the m^{th} group ($m = 1, \ldots, k$).

The objective of using cluster analysis in our case is two-fold: (1) to identify groups of individuals with similar risk attitudes and/or capacities; and (2) having done this, to examine whether these individuals exhibit particular demographic and personal characteristics. Based on the literature review, we will be able to answer the following questions for our data sample: (1) Does risk aversion vary by gender?, (2) Are women more likely to be interested in ethical investments?, (3) Does risk aversion vary by age?, (4) How does risk aversion vary with salary?, (5) How does risk aversion vary with job type (academic vs professional services)?, and (6) Are USS members more risk averse than members of the general public?

4. Empirical findings

4.1 Descriptive statistics

The questions asked in the survey are reproduced in the Appendix. The data sample includes an anonymous code for each individual, and a series of demographic and personal characteristics self-reported by the survey respondent (Section A of the Appendix) including: age (within five-year bands), gender, marital status (including married, civil partnership, single, divorced, separated, widowed), annual salary (within £10,000 bands), expected retirement age, length of USS membership, job-type (academic or professional services), whether the member could reasonably expect to live a long and healthy retirement, and whether the USS pension is expected to be the main source of income in retirement.

Table 3 – 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	
	5,377 (55%)	4,378 (45%)	
Marital status	Married (incl. civil part.)	Single (incl. sep., div., wid.)	
	6,360 (68%)	2,941 (32%)	
Job-type	Academic	Prof. services/Other	
	5,768 (59%)	3,987 (41%)	
	Agree	Neither agree nor disagree	Disagree
Expect long, healthy retirment	7,177 (74%)	2,071 (21%)	507 (5%)
USS pension will be main income	6,745 (69%)	1,682 (17%)	1,328 (14%)
Previously engaged with USS (by making AVCs/added years)	No	Yes	
	7,395 (76%)	2,360 (24%)	

Panel C (Age distribution)		
Age range	Number of members	Percent
<25	32	0.33
25 - 29	394	4.04
30 - 34	1,038	10.64
35 - 39	1,374	14.09
40 - 44	1,411	14.46
45 - 49	1,630	16.71
50 - 54	1,667	17.09
55 - 59	1,468	15.05
60 - 64	616	6.31
65 - 69	108	1.11
>70	17	0.17
Total	9,755	100

Note: The table presents summary information on the demographic and personal characteristics of the 9,755 members of USS who responded to the questionnaire. Numbers may not sum to 9,755 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.

Participants in the survey then answered a series of questions around a number of different themes establishing: (1) their previous additional contributions to USS (in terms of AVC contributions or buying additional years of service in the DB section); (2) their attitude to risk (Section B, with 14 questions[16]); (3) their capacity to bear risk (Section C, with 6 questions); (4) ethical beliefs in investing (Section D, with 6 questions, plus a question on attitude to Shariah-compliant funds, and a further 5 questions on the desirable properties of DC funds); and (5) intentions with respect to participating in the new DC section operated by USS (Section E, with 2 questions).

Table 3 provides some 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 engaged with USS in terms of 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 automatically participate in the new additional DC scheme (USS Investment Builder), unless they actively select the match.

4.2 Cluster analysis[17]

Cluster analysis works most effectively when the number of observations and the number of variables is relatively small because the algorithms used compute many pairwise comparisons.[18] To reduce the size of the data matrix (number of participants by number of variables), we split the sample by age of the participant, and form groups of participants based on the age distribution. Panel C of Table 3 shows the age distribution of the sample of respondents, and because of the relatively small number of respondents in their 20s (426 observations) and above sixty years of age (741), we concentrate our analysis on the remaining 8,588 members. We form three cohorts of respondents in their 30s (2,412), 40s (3,041) and 50s (3,135), and apply cluster analysis to each age cohort separately.

To reduce the dimensionality of the problem even further, we note that each theme asks a range of questions, so, using factor analysis, we analyse the correlation matrix of responses to identify a smaller number of common factors. To illustrate, there are six questions in the sample inviting responses on the individual's capacity for bearing risk (CFL). The correlation matrix in this case indicated that the responses were so

[16] Twelve questions (numbered 12-23) were used to assess attitude to risk. Two additional questions (numbered 24 and 25) were used as validity checks.
[17] The results are produced in Stata.
[18] Cluster analysis is a quantitative technique subject to the 'curse of dimensionality'.

highly correlated across respondents that we could reduce the potential number of questions to two (Q26 and Q27). A similar analysis suggested that there were just two potential questions in the case of ethical investment beliefs (Q32 and Q33) – revealing that, at most, two factors could explain most of the responses in these two themes. Table 4 shows the results of the factor analysis for the two themes. In both cases, there is a negative value on the second factor, indicating that just a single factor can explain the responses to the two sets of questions – and indeed the full set of questions for both themes.

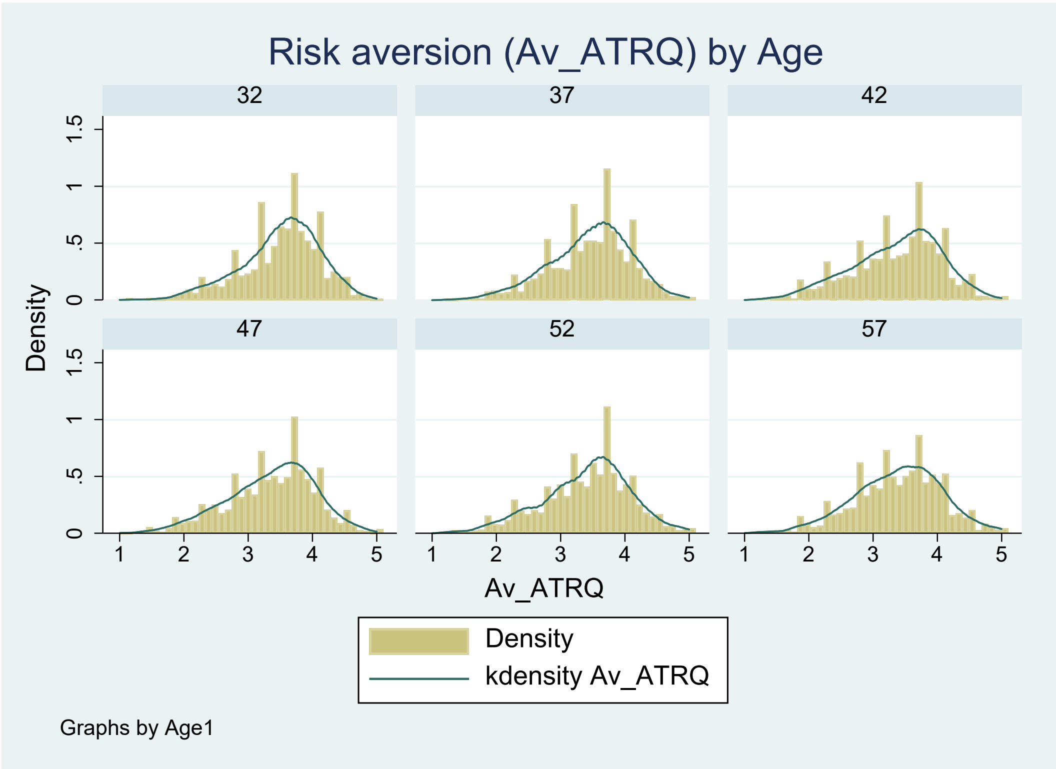
Table 4 – Factor analysis of responses to 2 questions on ethical investment beliefs and risk capacity

