School of Accounting, Economics & Finance

Their Own Worst Enemies: Behavioural Finance and the Investments of Australian Households

Christopher Anthony Bebbington

0000-0002-8424-0882

This thesis is presented for the Degree of
Doctor of Philosophy
of
Curtin University

June 2024

Declaration

To the best of my knowledge and belief this thesis contains no material previously published by any other person except where due acknowledgement has been made.

Preliminary analysis of elements of chapter 3 were included in my 2019 honours dissertation. None of those results appear in this thesis.

Signed:

Date: 27th of June 2024

The research and analyses presented in chapter 3 was produced for this thesis but has since been published in the Pacific-Basin Finance Journal. The following page provides an attribution statement which outlines the involvement of each co-author.

Abstract

This dissertation aims to explore how behavioural biases effect the decision making of Australian households within retirement savings schemes. Using two unique datasets from two of Australia's largest superannuation funds, I am able to explore the investment decision making of Australian households at three time periods over their time in superannuation: when they first join the fund; throughout their time in the fund; and when they decide to commence their retirement. The three empirical chapters are as follows:

Chapter 1 studies 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, I find that, on average, members are receiving sub-optimal performance (in the form of returns) due to inadequate maximisation of risk and return. When considering the determinants of the initial choice, I observe five distinct subpopulations, which display varying responses to the same stimuli. Investors display contrasting responses to rising market volatility, choosing either higher risk or lower risk option as a result. Furthermore, I see contrarian behaviour, anchoring, and investor behaviour that is not consistent with typical notions of risk aversion. The results demonstrate that behavioural biases can detrimentally affect the retirement balances of investors upon retirement.

Chapter 2 studies the investment allocation decisions of over 32,000 investors throughout their time in superannuation. Investors exhibit a "reduce risk or increase risk response" when faced with signals of increased market volatility. Investors behave as if they perceive patterns in prices. Different age cohorts display different decision-making "cultures", but all age groups display a bias towards choosing less risky allocations rather than riskier strategies. The findings suggest that behavioural biases can contribute to lower superannuation balances being available to people when they retire.

Chapter 3 explores how investors allocate their superannuation savings before and after commencing retirement. Using 4 measures of expected portfolio risk, I find

evidence of investors displaying increased risk aversion with age, males displaying higher levels of risk tolerance and the behavioural bias known as gambling with the house money, where prior period gains lead to investors opting for higher risk portfolios.

Acknowledgements

Firstly, I would like to express my sincere thanks and gratitude to my supervisors, Professor Robert Durand, Dr Joye Khoo and Dr Joyce Khuu for the continual support and guidance I have received over the past few years. We have shared many meetings, many coffees and I have been fortunate enough to receive many lessons along the way. I am especially appreciative of how they were always able to guide me in the right direction and I left each meeting with a renewed sense of motivation and purpose. I must also say that I feel especially grateful to have supervisors with whom I shared such a good relationship and greatly enjoyed working with. I cannot overstate how much they have each helped me with the many challenges that come with completing a PhD, and for that I am extremely grateful.

I also extend my sincere appreciation to Victoria Smart, who enabled me to access the unique dataset used in this research, without which the completion of this dissertation would not have been possible.

I would like to express a special thanks to my family and friends, all of which have played a significant role in helping my complete this thesis, especially the following people. Firstly, my fiancée (and soon to be wife), Chantelle, who has been with me every step of the way throughout this journey. I am extremely appreciative to have someone in my life who is so unwavering in their support for me. I am truly indebted for the self-belief and confidence she has given me and for the numerous proof reads she has completed. Being able to always share the minutest triumphs of my day is something I will always be appreciative of.

Secondly, my Mum and Dad, who have always supported me on whichever pathway I chose to pursue, even when I was still finding my way. I am extremely grateful for parents who allowed me to find my own path and I would not have attempted, or completed this thesis without the ongoing encouragement and support they continually provided.

Thirdly, I also thank my good friend Antoine. Sharing this journey in parallel with his has made the experience far more enjoyable. I consider myself fortunate to have always had a friend to accompany me to research events, engage in discussions about the challenges of teaching and supporting premier league football teams, and to share numerous coffee breaks with.

Lastly, this research was supported by an Australian Government Research Training Program (RTP) Scholarship, for which I am grateful to have received. I am also appreciative to Curtin University and the School of Accounting, Economics & Finance for the opportunity to gain valuable teaching experience throughout my studies.

Table of contents

Declaration i

Abstract ii

Acknowledgements iv

List of tables i

List of figures i

Chapter 1 Introduction 1

1.1. Motivation & background 1

1.2 Findings 4

Chapter 2 The Implications & Determinants of an Investor's Initial Choice 6

2.1 Introduction 6

2.2 Data, background and key variables 9

2.2.1 Data 9

2.2.2. Background & key variables 10

2.3. Implications of members' initial choice 14

2.4. Determinants of the initial choice 19

2.5. Conclusion 28

Chapter 3 Investor Decision Making Within Retirement Savings Schemes 30

3.1. Introduction 30

3.2. Data 33

3.3. Methodology 36

3.4. Results 42

3.4.1 Gender 47

3.4.2 Age 47

3.4.4 The VIX 48

3.4.5 Changes in the All-Ordinaries Index (the market). 49

3.4.6 Significant Events: The Dotcom Crash and the Global Financial Crisis. 51

3.5 Time to Retirement 54

3.6 Prior Period Loss 55

3.7 Investor Performance Against Their Own Benchmark 58

3.8 Conclusion 61

Chapter 4 The Retirement Decisions 63

4.1 Introduction 63

4.2 Data and key variables 66

4.2.1 Data 66

4.2.2 Key variables 67

4.3 Drawdown benchmarks 75

4.4. Methodology 79

4.5. Results 80

4.5.1 Gender 85

4.5.2 Age 85
4.5.3 Financial advice 86
4.5.4 Retirement balance 87
4.5.5 House prices 88
4.5.6 Change Analysis 89
4.6. Conclusion 90
Chapter 5 Conclusion 92
Appendices 94
Appendix A. Contributions flow chart 94
Appendix B. Breakdown of investment options 95
Appendix C. Break of investment options selected 96
Appendix D. Minimum pension drawdown rates 97
Appendix E. Preservation age 97
Appendix F. Investment option breakdown – Retirement dataset 98
References 99

List of tables

Table 2. 1. Summary statistics of variables... 13
Table 2. 2 Initial choice benchmark – Highest risk and return strategy 16
Table 2. 3 Initial choice benchmark – All Ords Accumulation Index 17
Table 2. 4 Akaike's Information Criterion & Bayesian Information Criterion 22
Table 2. 5 Summary statistics of 5 class model 23
Table 2. 6 Finite Mixture 5 class model... 25
Table 2. 7 Summary of results 25

Table 3. 1 Data Selection 35
Table 3. 2 Summary statistics of explanatory variables... 35
Table 3. 3 Correlation of explanatory variables... 35
Table 3. 4 Pepe-Mori tests 40
Table 3. 5 Survival times (months).. 41
Table 3. 6 AIC & BIC for Competing Models... 44
Table 3. 7 Model of members' decisions... 46
Table 3. 8 Model of members' decision with time to retirement controls................. 52
Table 3. 9 Model of members' decision with prior 6-month loss control.................. 53
Table 3. 10 Own benchmark summary statistics, Shapiro Wilk & Wilcoxon test 57

Table 4.1 Overall summary statistics 72
Table 4. 2 Summary statistics by retirement period... 73
Table 4. 3 Correlation matrix 74
Table 4. 4 Covariance matrix 74
Table 4. 5 Akaike Information Criterion & Bayesian Information Criterion Values
.... **Error! Bookmark not defined.**
Table 4.6. Bimodal equity allocations …………………………………………...82
Table 4. 7. Regression model.. 833
Table 4.8 Change in expected risk pre to post retirement.. 89

List of figures

Figure 2. 1 Akaike's Information Criterion & Bayesian Information Criterion........ 22

Figure 3.1 Investment options timeline.. 34
Figure 3. 2 Investors' choices 39
Figure 3. 3 Members' First Decision to Change... 41
Figure 3. 4 Members' Second Choice (after an initial choice for less risk)............... 43
Figure 3. 5 Members' Second Choice (after an initial choice for more risk) 44
Figure 3.6 Distribution of own benchmark returns for less risky choices 60
Figure 3.7 Distribution of own benchmark returns for riskier choices...................... 60

Figure 4.1 Cash rate vs proportion of cash 72
Figure 4.2 Modest drawdown female projections... 76
Figure 4.3 Comfortable drawdown female projections 76
Figure 4. 4 Modest drawdown male projections.. 78
Figure 4. 5 Comfortable drawdown male projections... 78
Figure 4. 6 Akaike's Information Criterion & Bayesian Information Criterion pre and post retirement – Beta & Stdev .... **Error! Bookmark not defined.**
Figure 4. 7 Akaike's Information Criterion & Bayesian Information Criterion pre and post retirement – Proportion of international shares & proportion of cash ....**Error! Bookmark not defined.**
Figure 4. 8 Pre-retirement asset allocation... 81
Figure 4. 9 Retirement asset allocation.. 81
Figure 4. 10 Post retirement asset allocation 82

Chapter 1 Introduction

1.1. Motivation & background

Retirement savings are designed to allow people to finance their lifestyles once they have ceased employment and are therefore no longer receiving regular income. There are numerous retirement savings systems around the world but the goal is the same, to ensure people have enough money to fund their lifestyles, ideally without the need for government assistance. This dissertation aims to examine how behavioural biases and external stimuli influence the decision making of superannuation members within their retirement savings accounts.

In Australia, the retirement system is known as superannuation. The purpose of the mandatory Superannuation (super) scheme that was introduced in Australia was to ensure that Australians would have an adequate source of retirement income. In addition, the scheme aims to reduce the financial burden of public pensions facing the Australian government. This is of particular importance given issues arising from rising public expenditure, occurring from an increasingly aging population (Parliamentary Budget Office, 2019). Furthermore, there is a growing concern that many Australians will not have enough superannuation to fully fund their retirement, particularly given recent increases in the cost of living. It has been predicted that men will outlive their retirement savings by 10 years and women by 12 years (World Economic Forum, 2019, p. 21). Given the current retirement age of 67 and the average life expectancy of 81.3 years and 85.4 years for males and females respectively (Australian Bureau of Statistics, 2021), this would equate to 70% of retirement years being funded by the public pension for males and 65% for females. According to the Association of Superannuation Funds Australia (2023), an individual looking to live a modest lifestyle in retirement will need over $32,000 in annual income, and an individual looking to live a comfortable lifestyle will need over $50,000 in annual income, both figures assume that the retiree owns their own home and are not renting. The Association of Superannuation Funds Australia 2023 retirement standard report provides a detailed breakdown of the budget for both a modest and comfortable lifestyle. A modest lifestyle equates to a weekly income of $621.02, which does not allow for any international travel, and limited domestic travel. While a comfortable lifestyle equates to $976.65 and allows for infrequent international travel and domestic travel. For a full breakdown of the modest and comfortable budget breakdown, refer to Association of Superannuation Funds Australia (2023). Furthermore, when comparing these figures with the average superannuation balances for males and females (aged 60-64) of $402,838 and $318,203 (Australian Taxation Office, 2021), the concerns raised about the adequacy of retirement savings appear justified.

