The Implications & Determinants of an Investor's Initial Choice within Retirement Savings Schemes

ABSTRACT

We study the implications and determinants of investors' initial choice upon joining a retirement savings scheme. That is, the first investment option investors allocate their retirement wealth towards. Using a unique dataset of over 14,000 members, we find that, on average, members are receiving sub-optimal performance (in the form of returns) due to inadequate maximisation of risk and return. When we consider the determinants of the initial choice, we observe five distinct subpopulations, which display varying responses to the same stimuli. We document investors displaying a "fight or flight" response to rising market volatility, choosing either higher risk or lower risk option as a result. Furthermore, we see contrarian behaviour, anchoring, and investor behaviour that is not consistent with typical notions of risk aversion. Our results demonstrate that behavioural biases can detrimentally affect the retirement balances of investors upon retirement.

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1. Introduction

This paper is motivated by the growing discussion on the adequacy of Australia's retirement system, known as superannuation (super). There are concerns that many Australians will not be able to fully fund their retirement lifestyle using their super savings alone and will rely on top-ups via the aged pension. While this may not seem a detrimental issue at the individual level, the Australian superannuation system was introduced to reduce the dependency on the aged pension, which in turn could reduce the financial burden it places on the Australian government. According to the Association of Superannuation Funds Australia (2021), a couple looking to live a modest lifestyle in retirement will need over $41,000 in annual income, and a couple looking to live a comfortable lifestyle will need over $63,000 in annual income, both figures assume that retirees own their own home and are not renting. Furthermore, the average superannuation balance per couple is $337,100 (Clare, 2017). Comparing this with the median balances for males and females aged 60 – 64 of $178,808 and $137,051, respectively (Association of Superannuation Funds Australia, 2021), and the concerns raised about the adequacy of the system appear justified[1].

Australian retirement savings plans are designed to ensure people have adequate wealth to financially support their lifestyles during retirement. Under the superannuation system, members accumulate funds in a retirement account, which are invested into assets to help grow their retirement wealth over their working lives. Funds contributed to a member's superannuation account fall within two categories concessional or non-concessional contributions. Superannuation Guarantee (SG) was introduced in July 1992 (Nielson and Harris 2010), under which employers are required to pay a percentage of an employee's wage into their superannuation account.[2] In addition to the SG contributions made by employers, members also have the option to make personal contributions into their superannuation account to increase their retirement balances further (see appendix A). The total funds contributed to a member's superannuation account is a key determinant of the balance of the account upon retirement and, therefore, a key determinant of one's retirement lifestyle. In addition, how the funds are invested, and the returns received over a member's time in super will also play an

[1] Based on the average return of a balanced investment option over the past 30 years of 4.7% (Drury 2022), a couple with the mean balance would have enough wealth to support a modest lifestyle for less than 8 years and a comfortable lifestyle for less than 6 years.
[2] Currently the Superannuation Guarantee rate is 10.5% but it has been legislated to increase by 0.5% every year until 1 July 2025 (Australian Taxation Office 2022).

important role in determining their retirement balance. Upon joining a super fund, members have a range of investment options to choose from, designed to cover a range of risk profiles. The initial choice made could potentially lead to sub-optimal performance if members do not seek to properly maximise their risk and return over their investment horizon.

It is well documented in the literature that the decisions people make regarding their investments within their retirement plans are "sticky", that is, people make few changes to their investment strategy over their lifetimes, they "stick" with their initial choice. People heavily favour the default option, that is the option allocated to members if no choice is made by the member, even if it is not necessarily the best option for them (Benartzi & Thaler 2002). This phenomenon is more pronounced when investors are presented with too many choices or if investors do not properly understand the best-suited choice for their current economic situation. Choi et al. (2002) study the effects of default options within 401(k) pension plans and find that members opt for the path of least resistance, which is typically the default option. Furthermore they find that member decision making can be influenced by altering the path of least resistance. Not only do members gravitate towards the default choice, but they are also reluctant to make changes after they have made their initial choice (Samuelson & Zeckhauser 1988; Mitchell et al. 2006). Furthermore, Thaler & Benartzi (2004) and Madrian & Shea (2001) have shown that the same behavioural biases that lead members to favour the default and become static when it comes to making changes can be used to positively influence retirement savings by increasing enrolment in optional retirement savings schemes.

In this paper, we examine the implications of members' initial choice using a unique dataset from an Australian superannuation fund. 86% of the members we observe made no changes to their strategy after their initial choice[3], as Bebbington et al. (2021) stated. The importance of saving sufficient wealth for retirement is one factor that could contribute to the procrastination and inertia displayed (O'Donoghue and Rabin 2001). They found that the complexity of the decision and the number of options available also increased the propensity to procrastinate. Default bias, procrastination and inertia are behavioural biases that have been observed within

[3] For the purposes of this paper, we refer to the "initial choice" as the first investment option selection members make upon joining the superannuation fund.

retirement savings plans. These behaviours could be especially damaging to the retirement balances of younger members, given the long-term nature of superannuation[4].

We seek to address two points of interest surrounding a member's initial choice. Firstly, what are the implications of a members' initial choice? We know that people within retirement savings schemes favour the default option, procrastinate and display inertia when it comes to making changes to their investment strategy (as stated above); most people we observe make no further changes to their retirement savings strategy. In addressing the implications of the initial choice, we utilise a benchmarked return to compare the actual monthly returns members received with the monthly returns they could have received – had they chosen the highest risk and return strategy available to them. We made comparisons for 2-years, 5-years and 10-years after the initial choice was made and found that, on average, members would have been better off choosing the highest risk and return strategy. We also benchmark member returns with those of the market portfolio by comparing the cumulative returns members received with the cumulative returns of the All Ordinaries Accumulation Index. The results of this comparison are consistent with the highest risk and return benchmark, the returns members received underperform the market portfolio. This effect is compounded by the fact that members are reluctant to make changes to their strategy. In this analysis, we are only comparing the raw returns members could have received; this comparison does not consider other factors, such as income, contributions and account balance.

Secondly, we seek to address the determinants of a member's initial choice. That is, what factors (either internal or external) influence the initial choice members will make? To model the determinants of the initial choice, we utilise a Finite Mixture Model (FMM). FMM assumes that there are latent classes within the dataset, FMM allows us to observe if these classes respond to the same stimuli in different ways. Members are allocated to classes based on unobservable characteristics; once allocated, a model is obtained for each subpopulation. We can then make inferences about each subpopulation by directly comparing how the same group of explanatory variables affects these classes differently. FMM allows us to capture the effect of our explanatory variables across these different latent groups. The explanatory variables used in this analysis include age, gender, expected volatility, market return, 12 month lagged market return, as well as dichotomous variables for the Global Financial Crisis (GFC) and Dotcom bubble, both of which occur during our observation period (July 1994 – May 2019).