	Eigenvalues		Factor1 loading
	Factor1	Factor2	
Ethical investment beliefs	1.52	-0.141	0.476
Risk capacity	0.643	-0.247	0.567

A number of questions on the themes of DC investment intentions had ambiguous responses, and so we only retained one DC investment intentions question (being Q39 on the intention to 'match' the additional employer's contribution). The responses to the questions on the desirable properties of DC investments were poorly answered in the survey, with many participants not providing any answers. Some of the responses were also ambiguous and therefore this set of questions was dropped from the subsequent analysis.

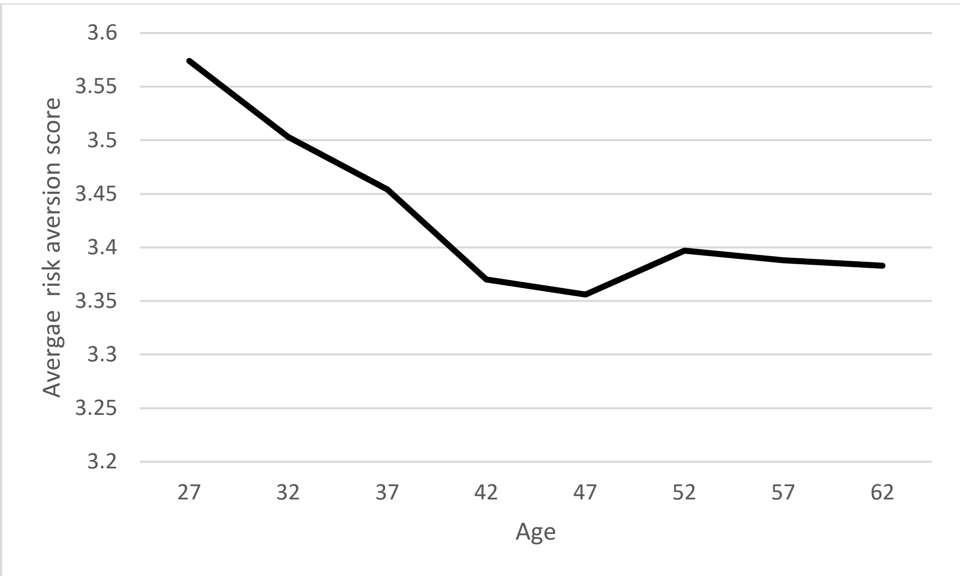
Finally, there was the set of responses around the theme of attitude to risk, but rather than apply factor analysis to this set of responses, each response was aligned on a 1-to-5 point Likert-scale to represent a risk attitude and then these responses were averaged across the 12 attitude to risk questions to provide an average risk aversion score (av_ATRQ). In Figure 1, we plot the distribution of av_ATRQ by age, with higher values representing greater risk aversion. While the distributions look similar, Figure 2 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 Figure 1 are the same ($\chi^2(7) = 27.38$). However, pair-wise tests of the difference in means of adjacent distributions indicates that only the 35-39 and the 40-44 age groups have statistically significantly different means. So we can conclude that, while there is a U-shaped distribution in Figure 2, the differences in the average ATRQ scores across age groups are economically small.

Figure 1 – Distribution of average risk aversion questions scores by age



Note: The figure shows the distribution of the attitude to risk questions score for selected ages, both in the form of a histogram and a kernel density

Figure 2 – The average risk aversion questions score by age



How do these 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 USS members have above-average salaries compared with the UK adult population. USS members are on average 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).[19] 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 correlated with income but do not vary much by age.[20]

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 each of the four sets of themed questions: (1) attitudes to risk (av_ATRQ); (2) interest in ethical investing (a single factor); (3) risk-bearing capacity (a single factor); and (4) DC investment intentions (the match). In addition, we also know from Question 9 in the Appendix whether the respondent has engaged with USS in the past through AVC contributions or the purchase of additional years in the DB section. 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 turn to the cluster analysis results.

4.3 Findings

We wish to identify whether there are patterns or clusters in these factors across the individuals in the sample. We are particularly interested in applying cluster analysis to the three age cohorts 30s, 40s and 50s across our five standardised variables:[21] (1) av_ATRQ (with a higher value denoting greater risk aversion); (2) a single ethics factor (with a higher value denoting a greater interest in ethical investing); (3) a single risk capacity factor (with a higher value denoting lower risk-bearing capacity); (4) match intentions (with a higher value indicating a stronger intention to match the employer contribution); and (5) Engage (which is a dummy variable taking the value unity if previous additional USS contributions have been made, and zero otherwise).

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 (1974) computes a pseudo-*F* statistic based on the ratio of the (between-clusters sum-of-squares)/(k-1) and the (within-cluster sum-of-squares)/(N-k), where k

[19] The standard deviation of the scores of both groups is very similar (both are close to 0.7), indicating that the difference between the scores is not statistically significant.

[20] We show later that these correlations are not statistically significant (see Table 12).