Superannuation is a form of mandatory retirement savings, which has been shown to reduce procrastination, a common issue for retirement savings (Larsen and Munk 2023). 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.[1] 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 pre-tax salary 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 important role in determining their balance upon reaching the retirement age. This dissertation will focus on the latter determinant.

The superannuation system and the US 401(k) have distinct differences, most notably, participation in superannuation is mandatory, compared to the voluntary participation of the 401(k). However, superannuation is analogous to 401(k) pension plans as both offer various investment options within the respective funds, allowing members to choose how their retirement savings are invested. This dissertation is focused on this similarity, thus the results of this dissertation are not limited to an Australian context and can be applied to investment decision making within retirement savings schemes,

[1] Concessional contributions are any contributions made using before tax income. Non-concessional contributions are any contributions using after tax income.

[2] Currently the Superannuation Guarantee rate is 11% but it has been legislated to increase by 0.5% every year until 1 July 2025 (Australian Taxation Office 2022). For example, a person earning $100,000 per annum, would currently receive $11,000 per annum in SG contributions.

especially in countries where retirement savings and an aging population are of concern.

The money contributed to super is invested in accordance with the member's selected investment option. Super funds provide members with a range of investment options, which vary by asset allocation and are designed to cover a range of risk profiles. For examples of how investment options vary by asset allocation, see Appendix B. Within super, members can allocate their funds to one or more of the investment options that best aligns with their risk profile. The funds within super remain inaccessible until the member reaches the retirement age (currently 67), at which point, the member can access their retirement savings through a pension phase draw-down, or through a lump sum withdrawal. Entering the pension phase and drawing down means members are no longer able to contribute to their retirement savings but they can now begin to withdraw funds on a regular basis. Alternatively, a lump sum withdrawal involves a member withdrawing their entire superannuation balance in one transaction.

A member that joins a super fund at the age of 20, could expect to be invested for over 40 years before reaching the retirement age. Due to the long term nature of superannuation, the investment option or options a member chooses to allocate their retirement wealth towards can have a substantial impact on their retirement balance, and forms the focus of this dissertation.

This dissertation will examine how members choose to allocate their funds, and factors that influence this decision at three stages throughout their time in superannuation. Chapter 2 will examine the implications and determinants of a member's initial choice upon joining a superannuation fund. The initial choice is the first investment option allocation a member chooses to allocate their retirement savings towards. As stated previously, this could be a 100% percent allocation to a single option, or a proportion of their wealth allocated across multiple options. Chapter 3 will assess the time that investors spend invested in a strategy, and examine the stimuli that influences subsequent changes to a member's investment option allocation. Any changes members make from their initial choice would be captured by the analysis of chapter 3. Lastly, chapter 4 will examine how members allocate their retirement savings before and after commencing retirement.

1.2 Findings

Chapter 2 studies the implications and determinants of investors' initial choice upon joining a retirement savings scheme using a unique dataset of over 14,000 members from 1994-2019. The implications of the initial choice are calculated by constructing two benchmarks. One which compares the returns members received with the returns they could have received had they chosen the highest risk investment option. The second compares returns they would have received if they had invested in the All Ordinaries (All Ords) Accumulation Index. I find that, on average, members are receiving sub-optimal performance (in the form of returns) due to inadequate maximisation of risk and return. The returns members receive (based off the investment option they selected with their initial choice) lead them to underperform both benchmarks. The determinants of the initial choice are the factors and stimuli that led the member to choose the allocation they did, rather than a different allocation. To model the determinants of the initial choice I utilise a Finite Mixture Model (FMM), which allows for the possibility of heterogeneity within the dataset. When considering the determinants of the initial choice, I observe five distinct subpopulations, which display varying responses to the same stimuli. Investors display contrasting responses to rising market volatility, choosing either a higher risk or lower risk option as a result. Furthermore, I see contrarian behaviour, anchoring, and investor behaviour that is not consistent with typical notions of risk aversion. The results demonstrate that behavioural biases can detrimentally affect the balances of investors upon retirement.

Chapter 3 extends on chapter 2 by studying the subsequent investment allocation decisions of over 32,000 investors throughout their time in superannuation from 1994-2019, using the same dataset as chapter 2. Subsequent decisions are labelled as any investment option allocation decision made after the initial choice. As the dependent variable for this analysis is the time investors spend invested in an option before deciding to change, I use survival analysis. I find investors exhibit a "reduce risk or increase risk response" when faced with signals of increased market volatility. Investors behave as if they perceive patterns in prices. Different age cohorts display different decision-making "cultures", but all age groups display a bias towards choosing less risky allocations rather than riskier strategies. The findings suggest that behavioural biases can contribute to lower superannuation balances being available to people when they retire.

Chapter 4 explores how investors allocate their superannuation savings before and after commencing retirement. This chapter utilises a different dataset to chapters 2 & 3, which contains the retirement decisions of over 18,000 members between 2021 and 2023. I use four measures of expected portfolio risk: beta, standard deviation, the proportion of international shares and the proportion of cash. Then, I run regression models for the quarter before, the quarter of, and the quarter after a member decides to commence retirement. I find evidence of investors displaying increased risk aversion with age; males displaying higher levels of risk tolerance and the behavioural bias known as gambling with the house money, where prior period gains lead to investors opting for higher risk portfolios.

Overall, this dissertation explores how investors allocate their wealth within retirement savings accounts and factors that influence this allocation. Behavioural finance helps explain the determinants of the potentially sub optimal decisions people are making. I find evidence of behavioural biases having a detrimental impact on the level of risk people take within their retirement portfolios, upon joining a fund, throughout their time in a fund, and when commencing retirement. Investors behave as if they perceive patterns in prices, display gambling with the house money behaviour and tend to reduce risk with age.

The remainder of this dissertation with be structured as follows: chapter 2 will discuss the implication and determinants of a member's initial choice when joining a superannuation fund; chapter 3 will examine factors and stimuli that influence the subsequent changes people make to their initial choice investment option over their time in super; chapter 4 will examine how members allocate their wealth before and after commencing retirement; lastly, chapter 5 will conclude the dissertation.

Chapter 2 The Implications & Determinants of an Investor's Initial Choice

2.1 Introduction

In this chapter I seek to examine the implications and determinants of investors' initial choice upon joining a superannuation fund. As stated in chapter 1, for the purposes of this chapter, the initial choice is the first investment option selection a member makes upon joining a new superfund. The initial choice could either be a 100% allocation to a single investment option, or it could be a portion of a member's wealth allocated across multiple investment options.

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 which 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). Additionally, 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 chapter, I examine the implications of members' initial choice using a unique dataset from an Australian superannuation fund. 86% of the members I observe made no changes to their strategy after their initial choice.[3] 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 retirement savings plans. These behaviours could be especially damaging to the retirement balances of younger members, given the long-term nature of superannuation[4]. 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.

I seek to address two points of interest surrounding a member's initial choice. Firstly, what are the implications of a members' initial choice? I 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 I observe make no further changes to their retirement savings strategy. In addressing the implications of the initial choice, I 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. I 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. I also benchmark member returns with those of the market portfolio by comparing the cumulative returns members received with the cumulative returns of the All Ords 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, I am only able to compare the raw returns members could have received; this comparison does not consider other factors such as income, contributions and account balance.

---

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

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

Secondly, I 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, I utilise a Finite Mixture Model (FMM). FMM assumes that there are latent classes within the dataset, and allows me 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 generated for each subpopulation. I can then make inferences about each subpopulation by directly comparing how the same group of explanatory variables affects these classes differently. FMM allows me to capture the effect of the explanatory variables across these different latent groups. The explanatory variables used in this analysis include: the age of the member at the time of making the initial choice, a dichotomous variable for gender, the expected market volatility as proxied by the VIX, the All Ords monthly return, the All Ords 12 month lagged return, and two dichotomous variables for the Global Financial Crisis (GFC) and Dotcom bubble, both of which occur during the observation period (July 1994 – May 2019).

Utilising FMM, I find that there are five subpopulations within my sample, which shows a typical OLS regression model would not be as well suited. Across the five classes, I 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 I 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 I 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, I provide evidence that there are five groups that respond to stimuli in different ways.

The remainder of the chapter 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 cover the determinants of the initial choice, and section 5 will conclude the chapter.

2.2 Data, background and key variables

2.2.1 Data

The dataset used throughout this chapter 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 dating 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 my 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 me 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, I 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 my analysis, a decision needs to have been made: either the member chooses to select a specific investment option, or they elect 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 the dataset). Members that were transferred across, joined WA Super on the same day and were allocated to the default investment option. This resulted in these members having the exact same values for the All Ords return, All Ords 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 me 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.

$$\sum_{n=1}^{N} w_i * r_i \,, 0 \leq w_i \leq 1 \sum_{n=1}^{N} w_i = 1 \tag{1}$$

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

2.2.2. Background & key variables

I 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 undertake. To address this, the dependent variable needs to proxy the expected risk of the strategy chosen by a given member. The different investment options available are designed to cover a range of different risk levels. I follow the findings of (Gray and Zhong 2021) to avoid imposing an order onto the data. 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 me to measure the risk of each investment option.

I 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 Ords Index. Summary statistics for the dependent variable are shown in Table 2.1.

Prior research has shown that the decision making of investors can be influenced by stimuli that is attention grabbing. For example Klibanoff et al., (1998); Barber and Odean, (2005, 2008) show that investor behaviour can be influenced by salient information. See also Durand, Limkriangkrai and Fung (2019), who review the literature on exogenous and endogenous selective attention and present an analysis of the behaviour of sell-side analysts exploiting the nuanced view of attention (which is perhaps more grounded in psychology literature). When a decision is made, I seek to capture the state of the market compared to historic states as it is likely that current market conditions may influence investors' behaviour. Therefore, the monthly return of the All Ords index is included in the analysis to proxy for the stimuli members receive. I use the All Ords return from the month prior to the member's initial choice. For example, a member that joins the fund in May, could be influenced by the All Ords return for April. The All Ords index was used rather than the All Ords accumulation index as the All Ords index is the headline figure salient to individual investors and is more likely to be reported by the media. Furthermore, the correlation coefficient between the All Ords index and the All Ords Accumulation index is 0.95 over the observation period. The monthly change in this price index is -0.003 or -0.3% (insignificantly different from zero).