[4] A member joining a super fund at the age of 20 could expect to be invested for over 45 years.

Bebbington et al. (2021) used the same explanatory variables when using survival analysis to model the time superannuation members spent in first and second choice strategies.

Utilising FMM, we find that there are five subpopulations within our sample, which shows a typical OLS regression model would not be as well suited. Across the five classes, we find evidence that members respond to the same stimuli differently. Class 1 follows the market trends, opting for riskier strategies when the market return is positive, and preferring less risky strategies when the market return is negative. On average, class 3 chooses the highest level of risk and is also the oldest class; here we see evidence of behaviour in contrast to prior literature regarding age and risk aversion. Class 2 is similar to class 3, only differing on the effect of age, here we see a negative relationship between age and risk. Members in class 2 elect for a less risky initial choice the older they are. Members from class 4 display contrarian behaviour, opting for higher risk when the market return is negative and *vice versa*. Class 5 contrasts with the other four groups. Members in this group are more likely to opt for a riskier strategy when market volatility is high, which is not what would be expected if they were displaying risk-averse behaviour. Overall, we provide evidence that there are five groups that respond to stimuli in different ways.

The remainder of the paper will be organised as follows: Section 2 will describe the dataset and the variables used based on relevant literature; Section 3 will cover the implications of the initial choice; Section 4 will go over the determinants of the initial choice; lastly, Section 5 will conclude the paper.

2. Data and key variables

2.1. Data

The dataset used throughout this paper has been provided by an Australian superannuation fund. It contains detailed information on the retirement savings of over 14,000 members, spanning a period of two years after the beginning of compulsory super contributions, from July 1994 to – May 2019. For each member within the fund, the dataset provides the date they initially joined the fund, the investment option they elected to allocate their retirement funds towards and the dates of any subsequent changes to their investment option. Throughout our observation period, members have up to ten different investment options available to them, designed to allow them to take on a desired level of risk. The options vary by asset allocation and members also have the option to invest a portion of their retirement savings across different investment options. For example, a member could choose to invest 30% into option A, 20% into option B and 50% into option C. If upon joining the superannuation fund, a member did not elect an investment option then they are automatically allocated to the default option. This option is constructed to suit a middle-level risk profile. Members were assigned an identification number which allowed us to track their decisions – specifically pertaining to their investment option choice – through time and maintain anonymity within the dataset. The dataset also contained demographic information for each member, including their age as of May 2019, gender, and postcode at that time. To determine a member's age at the time, they joined the super fund we subtract the time in-between the date joined and May 2019 from their age at May 2019.

In order for a member's decision to be included in our analysis, a decision needs to have been made; either the member chooses to select a specific investment option, or they choose to go with the default option. If no decision has been made, the observation should not be included in the analysis. For example, in February 2018, there was a merger between WA Super and ConceptOne (Patten 2017). As a result of this merger, 11,175 members were transferred from ConceptOne into WA Super (and thus into our dataset). Members that were transferred across joined WA Super on the same day and were allocated to the default investment option. We have removed these members from the dataset as this resulted in all of these members having the exact same values for the following explanatory variables: All Ordinaries return, All Ordinaries 12 month, VIX, GFC and Dotcom. As such, they were removed from the dataset.

In addition to information regarding each member's time in the super fund, the dataset also contained the monthly returns of each available investment option for the entire sample period. As new investment options were made available, the data captured the monthly returns of these options. This allowed us to observe the performance (in the form of monthly returns) each member received for each month over their time in the fund. For members that elected to invest a proportion of their wealth across different investment options, their monthly returns were calculated by taking the sum of each proportion multiplied by each return, as shown below in equation 1.

$$\sum_{n=1}^{N} w_i * r_i \,, 0 \; \leq \; w_i \leq 1 \; \sum_{n=1}^{N} w_i = 1 \qquad (1)$$

The weight invested into each investment option is represented by w_i, with r_i representing the return of investment option i.

2.2. Key variables

We seek to model how factors can influence a member's initial choice upon joining a retirement fund and, therefore, how these factors influence the level of risk members take on. To address this, we need a dependent variable that will proxy the level of risk the strategy option chosen by a given member. The different investment options available are designed to cover a range of different risk levels; to avoid imposing an order onto the data, we follow the findings of (Gray and Zhong 2021). Gray and Zhong (2021) argue that the market risk premium (Rm – Rf) is the only reliable factor in Australia. This is consistent with US evidence that investors only "see" beta (Barber, Odean and Zheng, 2005). Constructing betas for each investment option through time using the tangency portfolio (or market portfolio) which is the ex-ante optimal portfolio allows us to measure the risk of each investment option.

We construct betas for each of the different investment options as a proxy for expected risk. Beta is a measure of the systematic risk of a portfolio compared to the market portfolio. The higher the beta, the higher the level of risk and *vice versa*. Beta at time *t* is obtained by using historical observations as a proxy for future beta; betas are constructed by regressing the monthly returns of the investment options on the corresponding monthly returns of the All Ordinaries Index. Summary statistics for the dependent variable are shown in Table 1.

Bebbington et al. (2021) explored how demographic factors such as age and gender, and external stimuli such as market volatility, market movements and periods of financial turmoil influenced members' time in an investment option. We seek to explore now how these same factors influence the initial choice members make upon joining a superannuation fund, as a result, we have included the same explanatory variables in our analysis.

We use the All Ordinaries return index as a proxy for member attention. Prior research has shown that salient news and events can attract investor attention and thereby influence their decisions (Klibanoff et al., 1998; Barber and Odean, 2005, 2008; Durand, Limkriangkrai and Fung, 2019). The monthly return from the month prior to the month the member joins the fund is used. For example, a member joining the super fund in March will be (potentially) influenced by the All Ordinaries return for February.

The All Ordinaries lagged 12-month return index to assess whether members' may be anchoring their decisions based on historical market states. The anchoring effect refers to the disproportionate influence initially presented values can have on decision making (Tversky and Kahneman 1974). Within the context of our analysis, we will be examining whether members initial choice if being influence by historical market states. For example, if 12 months prior to a member joining the fund the market return is positive, we may expect to see members being influenced by this and electing a higher risk and return investment option with their initial choice.