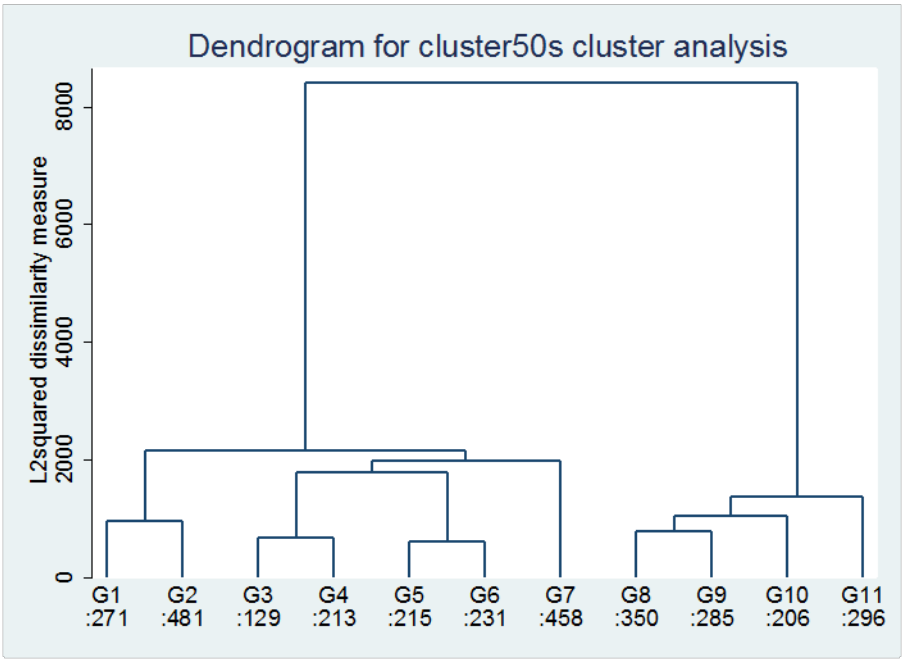
[21] Because cluster analysis minimises a weighted sum of error-sum-of-squares, the results will be influenced by the size of a particular variable. Therefore, each of the five variables of interest is standardised to have zero mean and unit variance.

is number of clusters and N is number of observations. The appropriate number of clusters is where the Calinski-Harabasz statistic is maximised. 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.

Figure 3 reports the dendrogram from applying Ward's method to the 50s age-cohort, and suggests that, across the five standardised variables, there are just two clusters in this sub-sample of the dataset. The vertical axis shows how the L2squared dissimilarity measure[22] 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 in this case.

Table 5 reports the Calinski-Harabasz pseudo-*F* statistics for both Ward's hierarchical and the *k*-means partition methods for each age cohort. The *F*-statistic takes its highest value for groupings of two clusters in all age cohorts (30s, 40s and 50s).

Figure 3 – Dendrogram from Ward's hierarchical clustering method for the 50s age cohort



Note: The dendrogram only reports groups with cut-off value of the L2squared dissimilarity measure > 500. There are 11 groups with cut-off > 500, and the numbers in each group are show below each group (e.g., 271 members in G1). There are many more groupings with cut-off < 500, until on the bottom row (not shown), there will be 3,135 groups with each member being in their own group, and therefore a dissimilarity measure of zero.

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

Table 5 – Identifying the number of clusters for the 30s, 40s and 50s age cohorts

Number of clusters	Ward's hierarchical method			*k*-means partition		
	30s	40s	50s	30s	40s	50s
2	410.37	801.59	1,025.24	574.45	801.59	1,031.03
3	351.78	688.71	703.21	549.02	787.34	854.71
4	354.59	590.33	608.08	532.31	720.20	735.83
5	365.11	554.00	568.01	512.05	685.69	691.73
6	378.65	513.40	535.47	501.94	625.60	627.11
7	364.86	490.02	505.32	480.91	629.91	609.11
8	358.72	469.99	484.40	450.45	596.06	605.97
9	348.05	456.19	465.51	440.56	560.92	579.33
10	340.49	450.03	448.31	427.85	538.42	541.56

Note: Numbers in the table are values of the Calinski-Harabasz pseudo-*F* statistic for each potential cluster

Table 6 – Cross-tabulation of clusters from the *k*-means partition and Ward's hierarchical methods for the 30s, 40s and 50s age cohorts

Panel A: 30s			
	Clusters2 (kmeans)		
g2 (Ward)	1	2	Total
1	833	243	1,076
2	589	747	1,336
Total	1,422	990	2,412

Panel B: 40s			
	Clusters2 (kmeans)		
g2 (Ward)	1	2	Total
1	2,346	0	2,346
2	0	695	695
Total	2,346	695	3,041

Panel C: 50s			
	Clusters2 (kmeans)		
g2 (Ward)	1	2	Total
1	5	1,993	1,998
2	1,137	0	1,137
Total	1,142	1,993	3,135

Note: Each panel shows the cross-tabulations of the number of observations by age-cohort of the two clusters formed by Ward's hierarchical method (g2) and *k*-means partition (Clusters2).

In addition, we examine the observations identified by the clusters from both the hierarchical and *k*-means partitions to assess whether the two methods classify the observations in the same two sets of clusters. The results of these cross-tabulations are reported in Table 6. Panel A shows the cross-tabulations of the observations in the 30s age-cohort of the two clusters (g2) formed by both Ward's hierarchical method and the *k*-means partition (Clusters2). So, for example, there are 833 observations that are in the first cluster defined by Ward's method and also in the first cluster defined by the *k*-means partition. However, there are 243 observations that are in the first cluster defined by Ward's method, but happen to be in the second cluster defined by the *k*-means partition method. The implication from Panel A, is that, for the 30s age-cohort, the two clustering methods produce different groupings, from which we conclude that clear and robust clusters do not exist for this age cohort. But this is not a severe problem, given the low numbers of USS members in their 30s with salaries above £55,000 and hence eligible for USS Investment Builder.

Turning to the other two panels for the 40s and 50s cohorts, the two methods produce very similar groupings for the 40s cohorts (Panel B), and identical groupings for the 50s cohort (Panel C). We can therefore be very confident that the clusters formed for the 40s and 50s cohorts are robust to the clustering method used.

We also examine the distribution of the demographic and personal characteristics of individuals allocated to each of the two groups. The results, reported in Table 7, illustrate the distribution of variables across members of the two sets of clusters for the 40s age-cohort and for the 50s age-cohort.

Examining the numbers for the 40s age cohort first of all, it can be seen that there are large differences between the two clusters, with Cluster 2 displaying higher pay, longer tenure, additional contributions, 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.[23] The additional contributions (in the form of AVC or added years contributions) is particularly noteworthy, since *all* members of the second cluster have made these added contributions, but, in contrast, *none* of the members of the first cluster have engaged. A multivariate analysis-of-variance test indicates that the differences in these variables between the two groups (e.g., differences in pay) are in aggregate statistically significant, indicating that the two clusters are statistically significantly different. There are, however, only small differences between the two clusters in terms of the degree of risk aversion and the propensity to match employer contributions.