The All Ords lagged 12-month return index is included 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 my analysis, I will be examining whether members' initial choice is being influenced by historical market states. For example, if 12 months prior to a member joining the fund, the market return is positive, I 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 commonly used as a measure of the expected volatility of the S&P500 and to gauge investor sentiment (Whaley, 2000). A higher VIX price would indicate increased volatility, uncertainty and a pessimistic outlook among investors; alternatively, a lower VIX price would indicate an optimistic market outlook, reduced uncertainty and lower levels of volatility. An ASX200 equivalent index exists and is known as the Australian Volatility Index (AVIX). However, data for the AVIX is unavailable until February 2008 and, as such, does not cover the entire observation period. Consequently, I use the VIX, for which data can be obtained for the entirety of the observation period. The correlation between the AVIX returns and VIX returns is 0.74 justifying the use of the VIX as a proxy for Australian investors' expectation of volatility. This is consistent with evidence that the Australian market is integrated with the US market (Durand et al., 2006; Chiah et al., 2016).

Members' demographic information 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 option.

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 the 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.

Table 2. 1. Summary statistics of variables
Panel A of Table 2.1 shows summary statistics for the explanatory variables, results are presented in decimal form. Panel B displays the mean beta for each of the available investment options.

Panel A

	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
All Ords return	0.0004	0.0399	-0.0072	-0.0710	0.1629
All Ords TM	0.0041	0.0603	0.0028	-0.1774	0.2134

Panel B Average beta by investment option

	Mean Beta
Cash	-0.00326
Diversified Conservative	0.13938
Bonds	0.00321
MyWASuper	0.35360
Diversified Moderate	0.25804
Diversified High Growth	0.45626
Sustainable Future	0.93909
Property & Infrastructure	0.13857
Australian Shares	0.98029
Global Shares	0.30625

2.3. 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). I see evidence of the same behaviour within the dataset, only 14% of members make any changes to their investment option after their initial choice. 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. Merton (1980) shows that there is a positive relationship between risk and expected return, as such, members that fail to utilise this relationship could be missing out on performance.

To address the implications of members' initial choice, I 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; I 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, I 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, I compare the cumulative monthly returns they received, with the cumulative returns they could have received if they had instead invested in the All Ords Accumulation Index. The market index is used as the market benchmark, which is the ex-ante optimal portfolio. Using this I can compare the performance of members against the market benchmark. To do this, I calculate a benchmark return for each member by subtracting the cumulative returns they would have received from either the riskiest option or the All Ords index, away from the cumulative returns they actually received[5], as shown in equation 2:

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

The benchmark returns refers to either the cumulative returns of the highest risk and return strategy, or the cumulative returns for the All Ords 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.

[5] The returns members received from their investment options do not include the investment fees associated with these funds.

Table 2. 2 Initial choice benchmark – Highest risk and return strategy

Table 2.2 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 2. 3 Initial choice benchmark – All Ords Accumulation Index

Table 2.3 presents the summary statistics for the investors' performance – benchmarked against the All Ords Accumulation Index. Results are presented in decimal form.

	Summary Statistics				Shapiro Wilk		Wilcoxon signed-rank test		
	Mean	Stdev	Min	Max	Observations	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

The results of the highest risk and return benchmark performance are presented in Table 2.3 In columns 1 – 3, I present the summary statistics for the benchmark calculation. I find 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, I do not observe any difference; members are missing out on performance due to their initial choice. According to literature, I would expect to see a greater propensity for males to choose higher risk strategies, which is not what I am observing. The Shapiro Wilk (Shapiro and Wilk, 1965) test provides evidence that the samples do not conform to a normal distribution. I 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 I see 812 members had a positive benchmark and were better off because of their initial choice. Contrastingly, 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, I am 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.

In Table 2.3, I present the results of the market portfolio benchmark, where member returns are compared with those of the All Ords Accumulation index 2-years, 5-years and 10-years after their initial choice. The results of Table 2.3 are consistent with those of Table 2.2, on average, members are underperforming the market portfolio. Consistent with the results of Table 2.2, I find on average, no differences between the outcomes for males and females. When looking at the 10-year comparison, I find 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. I would also like to note that I do not observe members' entire portfolio, and it is possible that members are saving for retirement in personal accounts in addition to their superannuation. Therefore, I am not observing their entire portfolio and as a result, their entire portfolio may be more (or less) conservative than it appears in the dataset. In light of this, I 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 require 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 2.2 and 2.3, members are on average moving themselves further away from an adequate retirement balance because of their initial choice. I 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, I 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.

2.4. Determinants of the initial choice

The implications of the initial choice can be detrimental to the retirement outcomes of the majority of members I observe. I seek to model the determinants of this initial choice by examining what factors and stimuli are influencing this important decision. In answering this question, I wish to avoid placing constraints on the data and have chosen to model a member's initial choice when joining a superannuation fund using FMM. FMM can be used to deal with the issue of unobserved heterogeneity within the population. I do not observe all characteristics that may be influencing the initial choice of members within the dataset, but I know that some of these characteristics may be equivalent. In essence, I am contending the possibility that the overall population of superannuation members is made up of homogenous subpopulations. An advantage of using FMM is that the data determines these homogenous groups or classes, rather than requiring me 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. I 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:

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

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:

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

Next, I need to determine the appropriate number of classes (or groups) for the analysis. I 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, I 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, I 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. I repeat this process for a 2-class model, 3-class model, and so forth until I reach a 7-class model. I record the AIC and BIC for each model specification, as can be seen in Table 2.4, with the results shown in Figure 2.1. Table 2.4 shows 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 demonstrates that the 2-class model is preferred to the 1-class model. Following this comparison, I see that the 5-class model has the lowest BIC (-39,547.95), making it the optimal model specification for the data.

To determine the probability of each member belonging to a specific class, I 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:

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

After calculating posterior probabilities I am able to calculate summary statistics for each of the 5 classes, which can be seen in Panel A of Table 2.5. Panel B shows the bimodal equity and non-equity allocations of members. Angew et al. (2003) found that member investment allocations are highly bimodal between all 100% equity allocations and 0% equity allocations. By using the investment option breakdowns (as shown in Appendix B) I am able to identify members with either a 100% allocation to equities or a 0% allocation to equities. However, I do not find results consistent with Angew et al. (2003) across all 5 classes.

Figure 2. 1 Akaike's Information Criterion & Bayesian Information Criterion
Figure 2.1 displays the AIC and BIC values for up to 7 possible classes. The lowest BIC value is preferred and highlighted.

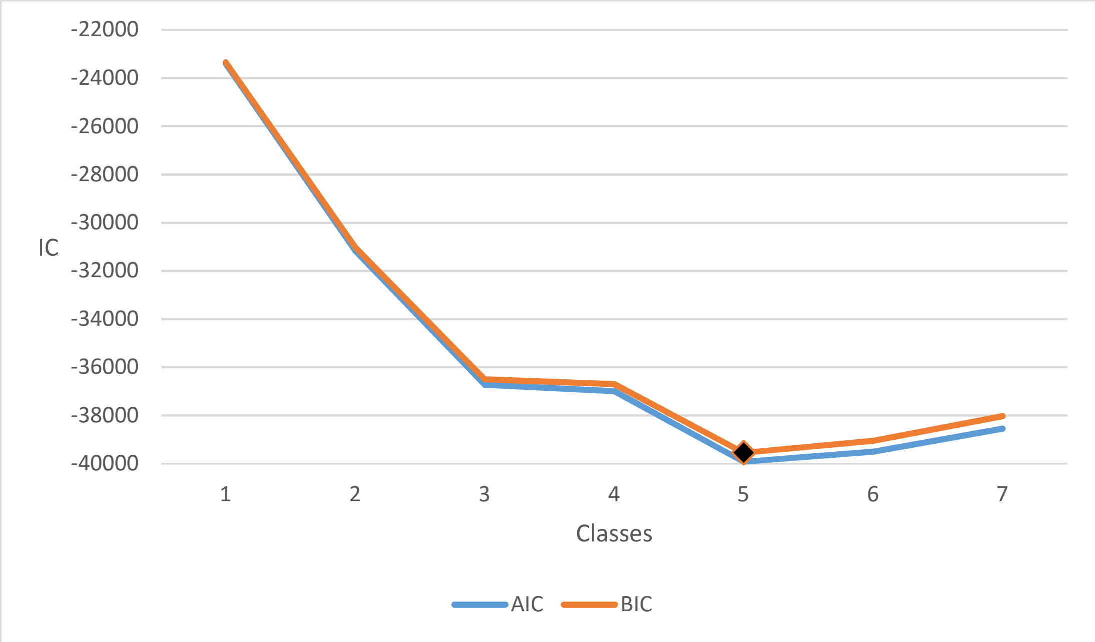


Table 2. 4 Akaike's Information Criterion & Bayesian Information Criterion
Table 2.4 reports the AIC and BIC values for model specifications 1 – 7. The Class with the lowest values are preferred and are displayed in bold.

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 2. 5 Summary statistics of 5 class model
Panel A of Table 2.5 displays the summary statistics of the preferred 5-class model in decimal form. Panel B displays the bimodal analysis of members who had 100% equity allocations and 0% equity allocation in % form.

Panel A

	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
All Ords return	-0.0116	0.0403	0.0020	0.0396	-0.0069	0.0322	0.0084	0.0472	0.0009	0.0343
All Ords TM	0.0002	0.0476	0.0101	0.0550	0.0063	0.0497	0.0147	0.0708	-0.0021	0.0598

Panel B

	Class 1	**Class 2**	**Class 3**	**Class 4**	**Class 5**
All equity	0.04	0.10	14.29	0.00	0.33
No equity	0.00	16.22	1.98	0.00	0.00

The use of FMM in this analysis allows me to observe how each subpopulation within the data responds in differing ways to the same stimuli. I have provided evidence that the 5-class model is the preferred model for the data, as shown by the IC calculation. An advantage of FMM is that it allows me to run a separate regression model for each of the 5 classes and coefficients for each class is reported separately, allowing me to make inferences about each group. Table 2.6 presents the results from the FMM, 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 2.6, I present a summary of the results which shows the significance and direction 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. I find 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). The following subsections will provide detailed discussion of the main results of FMM, by focusing on what I perceive as the most salient behaviour.

Members in class 1 can be labelled as the "trend chasers". They are the only class for which the All Ords 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 Ords return is positive. When the All Ords return in the previous month is negative, members opt for less risky strategies. Members in this class are choosing to reduce their risk when the market is declining, and increase their risk when the market is advancing. While I observe contrarian behaviour (as discussed later), I see that not all members follow this pattern when it comes to the initial choice. The 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).