The Chicago Board Options Exchange Volatility Index (VIX) is used to measure the expected volatility of the S&P500 (Whaley, 2000); we use the VIX as a proxy for investor sentiment. Typically, the higher the price of the VIX, the higher the expected volatility in the market and a lower VIX price would indicate the opposite, that is, lower market volatility. While an Australian equivalent would perhaps be more suitable for our analysis, data for the Australian Volatility Index is only available from February 2008, not covering our entire observation period. Bebbington et al. (2021) stated that the correlation between the AVIX and VIX returns is 0.74, making it a suitable replacement.

Members' demographic information captured in the dataset, such as their age and gender, is included in the analysis to allow for these influences to be observed. Age is associated with a higher level of risk aversion; as we get older, we tend to become increasingly sensitive to risk (Morin and Suarex, 1983; Bonsang and Dohmen, 2015; Betermier et al., 2017). In addition to this, evidence shows a negative association between age and investment skill, even though older investors tend to have greater experience and investment knowledge (Korniotis and Kumar 2011; Besedeš et al. 2012; Gamble et al. 2015). The existing literature around age and financial decision making suggests that as people age, they become more sensitive to risk and are more likely to choose a lower risk investment.

The differences between males and females in relation to their willingness to take on risk have been well researched. Studies have shown that males tended to take on higher levels of investment risk（Barber and Odean, 2001; Charness and Gneezy, 2012; Eckel and Füllbrunn, 2015). However, Barasinska et al. (2009) have shown that the difference between males and females may be less than first thought; by controlling for wealth, they found that women allocate a percentage of their portfolio to risky assets. Gender has been included as a dichotomous variable, taking the value of 1 if the member is male and 0 if the member is female.

Lastly, dichotomous variables are created for two periods of financial turmoil that occurred during our observation period (July 1994 – May 2019), the Dotcom Bubble and the Global Financial Crisis (GFC). The Dotcom bubble resulted from a sustained rise in US technology stocks before the eventual crash in the late `1990s and early 2000s (Blinder, 2013). The Dotcom variable takes the value of 1 if the initial choice occurred within the year 2000 and 0 if otherwise. The GFC period of economic turmoil from mid-2007 to early 2009 was a result of the US housing market crash (Reserve Bank of Australia 2019). The GFC variable takes the value of 1 if the initial choice occurred within 2008 and 0 if otherwise.

(insert Table 1 here)

3. Implications of Members' Initial Choice

As noted, evidence has shown that members within retirement savings schemes tend to make few changes to their investment option, procrastinate and display high levels of inertia (Samuelson & Zeckhauser 1988; O'Donoghue and Rabin 2001; Mitchell et al. 2006). We see evidence of the same behaviour within our dataset, only 14% of members make any changes to their investment option after their initial choice (Bebbington et al., 2021). This stickiness and reluctance to make changes highlights the importance of making an optimal initial choice. For many members, it will be the only choice they make, and the performance of this choice will heavily impact their retirement outcomes. We know from Merton (1980) that there is a positive relationship between risk and expected return, as such, members that fail to utilise this relationship could potentially be missing out on performance.

To address the implications of members' initial choice, we construct a benchmarked return for each member similar to that of Barber and Odean (2001), who create an "own-benchmark" for individual investors. This "own-benchmark" compares the abnormal returns a household would have received had they held their start of year portfolio for the entire year with the abnormal returns they actually received, we construct two similar benchmarked returns. Firstly, by comparing the cumulative monthly returns they received - from the investment option they selected - with the cumulative monthly returns they could have received had they instead chosen the strategy with the highest risk and return relationship. For example, if upon joining the super fund, a member had three choices, option 1, 2 and 3, with 1 being the lowest risk-return option and 3 being the highest risk-return option. If this member selected option 2, we would compare the cumulative returns they received by being invested in option 2 with the cumulative returns they could have received if they had chosen option 3. Secondly, we compare the cumulative monthly returns they received, with the cumulative returns they could have received if they had instead invested in the All Ordinaries Accumulation Index. The market index is used as the market benchmark, which is the ex-ante optimal portfolio. Using this we can compare the performance of members against the market benchmark.

To do this, we calculate a benchmark return for each member by subtracting the cumulative returns they would have received from the either the riskiest option or the Allords index, away from the cumulative returns they actually received, as shown in equation 2:

$$Benchmark = \text{cumulative returns received} - \text{cumulative benchmark returns} \tag{2}$$

Where the benchmark returns refers to either the cumulative returns of the highest risk and return strategy, or, the cumulative returns for the Allords index over the same comparison period (for example either 2-years, 5-years or 10-years respectively). For example, if comparing with the highest risk and return strategy, a negative benchmark return would suggest that a member would have been better off selecting the highest risk and return option. A positive benchmark would suggest that the member was better off with the investment option they chose. If a member selected the highest risk and return option upon joining the super fund, their benchmark return would be 0. The benchmark was calculated 2 years, 5 years and 10 years after the initial choice and for both males and females separately.

(Insert Table 2 here)

The results of the highest risk and return benchmark performance are presented in Table 2. In columns 1 – 3, we present the summary statistics for the benchmark calculation. We see that across 2 years, 5 years and 10 years, members would have achieved higher returns if they had chosen the highest risk and return investment option when joining the superannuation fund. When splitting the sample based on gender, we do not observe any difference, members are missing out on performance due to their initial choice. According to literature, we would expect to see a greater propensity for males to choose higher risk strategies, which is not what we are observing. The Shapiro Wilk (Shapiro and Wilk, 1965) test provides evidence that the samples do not conform to a normal distribution. We implement the Wilcoxon signed-rank test (non-parametric) to test if there is a significant difference between the two groups, that is, members with a positive benchmark and members with a negative benchmark. Across all periods members are, on average, achieving lower returns due to their initial choice and would have had better outcomes had they chosen the highest risk and return strategy. This finding is consistent and significant when controlling for gender. For example, at the 10-year comparison we see 812 members had a positive benchmark and were better off because of their initial choice, while 5,740 members had a negative benchmark and would have seen better performance if they chose the highest risk and return strategy. As stated earlier, for the purposes of this benchmark analysis, we are only examining the returns of the strategies that members are invested in and not necessarily the wealth of the member. In dealing with the issue of inadequate retirement savings, one area that could start to improve outcomes is the initial choice.