Turning to the results for the 50s age-cohort, there are similar differences between the two clusters for most of the variables, with the exception that ethical investment beliefs are now similar across the two groups. As with the 40s age cohort, *all* the members of the second cluster have previously engaged with USS, whereas *none* of the members

[23] We might normally expect that a cohort with higher pay would have higher risk capacity, but in this case the higher concentration of males (who might be the main source of retirement income in the family) and longer tenure (implying greater reliance on the USS pension as the main and possibly only occupational pension) mean that this higher-pay cohort has lower risk capacity. Further, the guaranteed DB pension will provide a lower percentage of the total USS pension for this cohort, reinforcing the lower risk capacity.

of the first cohort have. Again, a multivariate analysis-of-variance suggests that the differences between the two groups are in aggregate statistically significant.

This leads to an interesting and potentially significant conjecture. Although our data set is cross-sectional rather than longitudinal, it might be possible to treat the two 50s age-cohort groups as being the same two 40s age-cohort groups ten years on, although they have grown marginally less interested in ethical investing as they have aged. We can investigate this by combining the 40s and 50s age cohorts. Table 8 confirms that there are still two clusters in the combined age cohorts, while Table 9 confirms that the two clustering methods produce identical clusters.

Table 10 reports the distribution of the demographic and personal characteristics of individuals in their 40s and 50s allocated to each of the two clusters. We observe the same large differences between the two clusters previously observed in Table 7. But the important point is that the two clusters for the combined age cohorts are identical to the two clusters found when the two age cohorts were analysed separately, with the second of the two clusters, Cluster 2, displaying higher pay, longer tenure, higher additional contributions, less interest in ethical investing, lower risk capacity, a higher percentage of males, and a higher percentage of academics than the members of the first cluster, Cluster 1. A multivariate analysis-of-variance test indicates that the two clusters are statistically significantly different. As before, there are only small differences between the two clusters in terms of the degree of risk aversion and the propensity to match employer contributions. But the most important point to emerge from combining the two age cohorts and comparing the results with the two age cohorts separately is that *all* the members of one cluster (Cluster 2) have previously made additional contributions with USS, whereas *none* of the members of the other cluster Cluster 1) has previously made additional contributions.

Table 11 presents estimates of a probit model of the characteristics for the combined 40s and 50s age cohort clusters. A higher or more positive value of an estimated coefficient indicates a higher probability of the member being in Cluster 2, while a lower or more negative value indicates a higher probability of the member being in Cluster 1. So, for example, higher pay increases the probability of the member being in Cluster 2, while a higher expected retirement age increases the probability of the member being in Cluster 1.

Table 7 – Characteristics by clusters for the 40s and 50s age cohorts (*k*-means partition method)

	40s				50s			
	Cluster1		Cluster2		Cluster1		Cluster2	
Variable	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Av_ATRQ	3.39	0.68	3.26	0.70	3.43	0.66	3.33	0.70
Match	3.53	0.94	4.04	0.92	3.48	0.99	3.91	0.98
Engage	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00
Ethics_fact1	0.005	0.905	-0.058	0.950	-0.052	0.917	-0.053	0.929
rc_fact1	-0.003	0.647	0.165	0.638	-0.062	0.698	0.173	0.635
Age	44.5	2.5	45.2	2.4	54.2	2.5	54.7	2.5
Pay	£49,856	£20,951	£55,198	£20,792	£54,041	£26,575	£61,821	£25,196
Exp_retire	65.1	3.3	64.6	3.5	64.3	3.4	63.6	3.4
Tenure	10.7	6.9	14.0	6.4	14.9	10.1	20.0	8.9
Pens_wealth	£285,334	£241,162	£399,574	£247,750	£351,053	£338,147	£504,929	£335,506
F(5,3013)	33.24**							
F(5,3103)					51.25**			
Obs	2,346		695		1,993		1,142	
%female	46.7%		38.8%		46.12%		39.25%	
%couple	72.0%		73.0%		73.03%		73.50%	
%academic	55.8%		67.8%		59.51%		68.99%	
F(3,2887)	13.16**							
F(3,3000)					10.94**			

Note: The table shows the average characteristics for the two clusters formed for the 40s and 50s age-cohorts. The *F*-statistic for a multivariate analysis-of-variance is reported to test for the joint significant differences between clusters for the five common characteristics (Age, Pay, Exp_retire, Tenure, Pens_wealth) and for the three personal characteristics (%female, %couple, %academic); ** indicates statistical significance at the 1% level. Av_ATRQ is the member's average ATRQ score. Match indicates likelihood of the member matching the available 1% employer contribution. Engagement is a 0-1 dummy indicating if the member has previously engaged with the scheme by making AVCs or buying added years. Ethics_fact1 is the single factor indicating the degree of member interest in making ethical investments. rc_fact1 is the single factor indicating the member's risk capacity. Age is the member's age. Pay is the member's salary. Exp_retire is the member's expected retirement age. Tenure measures the number of years the member has been an active member of USS. Pens_wealth is the member's pension wealth. We measured this as (1/80) x Tenure x Pay x (1.051/1.022)^(65-Age); this incorporates the following assumptions about USS: a capitalisation factor for the pension at retirement of 20, a lump sum of 3 x the pension at retirement, pay growth of CPI + 2%, a discount rate of gilts + 0.75% (from the USS 2017 Actuarial Valuation), with Consumer Prices Index (CPI) = 3.1% in November 2017 and the 15-year gilt yield = 1.45% on 15 December 2017. 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 1 April 2016. %female measures the percentage of the cluster that is female. %couple measures the percentage of the cluster that is married or in civil partnership. %academic measures the percentage of the cluster that is academic rather than professional services.

Table 8 – Identifying the number of clusters for the combined 40s and 50s age cohorts

Number of clusters	Ward's hierarchical method	*k*-means partition method
2	1868.59	1868.59
3	1443.14	1646.05
4	1210.05	1448.40
5	1074.53	1361.13
6	1008.64	1320.07
7	971.91	1258.43
8	940.97	1190.57
9	912.89	1117.80
10	876.70	1066.76

Note: Numbers in the table are values of the Calinski-Harabasz pseudo-*F* statistic for each potential cluster

Table 9 – Cross-tabulation of the clusters from Ward's hierarchical and the *k*-means partition methods for the combined 40s and 50s age cohorts

	Clusters2 (kmeans)		
g2 (Ward)	1	2	Total
1	4,339	0	4,339
2	0	1,837	1,837
Total	4,339	1,837	6,176

Note: The table shows the cross-tabulations of the number of observations by age-cohort of the two clusters formed by Ward's hierarchical method (g2) and the *k*-means partition method (Clusters2).