Table 2. 6 Finite Mixture 5 class model

Table 2.6 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)
All Ords return	0.4018***	-1.0378***	-0.7765	-0.0309***	-0.0713***
	(33.96)	(-6.14)	(-1.09)	(-2.80)	(-5.24)
All Ords 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 2. 7 Summary of results

Table 2.7 shows a summary of the results in Table 2.6. + 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	-	-	-	-	+
All Ords	+	-		-	-
All Ords TM		+			-
GFC	-	+	+	+	+
Dotcom	-	-		-	-
N	2664	2060	252	3470	6461

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. I observe 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 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, I find evidence that the majority of members behave in such a manner (classes 2, 4 and 5), I 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, I 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, I find 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 to choose a lower risk strategy with their initial choice. Unlike the evidence presented for class 3, here I 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, I see that the All Ords 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 Ords return coefficient (-1.0378), but they follow the trends of the historical state of the market.

Similar to class 1, in class 4 I find evidence that members are sensitive to changes in the All Ords return index. I 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 Ords 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 Ords return from the previous month is negative. They are more likely to choose less risk when the market return is positive. This is in 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. My findings are consistent with this and show that the contrarian behaviour extends to their initial choice.

I find evidence that the initial choice elicits two contrasting responses to changes in market volatility, as measured by the VIX. The same stimuli leads one group to "fight" the rising market volatility, while the other elects "flight". Members "fight" rises in expected market volatility by choosing a higher risk to return strategy; members elect "flight" by choosing a lower risk to return strategy when facing rises in market volatility. I see the flight response with classes one to four, as shown by the negative and significant coefficients. Classes one to four make 57% of the sample. When looking at class five (43% of members), I see the fight response. Members in class five opt for a higher risk-return investment strategy when volatility in the market is higher. I see behaviour that would not be expected if traditional notions of risk aversion were coming into effect. I would expect to see members displaying a greater propensity for less risk when market volatility is high.

2.5. Conclusion

This chapter 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 the 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), I first examined the implications of the initial choice. I 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. I 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, I then examined the determinants of this first decision using a Finite Mixture Model. I provide evidence of 5 homogenous subpopulations within the dataset, each responding to stimuli in varying ways. I 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). I also find members within the sample exhibiting contrarian behaviour, consistent with (Grinblatt and Keloharju, 2000). I find members in class 3 having a positive relationship between age and expected risk, behaviour which is inconsistent with existing literature concerning age and risk aversion (Morin and Suarex, 1983; Bonsang and Dohmen, 2015 and Betermier et al. 2017). Lastly, I document members influenced by historical market states (anchoring).

The findings presented in this chapter have implications for members and professionals involved with retirement savings schemes. I 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 chapter 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.

Chapter 3 Investor Decision Making Within Retirement Savings Schemes

3.1. Introduction

This chapter builds on chapter 2 by examining the factors and stimuli that influence superannuation members to make subsequent changes to their investment option. There are three commonly acknowledged determinants of an individual's superannuation (super) balance upon retirement: the money contributed to their fund which is a function of their income; the way that it is invested- a function of the options open to them; and their time in the fund (as wealth and retirement should have a positive association with the length of the investment). In this chapter, I examine the latter two of these determinants. Firstly, I examine how investors decide to allocate funds once they have joined a super fund. Secondly, I address the length of time investors spend in a particular strategy. Typically, an investor's money is invested in one of the investment options offered by their chosen super fund. These options vary by asset allocation and are designed to cover a range of investor risk profiles.

As discussed in chapter 2, previous literature relating to investment decisions document that an investor may be overwhelmed by the complexity and number of fund options which may lead them to make sub-optimal decisions when selecting an investment option (Benartzi & Thaler 2002). O'Donoghue and Rabin (2001) found that people's propensity to procrastinate increases with the importance of the goal, the number of choices available, and the perceived complexity of the task. In keeping with this propensity to procrastinate, most investors I observe make no changes once they join the fund: around 85% simply keep the investment option that they first chose when joining the fund[6], such is the finding of chapter 2.

One explanation for the observed behaviour from Behavioural Finance argues that investors are quasi-rational (Russell and Thaler 1985). Investors follow heuristics or protocols[7] to simplify complex investment decisions, but these rules are not economically rational; the rules are consistent (and hence not irrational), but they do

[6] Such a finding is consistent with Benartzi & Thaler (2002), O'Donoghue and Rabin (2001), Samuelson & Zeckhauser (1988) and Mitchell et al. (2006).
[7] For example, preserve capital and spend dividends.

not accord with behaviour that maximises economic utility (the return risk trade-off). Subsequently, I find quasi-rational behaviour amongst the investors who do make a decision to switch investment options.

In this analysis I do not find risk aversion, a keystone of rational economics. Rather, I find instances where investors exhibit two contrasting responses to the same stimuli (increased volatility), both reduced and increased risk. I also find contrarian behaviour consistent with behaviour documented for households in Finland (Grinblatt and Keloharju, 2000). Contrarian behaviour is consistent with investors perceiving patterns in the market; such patterns should not exist in informationally efficient markets (Fama, 1970). I also see behaviour consistent with investors perceiving patterns when considering longer run returns; I argue that this behaviour is consistent with investors displaying representativeness or recency bias. Different age cohorts display different behaviour which I liken to age-based investor culture. Younger investors have a greater propensity to make decisions *per se* but, all things being equal, there is a greater propensity to choose less risk over more.

A positive relationship between risk and expected return is a central tenet of finance (Merton, 1980).[8] When I compare the results of investors that increased their risk exposure with those that reduced it, I found that increasing risk was associated with better returns. Given that younger investors have more time to benefit from the positive relationship of return to risk, behaviour where risk exposure is reduced is potentially very detrimental to their wealth when they retire. Younger investors should bear more risk to expose themselves to higher expected returns and, as they age, bear less risk and expose themselves to relatively lower returns.

Modelling investors' behaviour in superannuation requires an appropriate empirical methodology. Firstly, I need to model the time investors "stick with" a particular choice (in the first instance, their initial choice on entering the fund). Secondly, I seek to understand how they choose to end a particular strategy. I consider whether investors move to a riskier or less risky strategy.[9] Risk has a positive correlation with

[8] Müller, Durand and Maller (2011) present an example of an empirical analysis confirming the presence of a positive relationship of return and risk; page 307 lists other empirical work in this area.
[9] As I discuss below, I do not consider decisions to leave the scheme such as retirement.

return so, in considering risk, I have a sound proxy for expected return. I run the non-parametric rank-order correlation, which tells me the strength and direction of the relationship between two variables. The rank correlation of the return *ex post* risk and return of the strategies investors could choose is 0.6. To meet the modelling challenges posed by the questions I address, I utilise survival analysis[10] to model investors' time in an investment strategy and their choice when leaving it. The variable of interest in this model is the time that an investor remains in their initial strategy until a change in strategy occurs: the change will either be by choosing a riskier or less risky strategy. In this analysis I consider the same group of explanatory variables as chapter 2: age, gender, expected market risk, changes in the market and striking market episodes such as the Dotcom bubble of the early 2000's and the Global Financial Crisis as variables which may hasten or delay the movement to a riskier or less risky option. I include controls for a member's time to retirement and prior period gains or losses and find the results are robust.

Having modelled changes in investors' strategies, I then consider if those changes left members better or worse off. I do so by utilising an investor "own benchmark" (following Barber and Odean, 2001) comparing the returns an investor would have achieved with the allocated fund option they chose against what they would have achieved had they done nothing. As I only observe the assets they hold within super, I am unable to comment on whether the decision is optimal.[11] Instead, I look to address whether the decision they made is moving them closer to the required retirement balance or if it is moving them further away. This is of high importance due to the savings shortfall that exists within retirement savings schemes, both in Australia and globally. If the decisions being made are resulting is lower returns being received, then this decision could be seen as moving them further away from the required retirement savings balance. Consistent with finance theory that in the long run, there is a positive relationship of return and risk, I find on average, investors choosing more risk beat

[10] Survival analysis models are typically used when studying the time to a subsequent event. In biomedical research this is often time from treatment to mortality. However, this approach has been widely adopted by other disciplines where the interest is time to an event or defined outcome. See Lancaster 1990 for a more detailed explanation.
[11] 46% of Australians hold investments outside of their primary residence and their superannuation account.

their own benchmark. Investors choosing less risk, underperform their own benchmark.

The rest of this chapter is organised as follows. I discuss the data I used in Section 2 of the chapter and present the survival analysis in Section 3. In Section 4 I examine if investors were better or worse off after making decisions. Section 5 concludes the chapter.

3.2. Data

The unique dataset used in this chapter, is the same as chapter 2. It has been sourced from a major Australian Superannuation fund consisting of monthly data for 32,677 members (investors) who make over 68,000 decisions over a study period beginning in July 1994. This period starts two years after the introduction of compulsory super in Australia (Nielson and Harris, 2010) and ends in May 2019. The data contained information about investors' behaviour throughout their time in super, specifically whether they change their initial investment option, how long they spent in that option and the option that they switched into. As with chapter 2, a unique anonymous member identification number was used to track each member over their lifetime in super. The unique ID was important to protect the identity of members and it enabled me to observe the choices and behaviour of each member throughout the sample period. The dataset contained the members' investment information, the date they entered an investment option, the dates of subsequent changes, as well as the investment options they were invested in. A breakdown of the options available to members throughout the observation period can be found in Appendix B.

Figure 3.1 Investment options timeline

Figure 3.1 displays how the number of available investment options members had to select from changed over time. As can be seen below, from 2008 onwards the list of available investment options remained constant.

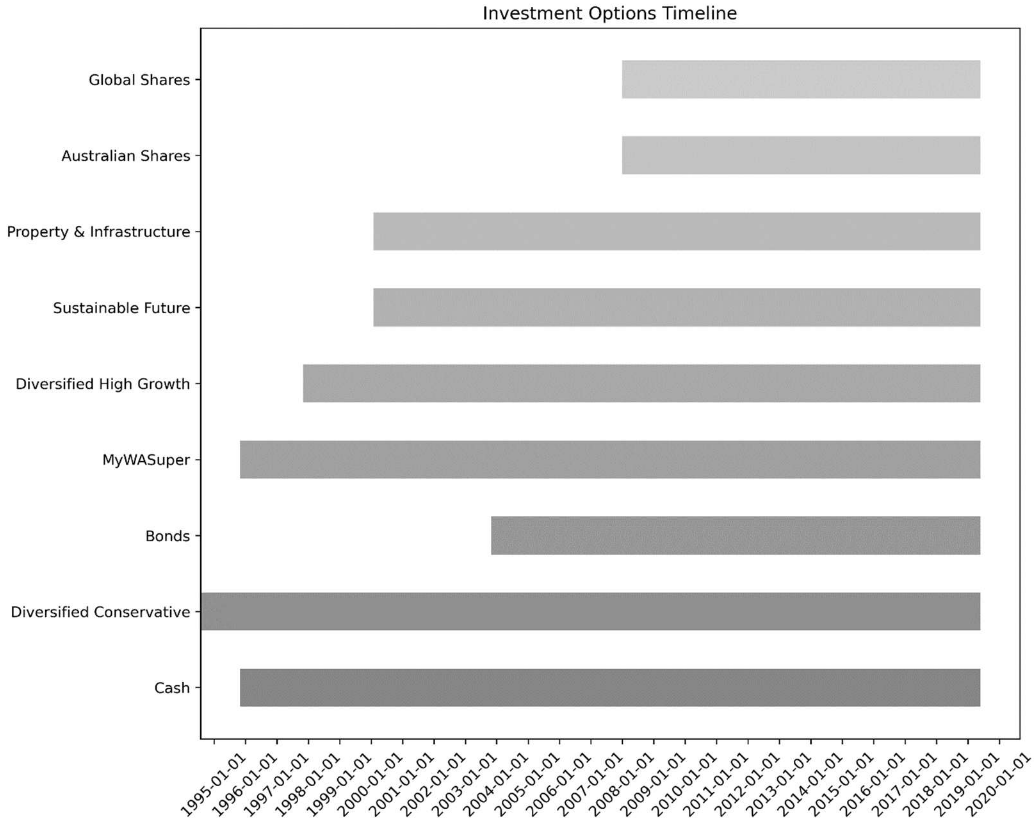


Figure 3.1 shows the timeline of investment options. As previously stated, investors also had the option to select any combination of the provided investment options. For example, rather than allocating 100% of their wealth to a single investment option, they could invest a portion of their wealth across multiple investment options; these investment option combinations were labelled as complex. Panel A of Appendix C shows a breakdown of the options selected by members during the observation period, while Panel B, shows summary statistics of the number of options members chose to allocate their wealth across. Demographic information for each member was provided and included their age at the end of the study period, current address and postcode (zip code), and gender. Table 3.1 summarises the data I examine.