(Insert Table 3 here)

In Table 3 we present the results of the market portfolio benchmark, where member returns are compared with those of the Allords Accumulation index, 2-years, 5-years and 10-years after their initial choice. The results of Table 3 are consistent with those of Table 2, on average, members are underperforming the market portfolio. Consistent with the results of Table 2, we see on average, no differences between the outcomes for males and females. If we look at the 10-year comparison, we see 1,398 members had a positive benchmark, and as a result outperformed the market portfolio, while 3,387 members had a negative benchmark and underperformed the market benchmark. The majority of superannuation members will make no further changes and are likely not maximising their return to risk ratio through effective wealth allocation, such is the importance of the initial choice. We do note some considerations, that is, we do not observe members' entire portfolio, and it is possible that members, in addition to their superannuation, are saving for retirement in personal accounts outside of super. Therefore, we are not observing their entire portfolio and as a result, their entire portfolio may be more (or less) conservative than it appears in our dataset. In light of this, we chose not to focus on the optimal investment option for members, but rather, is their initial choice moving them closer to or further away from the balance they required to fund their retirement lifestyle.

This is an important question, emphasised by the savings shortfalls outlined previously, which are an issue not just in Australia but around the world. Based on the results of Tables 2 and 3, members are on average moving themselves further away from an adequate retirement balance because of their initial choice. We provide evidence that the implications of the initial choice are substantial, with males and females on average being more likely to underperform as a result of their initial choice. Given this, we move on to look at the determinants of the initial choice, to examine the factors and stimuli, both internal and external, that may be influencing members' initial choice.

4. **Determinants of The Initial Choice**

The implications of the initial choice (as shown above) can be detrimental to the retirement outcomes of the majority of members we observe. We seek to model the determinants of this initial choice by examining what factors and stimuli are influencing this important decision? In answering this question, we wish to avoid placing constraints on the data and have chosen to model a member's initial choice when joining a superannuation fund using a Finite Mixture Model (FMM). FMM can be used to deal with the issue of unobserved heterogeneity within the population. We do not observe all characteristics that may be influencing the initial choice of members within our dataset, but we know that some of these characteristics may be equivalent. In essence, we are contending the possibility that the overall population of superannuation members is made up of homogenous subpopulations. An advantage of using FMM is that it uses the data to determine these homogenous groups, or classes, rather than requiring us to impose subgroups on the population. The same explanatory variables can then be used across each class, as each class produces a separate regression model. In summary, simultaneously, members are allocated to classes based on unobserved characteristics, and a regression model is run for each subpopulation using the same explanatory variables. We can then make inferences about each subpopulation by directly comparing how the same group of explanatory variables affects these classes differently. The FMM equation can be displayed as follows:

$$f(y_i|x_i,) = \sum_{q=1}^{Q} \pi_q f_q(y_i|x_i, \theta_q), 0 \leq \pi_q \leq 1, \sum_{q=1}^{Q} \pi_q = 1 \tag{3}$$

Such that, Q represents the number of homogenous subpopulations and $\pi_q$represents the proportion members being allocated to class q. The conditional distribution of y on the explanatory x variables, is shown by f_q. Lastly, the parameters of x_i is given by θ_q. Following the assumption of normality, the equation for the log-likelihood can be presented as:

$$LogLL = \prod_{n=1}^{N} log\{\sum_{q=1}^{Q} \pi_q f\left(y_i \middle| x_i, \theta_q\right)\} \tag{4}$$

The next issue is to determine the appropriate number of classes (or groups) for our analysis. To do this, we follow previous work utilising FMM by using information criteria (IC) to determine the appropriate number of classes. IC are used to measure the quality of a statistical model and allow for comparisons between models, as a means to make the optimal selection. There are a number of IC available, we calculate two of the most common, Akaike Information Criterion (AIC) (Akaike, 1987) and Bayesian Information Criterion (BIC) (Schwarz, 1978). Both the AIC and BIC calculations include a penalty term to penalise models with too many components, to avoid over fitted models. AIC will prefer the model that best minimises *-2LL + 2k*, with *k* referring to the number of components within the model. While BIC will select the model that minimises *-2LL + log (n) k*, with *n* representing the sample size. Between AIC and BIC, the BIC score is most often used as AIC research has shown that it is inconsistent and can overestimate the correct number of components (Koehler and Murphree, 1988; Soromenho, 1994). Furthermore, sufficient evidence shows that BIC correctly estimates the number of components, and is consistent across scenarios (Leroux, 1992; Roeder and Wasserman, 1997; Dasgupta and Raftery, 1998; Gannon et al. 2014). Lastly, Nylund, Asparouhov and Muthén (2007) run a Monte Carlo simulation study and determine the appropriate number of classes that can be best calculated using BIC.

To determine the IC for each model, we first run the model as a 1 class model – the output for which would be the same as a typical OLS regression model – and then calculate the AIC and BIC for the specification. We repeat this process for a 2-class model, 3 class model, and so on until we reach a 7-class model. We record the AIC and BIC for each model specification, as can be seen in Table 4, with the results shown in graph form in Figure 1. Table 4 shows us that the BIC for a 1 class model is -23,343.54, while the BIC for a 2-class model is -31,027.64, which tells us that the 2-class model is preferred to the 1 class model. Following this comparison, we see that the 5-class model has the lowest BIC (-39,547.95), making it the optimal model specification for our data.

(Insert Figure 1 and Table 4 here)

To find out the probability of each member belonging to a specific class, we calculate the posterior probabilities. The posterior probabilities consider the results of the model and all of the data for each member, to determine the probability that they belong to each class. The posterior probability is calculated using the rules of Bayes Theorem, as shown below:

$$Prob(class = q|x_i, y_i) = \frac{f(y_i|class = q, x_i)Prob(class = q|x_i)}{\sum_{q=1}^{Q} f\,(y_i|class = q, x_i)Prob(class = q|x_i)} \qquad (5)$$

(Insert Table 5 here)

The use of FMM in this analysis allows us to observe how each subpopulation within the data responds in differing ways to the same stimuli. We have provided evidence that the 5-class model is the preferred model for our data, as shown by the IC calculation. That is, there are 5 subpopulations within our entire dataset. An advantage of FMM is that it allows us to run a separate regression model for each of the 5 classes and coefficients for each of the 5 classes are reported separately, allowing us to make inferences about each group. Table 6 presents the results from the finite mixture model, with columns 1 – 5 showing the regression coefficients for classes 1 – 5 respectively. The coefficients presented can be interpreted in the same way as a typical OLS regression model, with z-scores included below each coefficient. In Table 6 we present a summary of the results, which shows the significance and direction (positive or negative) of the relationship between each explanatory variable and the dependent variable, by class. FMM highlights differing responses to the same group of explanatory variables across the 5 classes. We see contrasting responses in the form of following the trends of the market (class 1), as well as contrarian behaviour (class 4). Age has a differing impact across class, a positive association (class 3) and a negative association (classes 2 and 4). Lastly, we see the same “fight or flight” response documented by Bebbington et al. (2021). The following subsections will provide detailed discussion of the main results of FMM, by focusing on what we perceive as the most salient behaviour.