Table 10 – Characteristics by clusters for the combined 40s and 50s age cohorts (*k*-means partition method)

Variable	Cluster1 Mean	Std. dev.	Cluster2 Mean	Std. dev.
Av_ATRQ	3.41	0.67	3.30	0.70
Match	3.51	0.96	3.96	0.96
Engage	0.00	0.00	1.00	0.00
Ethics_fact1	-0.021	0.911	-0.055	0.937
rc_fact1	-0.030	0.672	0.170	0.636
Age	48.9	5.4	51.1	5.2
Pay	£51,780	£23,791	£59,304	£23,831
Exp_retire	64.8	3.4	64.0	3.5
Tenure	12.6	8.7	17.7	8.6
Pens_wealth	£315,546	£291,617	£464,893	£309,331
$F(5,6122)$	113.21**			
Obs	4,339		1,837	
%female	46.4%		39.1%	
%couple	72.5%		73.3%	
%academic	57.5%		68.5%	
$F(3,5891)$	26.69**			

Note: The table shows the average characteristics for the two clusters formed for the combined 40s and 50s age-cohorts. Both clustering methods produce the same results. The *F*-statistic for a multivariate analysis-of-variance is reported to test for the joint significant differences between clusters for the five common characteristics (Age, Pay, Exp_retire, Tenure, Pens_wealth) and for the three personal characteristics (%female, %couple, %academic); ** indicates statistical significance at the 1% level. For the definition of the variables, see Table 7.

Table 11 – Probit model of the two combined 40s and 50s age cohort clusters in terms of characteristics (*k*-means partition method)

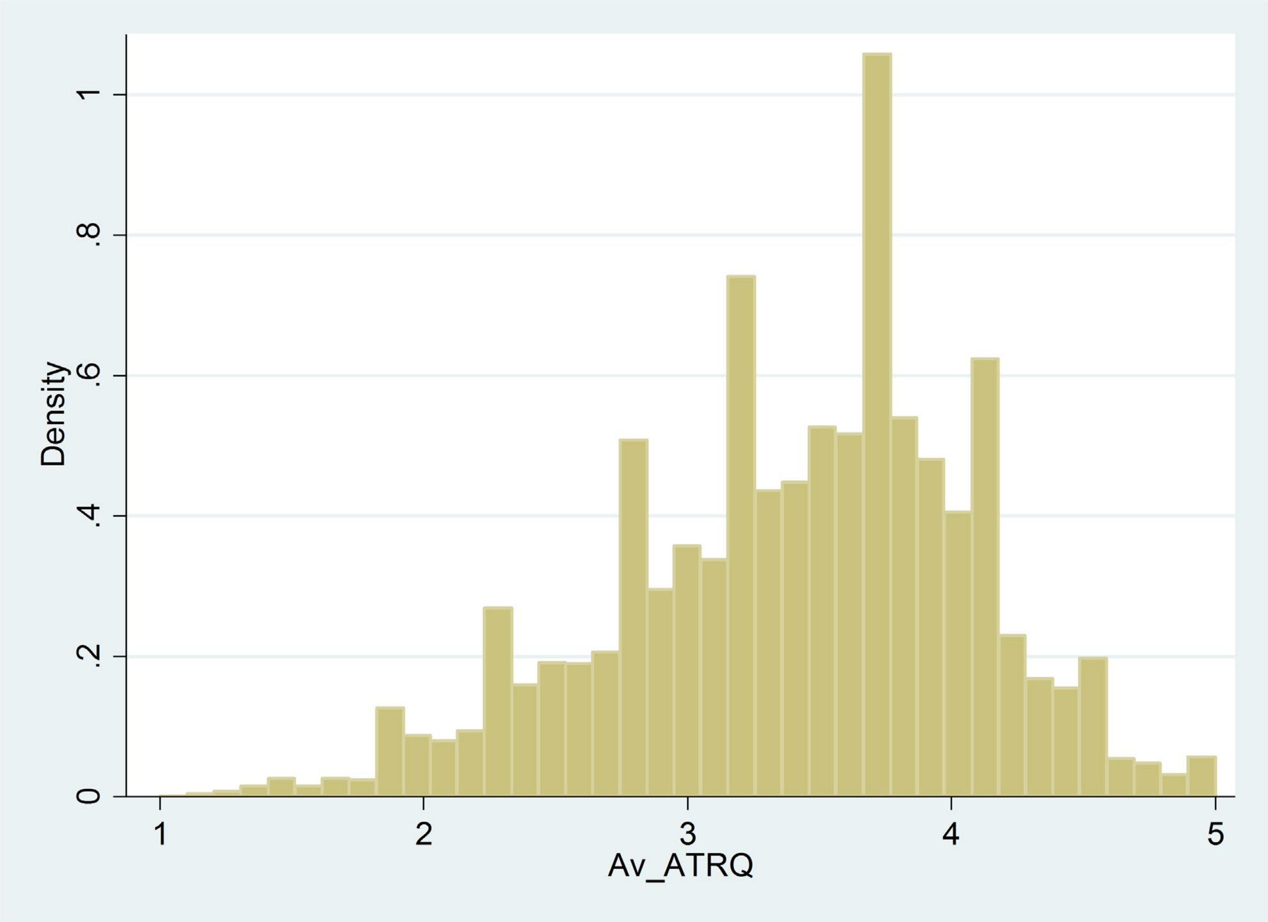
Characteristic	Coef.	Std. err.	z	P>|z|	[95% conf. interval]	
Age	0.021597	0.003723	5.80	0.000	0.014299	0.0288941
Pay	5.21e-06	1.44e-06	3.63	0.000	2.40e-06	8.02e-06
Exp_retire	-0.024425	0.005099	-4.79	0.000	-0.034419	-0.014430
Tenure	0.037754	0.004843	7.80	0.000	0.028263	0.047245
Pens_wealth	-3.08e-07	1.84e-07	-1.67	0.095	-6.70e-07	5.32e-08
Cons	-0.770864	0.384835	-2.00	0.045	-1.525127	-0.016602

Note: The table shows, for the 2 clusters formed by combining the 40s and 50s age cohorts, the results of a probit model of the five common characteristics (Age, Pay, Exp_retire, Tenure, Pens_wealth). For the definition of the variables, see Table 7. Number of obs. = 6,128, LR $\chi^2(5)$ = 525.74, Prob > χ^2 = 0.0000, R^2 = 0.075

In Tables 7 and 10, the fact that the additional contributions variable is such a striking indicator of which cluster a member belongs raises the possibility that these results are driven solely by this particular characteristic. To investigate this, we dropped the Engage variable and performed the cluster analysis using only the other four investment characteristics plus the personal characteristics. For the 40s cohort, the two alternative cluster methods (partition vs hierarchical) indicate two clusters as before, but each method produces a cluster that is both different from each other and different from the previous clusters. For the 50s cohort, the partition method produces two clusters, while the hierarchical method produces three clusters. So while it is impossible to say that that two clusters in Tables 7 and 10 depend only on the additional contributions variable, it would appear that the additional contributions variable has a sufficiently powerful impact that the clusters are nowhere near as strongly defined when this variable is dropped.