Chapter 2 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' initial choice upon joining a superannuation fund.. In this chapter, I seek to explore how these same factors influence members' time in an investment option. As a result, I have included the same explanatory variables in this analysis.

Table 3. 1 Data Selection

Table 3.1 depicts how the final analysis sample size was constructed. At least one change refers to the number of members that made at least one investment option change. At least two changes refers to the number of members that made at least two investment option changes. No changes made indicates the number of members that made no changes to their investment option over the entire observation period(July 1994 – May 2019).

	Members
At least two changes	2,063
At least one change	4,686
No changes made	27,911
Total analysis sample	**32,677**

Table 3. 2 Summary statistics of explanatory variables

Table 3.2 presents summary statistics of the monthly returns of the explanatory variables for the sampleperiod of July 1994 – May 2019. Means are reported in decimal form.

	Mean	StDev	Min.	Max.
VIX	0.0178	0.183	-0.574	0.626
All Ords Return	-0.0030	0.037	-0.071	0. 163
All Ords 6-month	-0.0000	0.051	-0.183	0.147

Table 3. 3 Correlation of explanatory variables

Table 3.3 presents the Pearson correlation coefficients of the explanatory variables.

	Months in Fund	VIX	All Ords Return
VIX	-0.186		
All Ords Return	-0.044	0.451	
All Ords 6-month	-0.065	0.254	0.705

To recognise the possibility that investment choices might be influenced by age, but to avoid issues of having a strongly correlated dependent and independent variable, dichotomous variables for each decade of birth were created, taking the value of 1 if the investor is born within a particular decade or 0 if otherwise. This is due to the dependent variable being the time an investor spends in a particular strategy, which will be strongly correlated with their age. For example, if the investor is born in 1989, they will have a value of 1 for the 1980s decade and a value of 0 for all other age variables. The 1930s/1940s variable was omitted from the analysis for two reasons. Firstly, there were not enough observations to output a proportional hazard ratio from the parametric survival model and secondly, it is important to omit one dummy variable from the model. This is because if there are n dummy variables, only n-1 dummy variables are included in the model.[12]

3.3. Methodology

Survival analysis allows me to consider how long investors remain committed to a particular strategy (their survival functions). As noted in the introduction, the dependent variable is the time an investor remains in their initial strategy until changing and, then the time such investor remains in their second strategy. During the sample time period, investment options available to investors changed with options added and removed. This in general did not cause problems because investors were mostly given more options and their decision to move into a new fund was captured by the data. I am concerned with modelling the time (often referred to as survival time) until the event of interest occurs, in this case, the time a member spends invested in a particular investment option. The survival function S(t) represents the probability that survival time is greater than time t, with T representing the event of interest. As T is a continuous variable I utilize the cumulative probability function, I set T=u, which means the probability of the event of interest occurring by $T \leq t$ can be seen in equation 1 as:

$$F(t) = \int_{-\infty}^{t} f(u)du \qquad (1)$$

F(t) represents the probability of the event of interest occurring at or before time $T \leq t$. Therefore, the probability of surviving by time $T \leq t$ can be written as:

$$S(t) = 1 - F(t) \qquad (2)$$

The hazard function $h_i(t)$ gives you the probability of the event occurring at time T = t, given the event has not already occurred. Using this, I arrive at the proportional hazard model:

$$h_i(t) = \lambda(t)e^{\boldsymbol{x_i \beta}} \qquad (3)$$

Where $h_i(t)$ represents the hazard rate for the i^{th} individual, $\lambda(t)$ represents the baseline hazard faced by individuals in the analysis, lastly, x_i and β represent a vector of

[12] In the results section I create dummy variables for the number of years a member has until they meet the retirement age. These are included in the analysis for robustness.

variables for the ith individual and a vector of coefficients respectively. While the analyses present what might appear to be regression coefficients, the estimates are hazard functions. The interpretation of hazard functions is different depending on the type of variable included in the survival model. Hazard functions are a representation of the instantaneous hazard an individual faces given a set of circumstances. The hazard ratio has a different interpretation depending on whether the explanatory variable is dichotomous or not. For dichotomous variables, the hazard ratio shows the estimated difference in hazard for $x = 1$ and $x = 0$, with $x = 1$ being that many more times likely to cause the event to occur than when $x = 0$. For example, if the hazard ratio for gender is 1.85, with gender equal to 1 for males and 0 for females, then men are 1.85 times more likely to leave the fund than females. For covariates, the hazard ratio represents the percentage increase or decrease of hazard estimates for every unit increase in the explanatory variable. For example, if age is the explanatory variable and the hazard ratio is equal to 1.20 then every unit increase in age increases the hazard estimate by 20%. It is important to note that for non-dichotomous variables, which are typically measured in percentages, a one-unit increase equates to a 100% increase in that variable. For example, if the All Ords return variable had a proportional hazard ratio of 4.5 that would equate to a 350% increase in the instantaneous rate of hazard at any given time for a 100% increase in the All Ords return variable.

Truncation bias is an important feature of survival analysis and is considered in the analysis. Truncation bias occurs when the start points, end points or both are not captured within the observation period (Rennert *et al.*, 2017). For example, if survival analysis was being used to examine the time it took unemployed people to find work, any participant that was already unemployed at the start of the observation period or was unemployed at the end of the observation period, would need to be censored to avoid truncation bias. This is because the amount of time prior to the observation window in which they had been unemployed is not known. Likewise, how long they stay unemployed after the observation period ends is also unknown. Including such observations in the survival analysis will lead to biased estimates of the time until the event being studied occurs. As I can observe the date members enter the fund, and therefore the time of their first investment option, left side truncation bias is not present in the data. The dataset contains right side truncation bias, as the observation period ends in May 2019, and I do not know how long members stay in their investment option after this point. To avoid truncation bias, I only calculate time in fund when the investment change date representing the exiting of fund is captured within the observation period. Members that change investment options before May 2019 are captured but those who are in a strategy in May 2019 will not be included in the analysis.

A further potential complication of this analysis arises as investors may exit in one of two ways: they could choose to move to a riskier allocated fund option (strategy), or they could choose to move to a less risky strategy. Although both choices result in members exiting the fund, the stimuli that influences members to switch to a riskier or less risky fund might be different. Figure 3.2 illustrates the decisions that the 32,677 members within the dataset made. For example, during periods of market turmoil, it might be the case that risk-averse members would adopt a more conservative approach and, consequently, may exhibit a different response to risk *ceteris paribus*. In this analysis I use the risk rankings given to the investment options by the superannuation fund itself, as stated earlier, these rankings are determined by asset allocation and can be seen in Appendix B. Nofsinger & Varma (2013) find that approximately 40% of investors repurchase a stock they previously held, this is not something I find strong evidence for, with only 12% of members that make a second choice returning to the level of risk they initially chose upon entering the fund. I also consider if the possibility of different exits will impact the analyses by conducting Pepe-Mori tests. The Pepe-Mori test compares the cumulative incidence functions of the competing risks for the event of interest, in this case a change in strategy. The null hypothesis for this test is that there is no difference between the two competing risks (Pepe and Mori. 1993) and the results are presented in Table 3.4.

Panel A of Table 3.4 indicates that the survival function for investors choosing to move to a riskier strategy is significantly different from investors choosing a less risky strategy. Therefore, the analyses for those choosing a riskier strategy and those choosing a less risky strategy need to be estimated separately. Panels B and C of Table 3.4 present Pepe-Mori tests for the second choice that investors make. As with the first choice, Panel C of Table 3.4 indicates that the survival functions of those who initially choose a riskier strategy and then make a second choice to a riskier strategy, and those whose second choice is to reduce their risk, are significantly different and that these will also be estimated separately. For those investors making a second choice after moving to a less risky strategy, I cannot reject the null hypothesis that the survival function for those moving to a less risky strategy is the same as for those choosing more risk. I need, and should, only estimate one survival function for the second decision made by this cohort.

Figure 3. 2 Investors' choices

Figure 3.2. Illustrates the paths that the 32,677 investors in the sample chose. Of the 32,677 investors in the sample, 27,911 made no decision and 4,686 changed their strategy; 2,546 (54%) chose a riskier option and 2,140 chose a less risky option. Of the 2,546 who chose a riskier option, 319 (12½% of the 2,546 whose first choice was for a riskier strategy) subsequently chose a riskier option while 517 (20%of the 2,546) chose a less risky strategy. Of the 2,140 who chose a less risky option, 646 (30% of the 2,140 investors whose first choice was to move to a less risky strategy) subsequently chose a riskier option while 581 (27% of the 2,140) chose a less risky strategy.