(Insert TABLE 6 & 7 here)

Members in class 1 can be labelled as the "trend chasers". They are the only class for which the All Ordinaries return variable is statistically significant and has a positive effect on the level of expected risk with the initial choice, with a coefficient of 0.4018. That is, members in this group elect a riskier investment option when joining the super fund, if, the previous month's All Ordinaries return is positive. When the All Ordinaries return in the previous month is negative, members opt for less risky strategies. These findings contrast with the findings of Bebbington et al. (2021), who, upon looking at subsequent investment option changes, find that members are displaying contrarian behaviour. While we observe contrarian behaviour (as discussed later), we see that not all members follow this pattern when it comes to the initial choice. Our results suggest that members in this group are sensitive to changes in the market, with the changes from the previous month impacting the level of risk many members will take on for the remainder of their time in super (based on the 86% of people that make no further changes to their investment strategy after their initial choice).

Class 3 is the old but bold group, having the highest average beta of 0.73 (the next highest average beta by class is class 1 with an average of 0.41) and is the oldest class with an average of 41.73. We are observing members in this class – on average – taking the highest level of risk with their initial choice, even though they are also the oldest class. Class 3 is also the only class where the effect of age is both statistically significant and positive (0.0029). This shows us that the older a member in this class is, the more likely they are to choose a riskier option with their initial choice. This finding is not consistent with prior literature on age and risk aversion. Morin and Suarex (1983); Bonsang and Dohmen, (2015) and Betermier et al (2017) all find that there is a positive relationship between age and risk aversion, as investors age, they become increasingly risk-averse. While across the five classes, we find evidence that the majority of members behave in such a manner (classes 2, 4 and 5), we also find evidence that this is not true for all members. This highlights one of the advantages of using FMM in this analysis, without which, we would be unable to observe this contrasting influence. A small group of members (class 3) display the opposite behaviour, their propensity for a riskier initial choice increases as they become older. There are only 252 members in class 3, suggesting that overall, the decisions of most members are consistent with the literature surrounding age and risk aversion.

Class 2 is similar to class 3, differing on the effect of age, and are, on average, the second oldest group (only behind class 3). The influence of age is the opposite of what was seen with class 3, here, we see a negative relationship between the level of risk chosen and the member's age when making their initial choice. The effect of age is statistically significant and negative (-0.0043), which shows that the greater the age of a member in this class, the more likely they are choose a lower risk strategy with their initial choice. Unlike the evidence presented for class 3, here we see evidence consistent with previous literature on age and risk aversion. Due to the larger size of class 2 (2,060 members compared to 252 for class 3), it suggests that of those influenced by age, the majority behave in a way consistent with prior literature, and those who do not are in the minority. In addition to the contrasting effect of age, we see that the All Ordinaries 12-month return variable is positive and statistically significant with a coefficient of 0.7538. This suggests that members in class 2 are anchoring on historical market changes, with a positive 12-month return making it more likely that members in this class will select a higher risk to return strategy for their initial choice. Members in class 2 display contrarian behaviour in the short term, as shown by the negative All Ordinaries return coefficient (-1.0378), but they follow the trends of the historical state of the market.

With class 4, as with class 1, we find evidence that members are sensitive to changes in the All Ordinaries return index. We see members in class 4 displaying contrarian behaviour; contrarian investing involves going against the market trends, buying when the majority is selling and selling when the majority is buying. Class 4 has a coefficient of -0.0309 for the All Ordinaries Return variable, showing a negative relationship between the returns of the market and the level of risk undertaken with the initial choice. Members in class 4 are more likely to select a riskier investment option for their initial choice when the All Ordinaries return from the previous month is negative. They are more likely to choose less risk when the market return is positive. This is in direct contrast to class 1 (the trend chasers), who followed the market trends, choosing riskier options when the index return was positive and *vice versa*. When looking at the Finnish market, Grinblatt and Keloharju (2000) found that domestic investors tended to be contrarians, which was in contrast to the more sophisticated investors, who were primarily foreign investors and momentum traders. Bebbington et al. (2021) found evidence that investors within retirement savings schemes display contrarian behaviour, our findings are consistent with this and show that the contrarian behaviour extends to their initial choice.

Upon studying members' subsequent changes to their investment options, Bebbington et al. (2021) found that members displayed a response analogous to the "fight or flight" response. That is, when members were faced with the same stimuli (increased market volatility), two responses emerged, the "flight" group, who chose to reduce their risk, and the "fight" group, who chose to increase their risk. We find evidence that the same phenomenon can be seen with members' initial choice in response to changes in market volatility, as measured by the VIX. The same stimuli can elicit two opposing responses, causing members to "fight" by choosing a higher risk to return strategy or to "flight" by choosing a lower risk to return strategy. We see the flight response with classes 1 -4 (57% of members in the sample), but with class 5 (43% of members), we see the fight response. Members in class 5 opt for a higher risk-return investment strategy when volatility in the market is higher. Consistent with Bebbington et al. (2021), we see behaviour that would not be expected if traditional notions of risk aversion were coming into effect. We would expect to see members displaying a greater propensity for less risky when market volatility is high.

5. Conclusion

This paper examines how behavioural biases impact members when making their initial investment choice upon joining a superannuation fund. The unique dataset used contained information on the initial investment option chosen by over 14,000 members from a major fund in Australia from 1994 to 2019, two years after the start of compulsory superannuation.

Given that 86% of the members within our dataset made no further changes to their investment option after their initial choice and the literature concerning procrastination and inertia within retirement saving schemes (of which this behaviour is consistent with), we first examined the implications of the initial choice. We compared the returns of the investment option members selected with the returns of the highest risk and return option and the returns of the market portfolio. We found that, on average, members would have received higher returns if they had opted for the highest risk and return strategy upon joining the super fund, or if they were invested in the market portfolio. Given the long-term nature of superannuation and that many members appear to be missing out on potential returns, the lower performance (in the form of investment returns) would be associated with lower account balances upon retirement, *ceteris paribus*.