Finally, we conducted a cluster analysis of the average risk aversion question scores (av_ATRQ) alone, using both clustering methods. Figure 4 presents a histogram of the distribution of the average scores across the 9,755 individuals in the sample. Recall that each individual has av_ATRQ based on their responses to the 12 ATRQs. Each question is based on a Likert score between 1-5, and so the average Likert score for each individual also has this same range. Higher values indicate greater risk aversion, and the histogram clearly shows a bunching or clustering of scores. The dendrogram for the single-linkage agglomerative hierarchical clustering method suggested 18 clusters in total (with 17 in one hierarchy). The partition method also identifies 18 clusters, although the number of members in each cluster differed from the hierarchical clustering method. To assess whether these differences in cluster membership were significant, we report in Figure 5 the relationship between ATRQ scores and the intention to match across 18 clusters for both the hierarchical method (panel A) and the partition method (panel B). Both panels show very similar patterns of responses, namely the lower the risk aversion, the higher the intention of the member to match the additional employer's contribution. We conclude from this that the two clustering methods produce sufficiently close clusters.

Figure 4 – Distribution of the average risk aversion scores across 9,755 survey respondents

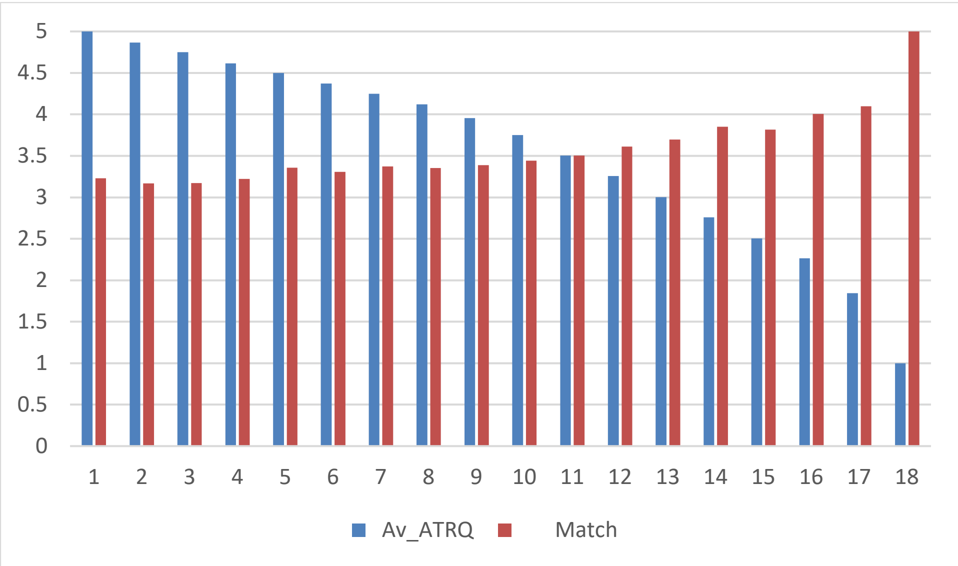


Given this, we estimated a regression model of the attitude to risk scores for each of the two clustering methods with the following potential explanatory variables: age, pay, expected retirement age, tenure, pension wealth, %female, %couple, plus the match and additional contributions factors. Table 12 shows that only %female and %couple are statistically significant for both clustering methods. For both methods, a 1% increase in females in a cluster increases av_ATRQ by 0.05, while a 1% increase in couples in a cluster reduces the av_ATRQ by a little over 0.02. The first result reconfirms one of the key findings of the study, while the second supports the idea that couples have lower risk aversion than singles because of risk sharing within the household. An examination of Table 10 shows how these findings influence the two clusters for the combined 40s and 50s age cohorts. The two clusters have av_ATRQs of 3.41 and 3.30, respectively. This difference is explained almost entirely by the higher percentage of females in the first cluster (46.4%) compared with the second

(39.1%), since the percentage of couples in the two clusters is broadly similar at 73%. Other variables, such as pay, do not have a statistically significant impact on the av_ATRQ. Even the match is not statistically significant, despite Figure 5.

Figure 5 – Relationship between average risk aversion scores and the intention to match across 18 clusters

Panel A - Ward's hierarchical method



Panel B - *k*-means partition method

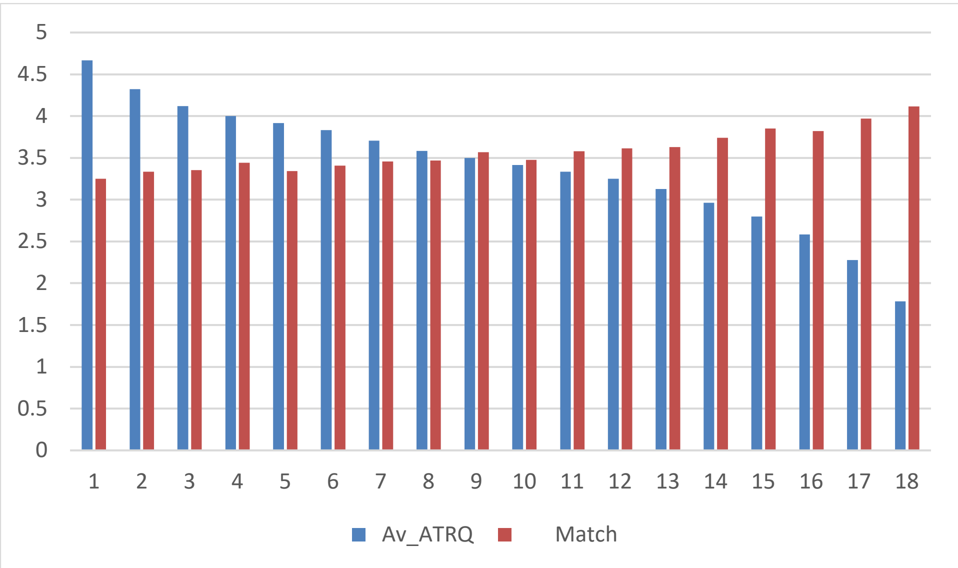


Table 12 – Regression model of the attitude to risk scores on the characteristics for Ward's hierarchical and the *k*-means partition methods