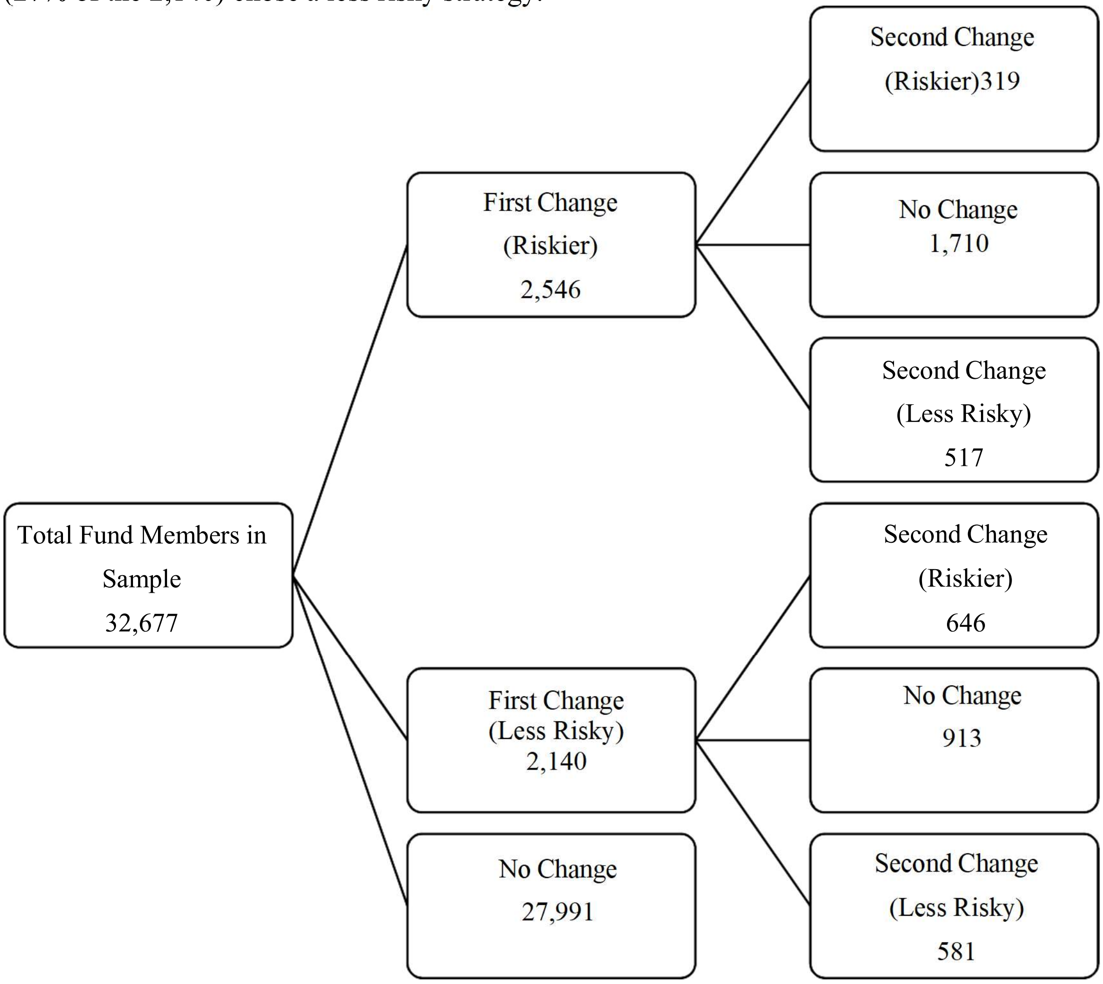


Table 3. 4 Pepe-Mori tests

Table 3.4 presents the Pepe-Mori test for the competing risks. The risk variable takes the value of 1 if themember switches to a riskier fund or 0 if they switch to a less risky fund. As the Pr > χ^2 is less than 0.0000, the null hypothesis that the two competing risks are not statistically different can be rejected. Panel A reports results for the initial choice made by investors (that is, to move to a less risky fund (Risk = 0) or a riskier fund (Risk = 1)). Panel B reports results for the second choice made by investors who initially moved into a less risky fund (that is, to move to a less risky fund (Risk = 0) or a riskier fund (Risk = 1)). Panel C reports results for the second choice made by investors who initially moved into a riskier fund (that is, to move to a less risky fund (Risk = 0) or a riskier fund (Risk = 1)).

Panel A

First Choice

Risk	Events Observed	Events Expected
0	2,140	2,624.39
1	2,546	2,061.61
Total	4,686	4,686

χ^2 = 220.53

Pr > χ^2 = 0.0000

Panel B – First choice less risky

Second Choice

Risk	Events Observed	Events Expected
0	581	586.23
1	646	640.77
Total	1,227	1,227

χ^2 = 0.09

Pr > χ^2 = 0.76

Panel C – First choice riskier

Second Choice

Risk	Events Observed	Events Expected
0	517	582.46
1	319	253.54
Total	836	836

χ^2 = 25.90

Pr > χ^2 = 0.0000

Table 3. 5 Survival times (months)

This table presents summary statistics for the survival time in the less risky and riskier investment option changes. Panel A represents the time in the fund until the first decision is made and Panels B & C present the time investors spend in their second strategy until deciding whether to move into a less risky or riskier strategy. Survival time is the time in months a member spends in an investment option.

Panel A

	Less Risky	Riskier
Mean	74.60	50.98
25% Percentile	15.65	11.34
50% Percentile	48.59	33.11
75% Percentile	116.32	82.75

Panel B – Less risky first choice

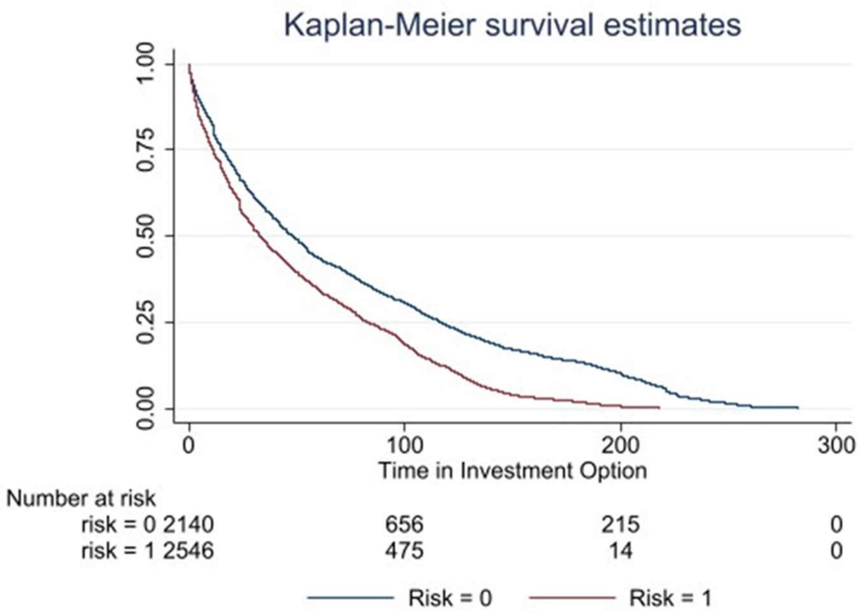
	Less Risky	Riskier
Mean	57.73	56.41
25% Percentile	11.84	11.72
50% Percentile	36.31	36.69
75% Percentile	94.42	96.00

Panel C – Riskier first choice

	Less Risky	Riskier
Mean	62.35	42.82
25% Percentile	11.77	10.36
50% Percentile	31.99	25.25
75% Percentile	99.02	76.18

Figure 3. 3 Members' First Decision to Change

Figure 3.3 presents Kaplan-Meier survival estimates of the number of months from member's first appearance in an investment option until they switch options. Risk = 0 represents the less risky changes and risk = 1 represents the risker changes.



Panel A of Table 3.5 presents summary statistics for the time investors spend in their first choice of investment strategy for the two different classes of investors – those choosing to take on more risk and those moving to a less risky strategy – and the differences are striking. Figure 3.3 depicts the Kaplan-Meier estimator of the two groups. The Kaplan-Meier Estimator can be used to compare the chances of survival of the two groups, those moving to a riskier or less risky strategy. The Kaplan-Meier survival function is shown in equation 4:

$$S(k) = \prod_{i=0}^{k-1}(1 - \frac{d_i}{n_i}) \qquad (4)$$

Where d_i represents the number of members that changed strategy at time t_i, and n_i represents the number of members that had not changed at time t_i.

3.4. Results

Panel A of Table 3.5 and Figure 3.3 show that investors moving to riskier options are quicker to do so than those moving to less risky options. On average, those choosing less risk stay with their first choice for 5 ½ years (65.87 months). Those choosing more risk stay with their first choice for less than 3 ½ years (39.4 months). On average, investors choosing a riskier strategy are doing so quicker than those moving into a less risky strategy, behaviour that is consistent with findings in Grinblatt and Keloharju (2009) and Markiewicz and Weber (2013). The survival function for those moving to a riskier strategy is above that for those moving to a riskier strategy in all time horizons.

The statistics for those who change may be usefully compared with the 27,911 of the 32,677 members in the WA Super dataset who did not make any investment option changes over the observation period. The average time in sample for these members who do not switch from their initial option is 53.99 months, a number that is greater than the risky changes and just smaller than the less risky changes. This may suggest that the lack of change from the initial option are not due to minimal time as a member super fund, but rather a reluctance to make changes. There is evidence of inertia or "stickiness" in retirement saving (Samuelson and Zeckhauser, 1988; O'Donoghue and Rabin, 2001; Mitchell et al., 2006). This evidence might suggest that all things being equal, inertia is associated with investors' propensity to choose a strategy with lower risk. Given the positive relationship of risk and return, the findings suggest that "stickiness" is associated with reduced wealth ceteris paribus. However, this may not be the full story as survival analysis suggests that investors born more recently have a greater propensity to make a decision *per se* than investors who are older. As such, "stickiness" might be a function of the different expectations or culture of investors born more recently.

I find a similar pattern emerges for the 2,546 investors (54.33% of the 4,686 who moved from their initial strategy) whose first choice is to move to a riskier option and then go on to make a second choice in Panel C of Table 3.5 and Figure 3.5. The survival function for those whose second choice involves moving to a riskier strategy is above that for those moving to a riskier strategy in all time horizons. Investors choosing less risk in their second choice stay with their changed strategy (that is, the choice made after leaving their initial strategy) longer than those moving to a riskier strategy. In contrast, I see no difference in the survival functions of the second choices of the investors who initially chose less risk Panel A of Table 3.5 and Figure 3.4).

Figure 3. 4 Members' Second Choice (after an initial choice for less risk)
Figure 3.4 presents Kaplan-Meier survival estimates of the number of months from members' second choice after they make a first choice to move to a less risky fund (that is, the choice depicted in option 0 in Figure 3.3).