After looking at the implications of the initial choice, we then examined the determinants of this first decision using a Finite Mixture Model. We provide evidence of 5 homogenous subpopulations within the dataset, each responding to stimuli in varying ways. We document a "fight or flight" response to market volatility, by which members faced with increased market volatility elect either a lower risk strategy (flight) or a higher risk strategy (fight). We also find members within our sample exhibiting contrarian behaviour, consistent with (Grinblatt and Keloharju, 2000). These same behaviours were also observed by Bebbington et al. (2021) when looking at the subsequent changes members make to their investment option, highlighting the similarities between the initial choice and any subsequent choices made. We see members in class 3 having a positive relationship between age and expected risk, behaviour which is not consistent with existing literature concerning age and risk aversion (Morin and Suarex, 1983; Bonsang and Dohmen, 2015 and Betermier et al. 2017). Lastly, we document members influenced by historical market states (anchoring).

The findings presented in this paper have implications for members and professionals involved with retirement savings schemes. We see that behavioural biases can affect investment decisions within a retirement savings setting, with members displaying sub-optimal decision making. Given that retirement savings balances are a concern within Australia and other countries, the results of this paper could be widely useful and of interest. Members within retirement savings plans and professionals in the industry need to be aware of how behavioural biases can affect retirement outcomes. Strategies could be put in place to attempt to alleviate the detrimental impact.

6. References

Akaike, H., 1987. Information measures and model selection. Int. Stat. Inst. 44, 277−291.

Association of Superannuation Funds Australia. 2021. "Retirement Standard". https://www.superannuation.asn.au/resources/retirement-standard.

Australian Taxation Office. 2022. "Key Superannuation Rates And Thresholds". *Ato.Gov.Au*. https://www.ato.gov.au/rates/key-superannuation-rates-and-thresholds/?page=22.

Barasinska, Nataliya, Oleg Badunenko, and Dorothea Schäfer. 2009. "Risk Attitudes And Investment Decisions Across European Countries - Are Women More Conservative Investors Than Men?". SSRN Electronic Journal. doi:10.2139/ssrn.1342731.

Barber, B. M., and T. Odean. 2001. "Boys Will Be Boys: Gender, Overconfidence, And Common Stock Investment". The Quarterly Journal Of Economics 116 (1): 261-292. doi:10.1162/003355301556400. Barber, B., & Odean, T. (2008). All that Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors. The Review Of Financial Studies. doi: 10.2139/ssrn.460660

Barber, Brad M., Terrance Odean, and Lu Zheng. 2005. "Out Of Sight, Out Of Mind: The Effects Of Expenses On Mutual Fund Flows". The Journal of Business 78 (6): 2095-2120.

Bebbington, Durand R.B, Khuu. 2021. "Investor Decision Making within Retirement Savings Schemes". Working Paper.

Benartzi, S., & Thaler, R. (2002). How Much Is Investor Autonomy Worth? The Journal Of Finance, 57(4), 1593-1616. doi: 10.1111/1540-6261.00472

Besedeš, Tibor, Cary Deck, Sudipta Sarangi, and Mikhael Shor. 2012. "Age Effects And Heuristics In Decision Making". Review Of Economics And Statistics 94 (2): 580-595. doi:10.1162/rest_a_00174.

Betermier, Sebastien, Laurent E. Calvet, and Paolo Sodini. 2017. "Who Are The Value And Growth Investors?". The Journal Of Finance 72 (1): 5-46.

Blinder, A.S., 2013. After the Music Stopped, Penguin, New York.

Bonsang, Eric, and Thomas Dohmen. 2015. "Risk Attitude and Cognitive Aging". Journal of Economic Behavior & Organization 112: 112-126. doi:10.1016/j.jebo.2015.01.004

Byrnes, James P., David C. Miller, and William D. Schafer. 1999. "Gender Differences In Risk Taking: A Meta-Analysis.". Psychological Bulletin 125 (3): 367-383. doi:10.1037/0033-2909.125.3.367.

Charness, Gary, and Uri Gneezy. 2012. "Strong Evidence For Gender Differences In Risk Taking". Journal Of Economic Behavior & Organization 83 (1): 50-58. doi:10.1016/j.jebo.2011.06.007.

Choi, James J., David Laibson, Brigitte C. Madrian, and Andrew Metrick. 2002. "Defined Contribution Pensions: Plan Rules, Participant Choices, And The Path Of Least Resistance". *Tax Policy And The Economy* 16: 67-113. doi:10.1086/654750.

Dasgupta, A., Raftery, A.E., 1998. Detecting features in spatial point processes with clutter via model-based clustering. J. Am. Stat. Assoc. 93, 294–302.

Drury, Barbara. 2022. "Super Fund Performance Over 30 Financial Years (To June 2022)". *Super Guide*. https://www.superguide.com.au/comparing-super-funds/super-funds-returns-financial-year.

Durand, R.B., Limkriangkrai, M., Fung, L., 2019. Exogenous and Endogenous Attention and the Convergence of Analysts Forecasts, Journal of Behavioral Finance 20, 154-172.

Eckel, Catherine C., and Sascha C. Füllbrunn. 2015. "Thar SHE Blows? Gender, Competition, And Bubbles In Experimental Asset Markets". American Economic Review 105 (2): 906-920. doi:10.1257/aer.20130683.

Gannon, B., Harris, D., Harris, M., 2014. Threshold effects in nonlinear models with an application to the social capital-retirement-health relationship. Health Econ. 23, 1072–1083.

Gray, Philip, and Angel Zhong. 2021. "Assessing the Usefulness Of Daily And Monthly Asset-Pricing Factors For Australian Equities". *Accounting & Finance* 62 (1): 181-211. doi:10.1111/acfi.12786.

Grinblatt, M., Keloharju, M., 2000. The Investment behaviour and Performance of Various Investor Types: A Study of Finland' s Unique Data Set, Journal of Financial Economics 55, 43-67.

Klibanoff, Peter, Owen Lamont, and Thierry A. Wizman. 1998. "Investor Reaction To Salient News In Closed-End Country Funds". The Journal Of Finance 53 (2): 673-699.

Koehler, A.B., Murphree, E.S., 1988. A comparison of the Akaike and Schwarz criteria for selecting model order. Appl. Stat. 37, 187–195.

Korniotis, George M, and Alok Kumar. 2011. "Do Older Investors Make Better Investment Decisions?". Review Of Economics And Statistics 93 (1): 244-265.

Leroux, B.G., 1992. Consistent estimation of a mixing distribution. Ann. Stat. 20, 1350–1360.

Madrian, B. C., and D. F. Shea. 2001. "The Power Of Suggestion: Inertia In 401(K) Participation And Savings Behavior". The Quarterly Journal Of Economics 116 (4): 1149-1187. doi:10.1162/003355301753265543.