	Ward's hierarchical method				*k*-means partition method			
Variable	Coef.	Std. err.	*t* stat.	*p*-value	Coef.	Std. err.	*t* stat.	*p*-value
%female	0.047440	0.005779	8.2092	6.26e-07	0.047204	0.003622	13.0325	1.39e-09
%couple	-0.020056	0.009755	-2.0561	0.0576	-0.023730	0.010066	-2.3574	0.0324
Cons.	7.437275	0.003735	19.9112	3.37e-12	7.560911	0.505842	14.9472	2.04e-10
R^2	0.972143				0.978730			
Adj. R^2	0.968429				0.975894			
Std. err.	0.202933				0.113704			
No. obs.	18				18			

Note: The table shows, for the 18 clusters formed by each of the Ward's hierarchical method and the *k*-means partition method, the results of a regression of the average risk attitude question score (av_ATRQ) in each cluster on, respectively, the percentage of females (%females) and the percentage that is married or in civil partnership (%couples) in the same cluster. For the definition of the variables, see Table 7.

To summarise our survey findings:

- USS members in their 20s and 60s are either sufficiently few in number or in interest to answer the attitude to risk questions
- There are no clearly identifiable and robust clusters for members in their 30s
- There are two distinct clusters of USS members in their 40s and 50s, and, although they do not fall neatly into clearly identifiable individual personas, they clearly separate into one cluster that has previously engaged with USS (in terms of previous AVCs or added years contributions) and one cluster that has never previously engaged; whether or not a member has previously made additional contributions with USS provides potentially useful information to the trustee about their likely level of future engagement and investment attitudes and beliefs
- Members of the 'additional contributions' cluster typically have higher pay, longer tenure, less interest in ethical investing, lower risk capacity, a higher percentage of males, and a higher percentage of academics than members of the 'disengaged' cluster
- Conditioning only on the attitude to risk responses, there are 18 clusters, with similar but not identical membership, depending on which clustering method is used. The differences in risk aversion across the 18 clusters could be explained largely by differences in the percentage of females and the percentage of couples. Risk aversion increases as the percentage of females in the cluster increases, while it reduces as the percentage of couples increases because of greater risk sharing within the household. Characteristics that other studies have found important determinants of risk attitudes, such as age, income and (pension) wealth, do not turn out to be as significant for USS members. 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
- Intention to match – even if this was not followed through – is a useful indicator of attitude to risk as Figure 5 shows: the greater the intention to match, the lower the risk aversion.

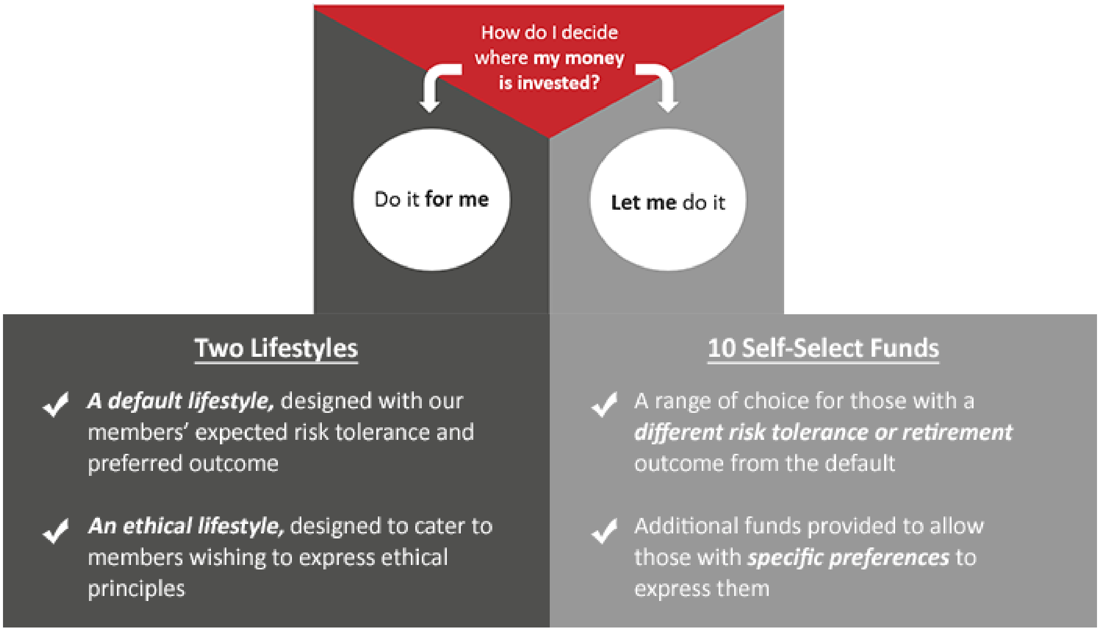
5. Implications for the default investment strategy and for the other funds offered

In this section, we outline the implications of the survey findings for the design of the default investment strategy – especially in the light of the hybrid scheme's DB underpin – and for the other funds offered by USS.

There is evidence that individual attitudes to risk are largely determined by investment experiences in early life and do not change much over time, although they can, to some extent, be modulated by recent investment performance (Malmendier and Nagel (2011)). By contrast, capacity for loss can change quite suddenly and dramatically, for example, if there is a shock to current wealth or if there is a change in marital status.[24] However, the DB underpin in USS gives members a much stronger capacity for taking greater risk with their DC savings than might otherwise be the case. It is also interesting to recall from Figure 2 that risk attitudes do not greatly differ across age bands in the USS survey responses.

USS offers members two principal approaches to selecting their investment strategy through the current choice architecture: 'do it for me' and 'let me do it'.[25] See Figure 6.

Figure 6: The USS approach to member investment choice



In the first case, members let the trustee choose the investment fund(s) and any changes to these over time – two 'do it for me' lifestyle funds are available: the default lifestyle option and the ethical lifestyle option. An alternative approach that places members in alternative defaults based on characteristics other than just age is used by QSuper. As Table 2 shows, QSuper segments its members by age and pot size and automatically switches members when their age or pot size crosses a threshold. However, the cluster analysis for USS did not find strong evidence of distinct groups, and the QSuper approach has been designed reflecting interactions with the means-tested Australian state pension.

Such an approach might also work well for USS members, as long as the risk exposures of the eight (non-ethical and non-Shariah-compliant) funds reflect the genuine risk attitudes of USS members and the additional risk-bearing capacity arising from the DB underpin is incorporated into the investment strategy.

[24] Potentially, couples have greater risk bearing capacity than singles. This is in addition to the risk sharing benefits previously mentioned.
[25] A third approach that USS could consider in future – 'help me do it' – will be examined shortly.