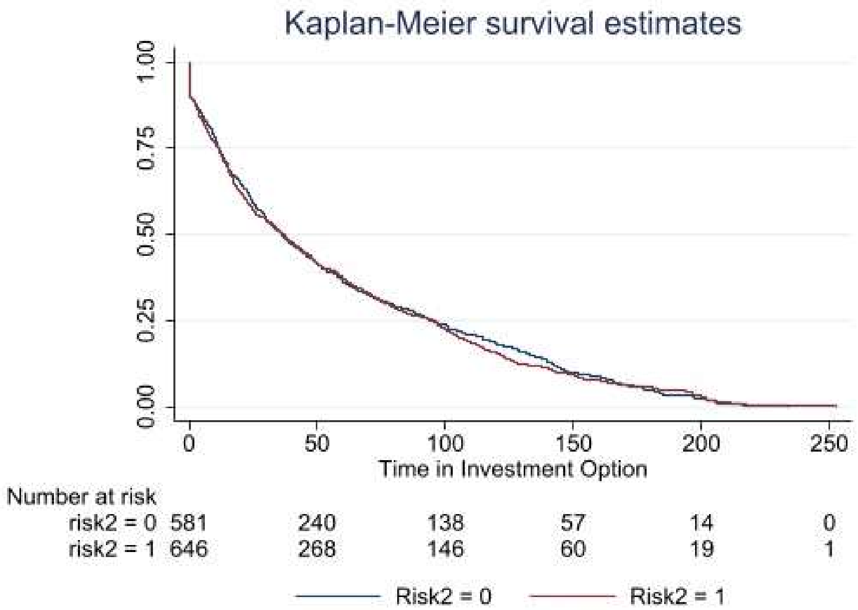
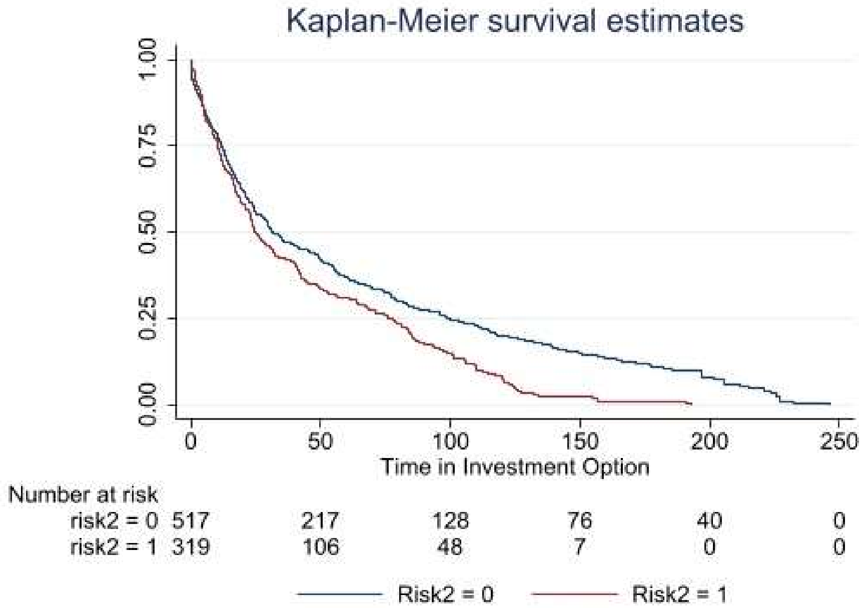


Figure 3. 5 Members' Second Choice (after an initial choice for more risk)

Figure 3.5 presents Kaplan-Meier survival estimates of the number of months from members' second choice after they make a first choice to move to a riskier fund (that is, the choice depicted in option 1 in Figure 3.3).



There are different models of survival analysis which can be utilized for determining the time until a specified event occurs. I compare parametric and non-parametric survival models in Table 3.6. Using Akaike's Information Criterion (AIC) and the Bayesian Information Criterion, (BIC), the Gompertz Proportional Hazard model, which presents the lowest AIC and BIC, is preferred for the first choice and I continue with this specification to model the second choices.

Table 3. 6 AIC & BIC for Competing Models

Table 3.6 compares three competing parametric proportional hazard models and the non-parametric Coxmodel by presenting estimates of Akaike's Information Criterion (AIC) and the Bayesian Information Criterion (BIC). The Gompertz model has the lowest BIC values making it the preferred model.

Parametric: Proportional Hazard Models	AIC	BIC
Exponential	8,284.94	8,355.05
Gompertz	**8,187.36**	**8,263.31**
Weibull	8,286.68	8,362.63
Non-Parametric Model		
Cox	34,408.97	34,473.23

The results are presented in Table 3.7. Panel A presents the survival functions for the first decision of those who choose a less risky strategy when making their first choice after joining the fund (equation 1); equation 2 in Panel A presents the subsequent survival functions for the second decision they make (both to move to a riskier or less risky decision). Panel B presents the survival for the first decision of those who choose a *riskier* strategy when making their first choice after joining the fund (equation 3). Equations 4 and 5 present the survival functions for investors who, after initially choosing a riskier strategy, make a decision to decrease their risk (equation 4) or increase it (equation 5). I now focus on the estimates of hazard ratios presented in Table 3.7 and their interpretation in the following sub-sections.

Table 3. 7 Model of members' decisions

Table 3.7 presents the hazard ratios of the time members spend in their first investment option as estimated by the Gompertz Proportional Hazard Model. For dummy variables the hazard ratio displays the estimated difference in hazard for x =1 and x = 0, with x=1 being that many more times likely to leave the fund than when x = 0. For non-dummy variables the hazard ratio shows the percentage increase or decrease of hazard estimates for every unit increase in that explanatory variable. Z-stats are presented in parentheses. *** indicates significance at the 1% level, ** at 5% and * at 10%

	Panel A		**Panel B**		
	1st choice Less Risky	2nd Choice	1st choice Riskier	2nd Choice Less Risky	2nd Choice Riskier
Equation number:	(1)	(2)	(3)	(4)	(5)
Gender	1.02	0.96	1.19***	0.91	1.20
	(0.52)	(-0.74)	(4.17)	(-0.96)	(1.53)
Age 2000s	11.22***	0.34***	5.76***	0.76	0.26***
	(11.97)	(-3.69)	(9.02)	(-1.13)	(-3.70)
Age 1990s	3.93***	0.40***	2.03***	0.28***	0.37***
	(14.06)	(-6.07)	(9.37)	(-5.27)	(-3.33)
Age 1980s	2.42***	0.34***	1.64***	0.25***	0.32***
	(10.76)	(-7.63)	(6.70)	(-5.90)	(-3.95)
Age 1970s	1.48***	0.37***	1.46***	0.25***	0.31***
	(5.48)	(-7.30)	(4.99)	(-6.16)	(-4.01)
Age 1960s	0.99	0.54***	1.15*	0.30***	0.45***
	(-0.01)	(-4.50)	(1.91)	(-4.82)	(-2.75)
VIX	1.02***	1.00	1.05***	1.01**	1.05*
	(7.72)	(0.79)	(11.24)	(2.23)	(1.84)
All Ords Return	1.32	526.72***	0.04***	69.42**	0.06
	(0.34)	(7.00)	(-2.77)	(2.00)	(-0.76)
All Ords 6-month	0.28**	0.02***	0.67	0.05*	0.28
	(-1.95)	(-4.35)	(-0.59)	(-1.89)	(-1.37)
Dotcom	0.74***	3.60***	0.41***	1.90**	3.45***
	(-5.03)	(3.95)	(-4.48)	(2.54)	(4.39)
GFC	2.43***	0.75**	0.72***	0.56**	1.42
	(6.16)	(-2.03)	(-6.19)	(-2.33)	(0.47)
Constant	0.004***	0.04***	0.004***	0.05***	0.003***
	(-50.56)	(-23.41)	(-48.67)	(-12.77)	(-7.62)
N	2,140	1,227	2,546	517	319

3.4.1 Gender

Gender, a dummy variable taking the value of one if the investor is a male, is significant only in the model where investors' first decision is to move to a riskier option. All things being equal, males are 1.19 times more likely to move to a riskier option than females. This is consistent with the literature cited above in section 2.2.2, suggesting males are less risk averse than females and as such, is not surprising. I do not, however, find that gender is significant in the second decision for investors who have moved to a riskier option.

3.4.2 Age

The effect of age is captured using five dummy variables to denote the decade in which an investor was born. For example, Age 2000s takes taking the value of 1 if the investor is born within the 2000's or 0 if otherwise, Age 1990s takes taking the value of 1 if the investor is born within the 1990's or 0 if otherwise, and so on. Age plays an unexpected role in this analysis. I find greater hazard ratios for generations born more recently than those born earlier. This is consistent with a greater propensity for those born more recently to make a decision per se.[13] I cannot relate these hazard ratios to increased risk aversion or lower investment skill. Rather, cohorts born within different decades exhibit different behaviour; this is akin to investors' culture changing as time progresses.

This is illustrated by focusing first on the first decision when it involves moving to less risk (equation 1). I find that the magnitude of the hazard ratios falls monotonically, it is highest for investors born in 2000's (11.22) and lowest for investors born in the 1960's (0.99 which is insignificantly different from 1). Again, I see the same monotonic pattern for investors whose first choice is for exposure to more risk: hazard ratios fall from 5.76 for investors born in the 2000's to 1.15 for those born in the 1960's. For both decisions to change to a less risky or more risky strategy, the higher hazard ratios for investors born later indicate that younger investors have a greater likelihood of making a decision to switch.

[13] For example, using hazard ratios from equation 1, all things being equal, a person born in the 2000's is 11.22 more times likely than someone in the base case cohort (1940s – 1950s) to have made her first decision to move to a less risky strategy and a person born in the 1980's is only 2.42 times more likely than a member of the base group to have made this.

Additionally, when comparing equations 1 and 3, I see that it is more likely that an investor born in the 2000's moves to a less risky option than a riskier option (the respective hazard ratios are 11.22 and 5.76). Similarly, when comparing the hazard ratios for all age cohorts I see that it is more likely that investors first choice is to move to a less risky than a riskier strategy for investors born in the 1990's and 1980's. While the hazard ratios are different for those choosing less risk than more risk, the difference is trivial (1.48 for the former and 1.46 for the latter). The hazard ratio for the cohort born in the 1960's is only significant (and then only at the 10% level) for those choosing a riskier strategy. The greater magnitude of hazard ratios for those choosing a less risky rather than a risker option lends itself to an economic interpretation. It suggests that, when comparing people of the same age with those in the base cohort (that is those born in the 1940s-1950s) it is more likely that someone will choose less rather than more, risk. This finding may have implications for investors' well-being in retirement. Younger investors choosing less risk gives them less time to benefit from the expected positive relationship of risk and return and, consequently, leave them with lower retirement balances than they might have wished for.

Where age indicator variables are significant in the survival functions for the second choice (equations 2, 4 and 5) they are below 1, indicating that there is less likelihood that an investor born in those decades will decide to end their time in their second strategy ceteris paribus. Such hazard ratios suggest that age is important to control for other features but I cannot relate it to age related hypotheses such as increasing risk aversion or decreasing investment skill.