Merton, R.C., 1980. On Estimating the Expected Return on the Market. An Exploratory Investigation, Journal of Financial Economics 8, 323-361.

Mitchell, Olivia S., Gary R. Mottola, Stephen P. Utkus, and Takeshi Yamaguchi. 2006. "The Inattentive Participant: Portfolio Trading Behavior In 401(K) Plans". SSRN Electronic Journal.

Morin, Roger-a, and A. Fernandez Suarez. 1983. "Risk Aversion Revisited". Journal Of Finance 38 (4): 1201-1216.

Nylund, Karen L., Tihomir Asparouhov, and Bengt O. Muthén. 2007. "Deciding On the Number of Classes In Latent Class Analysis And Growth Mixture Modeling: A Monte Carlo Simulation Study". *Structural Equation Modeling: A Multidisciplinary Journal* 14 (4): 535-569.

O'Donoghue, T., and M. Rabin. 2001. "Choice And Procrastination". The Quarterly Journal Of Economics 116 (1): 121-160. doi:10.1162/003355301556365.

Patten, Sally. 2017. "Super Funds Accept APRA's Merger Reality". *Australian Financial Review*. https://www.afr.com/wealth/superannuation/super-funds-accept-apras-merger-reality-20170927-gyph0z.

Reserve Bank of Australia. 2019. "The Global Financial Crisis". *Rba.Gov.Au*. https://www.rba.gov.au/education/resources/explainers/pdf/the-global-financial-crisis.pdf.

Roeder, K., Wasserman, L., 1997. Practical bayesian density estimation using mixtures of normals. J. Am. Stat. Assoc. 92, 894−902.

Samuelson, W., & Zeckhauser, R. (1988). Status quo bias in decision making. Journal Of Risk and Uncertainty, 1(1), 7-59. doi: 10.1007/bf00055564

Schwarz, G., 1978. Estimating the dimensions of a model. Ann. Stat. 6 (2), 461−464.

Shapiro, S. and Wilk, M., 1965. An Analysis of Variance Test for Normality (Complete Samples). *Biometrika*, 52(3/4), p.591.

Soromenho, G., 1994. Comparing approaches for testing the number of components in a Finite Mixture Model. Comput. Stat. 9, 65−78.

Thaler, R., & Benartzi, S. (2004). Save More Tomorrow™: Using Behavioral Economics to Increase Employee Saving. Journal Of Political Economy, 112(S1), S164-S187. doi: 10.1086/380085

Tversky, Amos, and Daniel Kahneman. 1974. "Judgment Under Uncertainty: Heuristics and Biases". *Science* 185 (4157): 1124-1131. doi:10.1126/science.185.4157.1124.

Whaley, Robert E. 2000. "The Investor Fear Gauge". The Journal Of Portfolio Management 26 (3): 12-17

Wilcoxon, F., 1945. Individual Comparisons by Ranking Methods. *Biometrics Bulletin*, 1(6), p.80.

Table 1 – Summary Statistics of Variables

Table 1 shows summary statistics for the explanatory variables, results are presented in decimal form.

	Mean	S.D.	Median	Min	Max
Beta	0.3194	0.1141	0.3008	-0.0209	1.0236
Age	33.3560	13.8495	32	11	75
VIX	18.8218	8.4393	16.3	9.51	59.89
Allords return	0.0004	0.0399	-0.0072	-0.0710	0.1629
Allords TM	0.0041	0.0603	0.0028	-0.1774	0.2134

Table 2 Initial Choice Benchmark Summary Statistics

Table 2 presents the summary statistics for the investors' performance – benchmarked against the highest risk and return strategy that was available to them at the time of joining the super fund. Results are presented in decimal form.

	Summary Statistics			**Shapiro Wilk test**		**Wilcoxon signed-rank test**		
	Mean	Median	S.D.	Observations	z-score	Positive	Negative	z-score
2 year	-0.1167	-0.1262	0.1752	14,624	13.554	4,699	9,925	-66.94
Male	-0.1222	-0.1393	0.1693	7,030	11.057	2,018	5,012	-50.11
Female	-0.1117	-0.1087	0.1803	7,594	12.523	2,681	4,913	-44.47
5 year	-0.0733	-0.0474	0.1550	11,523	13.852	4,699	6,824	-43.35
Male	-0.0836	-0.0846	0.1512	5,592	11.547	2,018	3,574	-35.82
Female	-0.0360	-0.0278	0.1579	5,931	12.689	2,681	3,250	-25.24
10 year	-0.1326	-0.1640	0.1030	6,552	12.574	812	5,740	-64.332
Male	-0.1390	-0.1794	0.0970	3,398	11.130	316	3,082	-47.73
Female	-0.1257	-0.1404	0.1088	3,154	10.607	496	2,658	-42.99

Table 3 Initial Choice Benchmark Summary Statistics

Table 3 presents the summary statistics for the investors' performance – benchmarked against the All Ordinanies Accumulation Index. Results are presented in decimal form.

	Summary Statistics				Shapiro Wilk		Wilcoxon signed-rank test		
	Mean	Std.Dev.	Min	Max	Obersvations	z-score	Positive	Negative	z-score
2 year	-0.035	0.107	-0.508	0.484	12789	9.970	4,525	8,264	-34.56
Male	-0.037	0.106	-0.440	0.409	5784	7.993	1,988	3,796	-24.66
Female	-0.033	0.108	-0.508	0.484	7005	8.450	2,537	4,468	-24.30
5 year	-0.092	0.118	-0.662	0.396	9670	12.33	2,233	7,437	-62.68
Male	-0.094	0.1179	-0.519	0.396	4270	10.10	1,289	4,111	-46.23
Female	-0.090	0.1174	-0.662	0.332	5400	10.91	944	3,326	-42.32
10 year	-0.091	0.128	-0.702	0.115	4785	13.29	1,398	3,387	-36.86
Male	-0.097	0.127	-0.635	0.115	2104	10.97	576	1,528	-25.90
Female	-0.087	0.128	-0.702	0.115	2681	11.82	822	1,859	-26.26

Figure 1 – AIC & BIC

Figure 1 displays the AIC and BIC values for up to 7 possible classes. The lowest BIC value is preferred and highlighted.