In the second case, members make all the decisions. It is important to assess whether members are making decisions that are appropriate, given their personal circumstances. By appropriate, we mean 'optimal across the life cycle' (i.e., by maximising the member's expected lifetime welfare). This essentially means 'risking-up' sufficiently when young (especially given the size of the DB underpin) and 'de-risking' in the lead up to retirement.

The cluster analysis indicates that the ATRQ scores are broadly similar across the two clusters identified for the combined 40s and 50s age cohorts as well as across the full age range more generally (see Table 10 and Figure 2).[26] This, in turn, suggests that only a small number of funds are required to reflect heterogeneity in USS members' risk attitudes. The current offering of 10 funds might well be more than is needed to reflect risk attitudes alone. It might be acceptable to offer just four additional funds: (1) a well-diversified fund with a higher level of risk than the default fund, (2) a well-diversified fund with a lower level of risk than the default fund, (3) an ethical fund and (4) a Shariah-compliant fund. However, we acknowledge that self-select funds may also be offered to meet the more esoteric requirements of a small minority of members who would like more control over investment regardless of their risk preferences or capacity. The 10 'let me do it' funds currently offered by USS are in line with market norms for trust-based schemes in the UK, with many schemes offering even more choice.

What we have not been able to do yet is monitor USS members' investment behaviour over time. It would be interesting to have answers to the following types of questions: (1) Do the members who selected funds different from the default fund previously engage with USS? (2) Do the members who selected funds different from the default fund actively manage their funds?, and (3) Are members actions aligned with their prior stated intentions? These questions can only be answered as part of a longitudinal study that combines information from the survey responses with the Management Information (MI) database that allows engagement, contributions and investment behaviours to be analysed.[27]

6. Conclusion

In this study, we used a cluster analysis of an attitude to risk survey conducted in September-October 2015 as an input to the overall research programme to segment the USS membership and support the design of the USS Investment Builder fund range introduced as part of the move to a hybrid scheme structure in October 2016. This exercise is intended to complement the initial segmentation that USS used to design the initial investment funds offered to members.

We used factor analysis to reduce the dimensionality of the problem associated with having a large range of questions and answers across different themes, covering

[26] The difference between 3.41 and 3.30 in Table 10 is however statistically significant, although economically small.

[27] However, an early indication is that actions are not always well aligned with intentions. For example, many members did not follow through on the match, despite intending to do so. Nevertheless, as Figure 5 showed, the intention to match appears to be a useful indicator of attitude to risk, despite this not being statistically significant (see Table 12).

members’ previous engagement, attitude to risk, capacity to bear risk, ethical concerns in investment, and investment/pension saving intentions. We then applied hierarchical and partitioning clustering methods to these factors to attempt to identify clusters across participants in the survey. Following this, we examined demographic and personal characteristics of the participants that were identified within each of these clusters.

We were able to identify two distinct clusters in the 40s and 50s age cohorts:

- A cohort 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 USS (in terms of previous AVCs or added years contributions)
- A cohort 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 USS (in terms of previous AVC or added years contributions).

There were only small (and statistically insignificant) differences between the two clusters in terms of the average degree of risk aversion and the propensity to match employer contributions: the first cluster was marginally more risk averse (since it contains a higher percentage of females) and less likely to match than the second cluster. The intensity of the intention to match was a good indicator of risk aversion – the greater the intensity, the lower the risk aversion. Similarly, previous additional contributions was a powerful indicator of which cluster a member would belong.

The similarity in risk aversion scores across all ages and, in particular, for the two clusters in the 40s and 50s age cohorts suggests that a single default fund will be suitable, so long as the default reflects the genuine risk attitudes of the USS membership, which is broadly similar to those of the national population with salaries above £30,000, and takes account of greater risk-bearing capacity due to the DB underpin. In short, there is no evidence of a requirement for multiple defaults within the current scheme structure, which simplifies matters considerably. In addition, the low level of heterogeneity in risk tolerance across the membership suggests that it might be acceptable to offer just four funds in addition to the default fund (rather than the current 10) to satisfy the diversity of risk appetites: (1) a well-diversified fund with a higher level of risk than the default fund, (2) a well-diversified fund with a lower level of risk than the default fund, (3) an ethical fund and (4) a Shariah-compliant fund. However, we acknowledge that self-select funds may be in place to meet the particular requirements of a small minority of members who would like more control over investment regardless of their risk preferences.

The appropriate communication and engagement strategy follows on naturally from our empirical findings. This involves informing all members at joining about the default fund in place for those who are not interested in engaging with their scheme. Self selectors, by contrast, need to be warned about both reckless conservatism and reckless adventurism and subsequently need to be guided or nudged at key ages (e.g., 30, 40, 50 and 60) into adjusting the risk exposure of their pension fund in order to maximise their lifetime welfare. Particular effort should go into designing a suitable engagement programme for those members who have not previously engaged with USS.

For future research USS would like to combine the findings from the risk appetite survey and new surveys with information from the MI database on members' actual decision making and behaviours to assess the appropriateness of these decisions. In future work, USS therefore plans to investigate the following issues:

- To test the foundations of the USS Investment Builder by understanding member behaviour better and to recommend any possible amendments that may be required as the scheme matures and members fund sizes increase. This would include:
    - Observing whether USS members have behaved in ways that confirm or challenge existing behavioural finance studies, e.g., how they have made investment decisions for different types of contributions to USS Investment Builder and how they have combined investment funds to meet their retirement objectives;
    - Observing whether members who have used the 'let me do it' route appear to be in the appropriate self-select funds given their risk attitudes and personal circumstances and whether further nudges and risk warnings are necessary;
    - Observing what role, if any, the time to retirement has on investment decisions, i.e., do members in the 'let me do it' funds make the decision to de-risk in the lead-up to retirement or do they 'set and forget' as has been observed in other studies?

- To consider in future the design of the de-risking glidepath to retirement within the default fund, and whether alternative glidepaths might be required for members who have different objectives for their USS Investment Builder funds in retirement. That would include reviewing the appropriate glidepath into, and through, retirement depending on whether members expect to draw all their funds as cash at retirement and re-invest, stay invested and draw down over a short period of time, draw a steady income, or stay wholly invested and preserve their DC funds for use later in life or for inheritance purposes.

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Appendix: USS Questionnaire

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

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.

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 stockmarket.
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.

(new page)

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.

(new page)

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.

(new page)

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.

(new page – note different response grid)

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 stockmarkets 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 stockmarket 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.

Final landing page after the survey has been completed:

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.