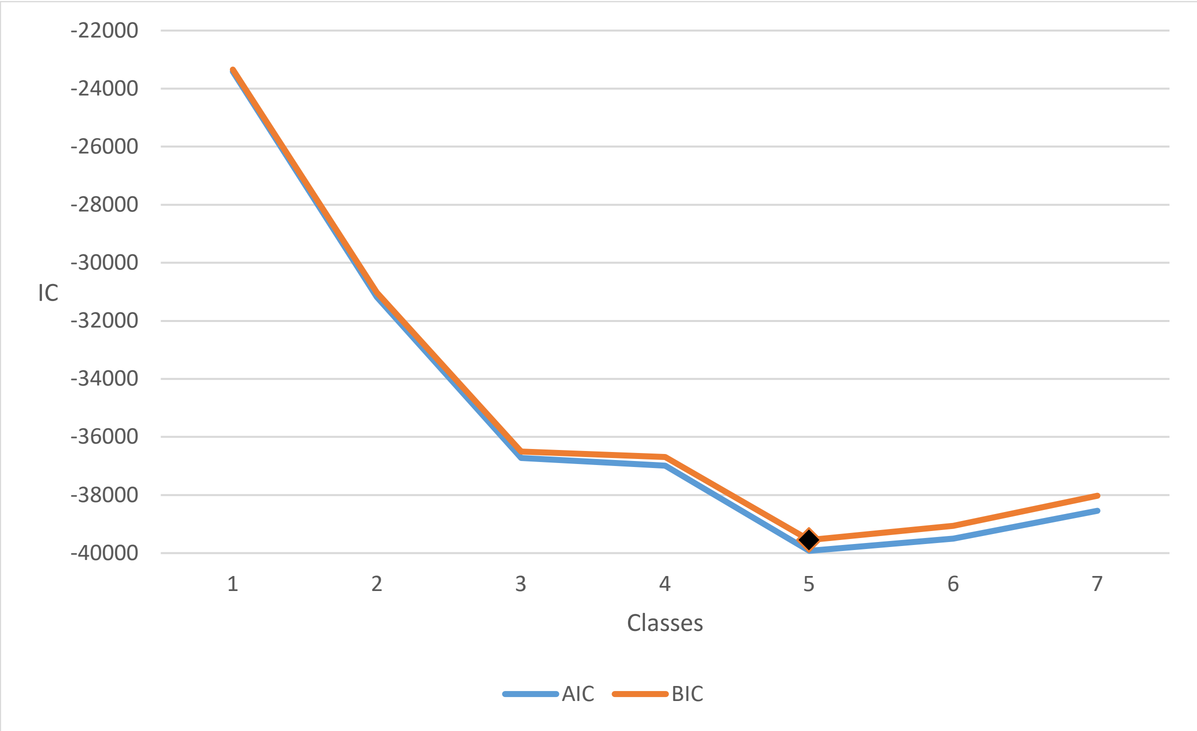

Table 4 – AIC & BIC

Table 4 reports the AIC and BIC values for model specifications 1 – 7. The Class with the lowest values are preferred and are displayed in bold.

Classes	AIC	BIC
1	-23412.03	-23343.54
2	-31172.22	-31027.64
3	-36721.45	-36500.77
4	-36990.35	-36693.57
5	**-39920.82**	**-39547.95**
6	-39496.51	-39055.15
7	-38540.26	-38022.80

Table 5 – Descriptive Statistics of 5 Class Model

Table 5 displays the summary statistics of the preferred 5-class model. Results are presented in decimal form.

	Class 1		**Class 2**		**Class 3**		**Class 4**		**Class 5**	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Beta	0.4101	0.0591	0.2755	0.1938	0.7342	0.2053	0.2552	0.0391	0.3142	0.0350
Age	31.99	11.73	39.03	15.50	41.73	12.59	33.49	14.29	31.71	13.30
VIX	17.31	7.56	18.71	7.46	16.56	7.84	19.71	10.78	19.09	7.52
Allords return	-0.0116	0.0403	0.0020	0.0396	-0.0069	0.0322	0.0084	0.0472	0.0009	0.0343
Allords TM	0.0002	0.0476	0.0101	0.0550	0.0063	0.0497	0.0147	0.0708	-0.0021	0.0598

Table 6 – Finite Mixture 5 Class Model

Table 6 presents the results of the preferred 5-class finite mixture model. Coefficients and z-statistics (in brackets) are displayed. ***, ** and * denote significance at the 1%, 5% and 10% level respectively.

	Class 1	**Class 2**	**Class 3**	**Class 4**	**Class 5**
Age	0.0000	-0.0043***	0.0029**	-0.0001***	-0.00004*
	(0.5400)	*(-11.34)*	*(2.03)*	*(-5.55)*	*(-1.76)*
Gender	-0.0003	-0.0146**	-0.0155	0.0008*	-0.0001
	(-0.7100)	*(-2.08)*	*(-0.55)*	*(1.75)*	*(-0.26)*
VIX	-0.0054***	-0.0055***	-0.0094***	-0.0002***	0.0029***
	(-146.00)	*(-8.40)*	*(-3.73)*	*(-4.90)*	*(63.95)*
Allords return	0.4018***	-1.0378***	-0.7765	-0.0309***	-0.0713***
	(33.96)	*(-6.14)*	*(-1.09)*	*(-2.80)*	*(-5.24)*
Allords TM	0.0074	0.7538***	0.5593	-0.0089	-0.0499***
	(0.9100)	*(6.80)*	*(1.50)*	*(-1.34)*	*(-7.69)*
GFC	-0.0325***	0.1293***	0.2330**	0.1304***	0.0654***
	(-28.40)	*(8.03)*	*(2.17)*	*(103.89)*	*(52.89)*
Dotcom	-0.2831***	-0.1050**	-0.2332	-0.1278***	-0.1038***
	(-162.46)	*(-2.08)*	*(-1.09)*	*(-52.21)*	*(-62.63)*
Constant	0.5149***	0.5407***	0.5594***	0.2511***	0.2559***
	(498.93)	*(31.02)*	*(6.45)*	*(253.76)*	*(227.14)*
N	2664	2060	252	3470	6461

Table 7 – Summary of results

Table 7 shows a summary of the results in Table X + and - indicate that the results was significant at either the 1% or 5% level and give the sign of the coefficient.

	Class 1	Class 2	Class 3	Class 4	Class 5
Age		-	+	-	
Gender		-			
VIX	-	-	-	-	+
Allords	+	-		-	-
Allords TMH		+			-
GFC	-	+	+	+	+
Dotcom	-	-		-	-
N	2664	2060	252	3470	6461

Appendix A. Contributions Flow Chart

Appendix A presents a flow chart of how concessional and non-concessional contributions are typically made into a member's superannuation account. The solid line represents mandatory payments (employee salary and concessional contributions made by the employer) and the dotted line represents optional payments (non-concessional contributions made by the member using their after tax income).