3.4.4 The VIX

The VIX is the proxy for the expected risk in the market and is greater than 1 and significant in models of investors' first choices (equations 1 and 3). It is also greater than 1 and significant in the two survival functions estimated for the second choice made by investors whose first choice was for more risk (equation 4 and 5). Increasing risk therefore increases the likelihood of someone moving either to take on more risk or less risk (and decreasing risk vice versa). This is not what would be observed if classical notions of risk aversion came into play: if I was to see risk aversion, higher risk would be associated with a greater chance of choosing a less risky strategy and a reduced chance of choosing more risk. Indeed, with the first-choice investors make, VIX has a greater effect on those choosing a riskier option (with a significant hazard ratio of 1.05) than those choosing less risk (where the hazard ratio is 1.02). Consistent with this, for the second choice, an increasing VIX has a greater effect on those choosing a riskier option (with a significant hazard ratio of 1.05) than those choosing less risk (where the hazard ratio is 1.01).

Kuhnen and Knutson (2005) document that, and how, investors can respond to the same stimuli differently by either making risk-seeking mistakes or risk-aversion mistakes. I believe I am seeing a similar phenomenon here with investors choosing different responses to the same stimuli (increase volatility). One group chooses to increase their risk during times of increased volatility while the other group opts for less risk when volatility is higher. This is not the response I would expect if investors were behaving consistent with traditional notions of risk aversion.

3.4.5 Changes in the All-Ordinaries Index (the market).

Investors display high sensitivity to changes in the All-Ordinaries index, I find this variable to be statistically significant (equations 2, 3 and 4). I observe contrarian behaviour, a phenomenon associated with overreaction.[14] Contrarian behaviour amongst individual investors has been documented previously. Grinblatt and Keloharju's (2000) study of Finnish households found that they are contrarian in contrast to the more sophisticated players in the Finnish market, foreign investors who are momentum traders (Grinblatt and Keloharju, 2000).

The results suggest that the stimuli of a positive change in the All Ords makes investors moving to a riskier first choice less likely to move to that strategy (and vice versa). The hazard ratio of 0.04 (equation 3) indicates that, if the All Ords Index increased by 100%, there would be a 96% reduction in the chance that the investor would make their move to a riskier strategy. However, using the minimum and maximum values for the change in the All Ords (the values of -0.071 and 0.163 reported in Table 3.3)

[14] De Bondt and Thaler (1985) and Lo and MacKinlay (1990) are early and influential studies linking contrarian investment to overreaction. Lee, Chan, Faff and Kalev (2003) discuss contrarian investing in an Australian context.

to illustrate the economic consequences of this estimate in the most extreme observations. An investor would have been 6.82% more likely to have moved to a riskier strategy when the return was -.071 and 15.65% less likely to move to a riskier strategy when the change was 0.163. This is not what would be expected if investors were displaying risk-averse behaviour (and risk-aversion is what I would expect to see if investors were economically rational rather than quasi-rational). Changes in the All-Ordinaries index are also associated with hazard ratios significantly different to 1 in equations 2 and 4. In both instances, positive changes in the All-Ordinaries lead to a greater chance of moving to a less risky strategy. Again, this is consistent with contrarian investment behaviour.

Changes in this index in the preceding six months appear to be associated with a reduction in the likelihood of making a decision. Hazard ratios are found to be statistically significant in three instances. Firstly, in the case of where the first decision is to move to a less risky strategy. Secondly, where, having first chosen a less risky strategy, investors' make a second choice to move either to a less or more risky strategy. Finally, where investors have initially chosen a riskier strategy and make a second choice to reduce their exposure to risk. In all these decisions, the hazard ratios are significantly lower than one indicating that the decision is made less likely.

These findings for lagged returns stand in contrast to the contrarian behaviour I find for the changes in the All-Ordinaries index. When six-month returns are positive, investors appear content to remain with their strategies than when returns are negative, vice versa. In an informationally efficient market, there are no patterns in returns: returns are random. The behaviour I document is consistent with investors believing that there are regimes or patterns in prices. This is consistent with a range of behaviour biases such as representativeness (or the law of small numbers) where conclusions are drawn, or patterns discerned, on the basis of a small number of observations (Tversky and Kahneman, 1971). It is also consistent with recency bias where investors are more conscious of recent events and overweight this information when making a decision (see, for example, Ashton and Kennedy, 2002; Lee, O'Brien and Sivaramakrishnan, 2008; Kliger and Kudryavtsev, 2010; Nofsinger and Varma, 2013).

3.4.6 Significant Events: The Dotcom Crash and the Global Financial Crisis.

Many of the investors in the dataset experienced one or two catastrophic events: the Dotcom crash and the Global Financial Crisis. The Dotcom variable takes the value of 1 if the decision occurred within the year 2000 and 0 if otherwise. The GFC variable takes the value of 1 if the decision occurred within 2008 and 0 if otherwise. For example, if a member makes their first decision during 2008 then the GFC variable would be equal to one. Unless their second decision was also during 2008, their GFC variable will be equal to zero for the second decision model. Dotcom is less than 1 and significant in models of investors' first choices (equations 1 and 3). In other words, investors delay decisions to move to a less risky portfolio and also delay decisions to move to a riskier portfolio. I noted that investors can respond to the same stimuli differently by either making risk-seeking mistakes or risk-aversion mistakes when discussing the VIX (Kuhnen and Knutson, 2005). It would appear that this behaviour was also exhibited in the Dotcom crash. When considering the second decision investors make (equations 2, 4 and 5), I find that the Dotcom crash increased the likelihood of someone moving either to take on more risk or less risk.

For the first choices investors make (equations 1 and 3), investors' responses to the GFC are closer to what I might have expected if investors displayed risk aversion: the choice of a less risky portfolio became more likely and, in contrast, the choice of a riskier portfolio became less likely. The GFC made a second choice to change from an initial choice of a less risky portfolio less likely per se. For those investors whose initial choice was to move to a riskier strategy, I find that the likelihood of moving to either a less risky portfolio was less likely.

ision with time to retirement controls

he time members spend in their first investment option as estimated by the Gompertz Proportional Hazard Model. Table
l for the time until retirement. *** indicates significance at the 1% level, ** 5% and * 10%

A		**Panel B**		
hoice	2nd Choice	1st Choice	2nd Choice	2nd Choice
Risky		Riskier	Less Risky	Riskier
	(2)	(3)	(4)	(5)
	1.012	1.147***	1.222**	0.969
0)	(0.839)	(0.001)	(0.034)	(0.813)
***	1.018***	1.062***	1.034***	1.045*
0)	(0.000)	(0.000)	(0.000)	(0.069)
	1.051	0.032***	0.004***	0.000***
5)	(0.965)	(0.002)	(0.004)	(0.000)
)	5.778**	0.984	6.665	2,110.44***
9)	(0.021)	(0.981)	(0.180)	(0.006)
***	0.708***	0.736***	1.028	3.362
0)	(0.001)	(0.000)	(0.892)	(0.223)
***	2.347***	0.372***	1.328**	3.810***
0)	(0.000)	(0.000)	(0.018)	(0.000)
***	0.091***	0.017***	0.025***	0.241***
0)	(0.000)	(0.000)	(0.000)	(0.000)
)	1,227	2,546	517	319
	YES	YES	YES	YES

Table 3. 9 Model of members' decision with prior 6-month loss control

Table 3.9 includes a dummy variable to control for the members' prior returns received. The dummy variable is equal to 1 if the member had a negative return over the 6-months prior to their decision to change strategy, and 0 if otherwise. *** indicates significance at the 1% level, ** 5% and * 10%

	1st Choice Less Risky	2nd Choice	1st Choice Riskier	2nd Choice Less Risky	2nd Choice Riskier
Equation number	1	2	3	4	5
Gender	1.029	1.000	1.191***	0.890	1.172
	(0.528)	(0.993)	(0.000)	(0.251)	(0.188)
Age 2000s	8.458***	0.339***	5.469***	0.384**	0.430**
	(0.000)	(0.000)	(0.000)	(0.038)	(0.012)
Age 1990s	3.761***	0.366***	2.010***	0.281***	0.390***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
Age 1980s	2.392***	0.329***	1.621***	0.252***	0.378***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Age 1970s	1.408***	0.362***	1.477***	0.264***	0.333***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age 1960s	0.993	0.534***	1.137*	0.315***	0.482**
	(0.915)	(0.000)	(0.095)	(0.000)	(0.012)
VIX	1.022***	1.037***	1.055***	1.017***	1.047*
	(0.000)	(0.000)	(0.000)	(0.007)	(0.056)
All Ords Return	0.475	5.544*	0.028***	9.779	0.129
	(0.249)	(0.088)	(0.000)	(0.170)	(0.574)
GFC	1.655***	0.475***	0.693***	0.489***	1.020
	(0.010)	(0.000)	(0.000)	(0.004)	(0.980)
Dotcom	0.772***	3.374***	0.413***	1.886***	3.057***
	(0.000)	(0.000)	(0.000)	(0.009)	(0.000)
Prior 6-month negative	2.604***	0.782***	1.162***	1.265	0.577***
	(0.000)	(0.008)	(0.010)	(0.335)	(0.000)
Constant	0.004***	0.021***	0.004***	0.042***	0.025***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	2,140	1,227	2,546	517	319

3.5 Time to Retirement

A possible explanation for the differences in the time to change investment option, both to a riskier or less risky strategy could be one's time until retirement. As members approach the retirement age, the factors that influence their decision-making might differ. The stimuli members observe may have a differing effect depending on their proximity to retirement. For example, a member in their twenties with over forty years until retirement may be influenced by market movements and expected volatility differently from those who are within five years of retirement. As stated earlier, the dependent variable in this analysis is the time spent in a strategy, as such, I am unable to include the time until retirement as a control variable due to it being strongly correlated with the dependent variable. As a result, I create dummy variables to represent the years until a member reaches the retirement age. The dummy variable will be equal to 1 if the member is that many years away from the retirement age and 0 if otherwise. For example, a member aged 45 would have 22 years until they reach the retirement age (67), as such, the dummy variable for the variable 22 years would be equal to 1 and 0 zero if otherwise. I also exclude the decade of birth dummy variables from this robustness analysis to avoid correlated independent variables. Table 3.8 mirrors Table 3.7 and presents the results of the survival functions for the first decision of those that chose to move to a less risky or riskier strategy with time to retirement controls.

Examining the first choice, the use of dummy variables for years to retirement leaves the results substantially unchanged. The results are consistent when looking at members' first change of strategy, regardless of whether they are moving into a riskier or less risky strategy I see the same effects, as shown by equations 1 and 3. However, when looking at members' second investment option change, I see that there are some differences. For example, equation 2 I see the All Ords return variable is no longer significant. When looking at the All Ords 6-month variable I see that the effect is now reversed but is statistically significant. In Table 3.7 the All Ords 6-month variable with 0.02 and significant at the 1% level, showing that when the All Ords return 6 months prior to a decision being made is positive, members are slower to change into their second choice investment option. When I include the time to retirement control, this effect is reversed. This would suggest that for those members that do make a second change to their investment option, their proximity to retirement does play a role in the time they spend in a strategy. The inclusion of time to retirement controls shows that for members' first choice, the inferences are unchanged. In some instances, particularly when looking at members' second choice they do change. Overall however, the finding that members are perceiving patterns and acting accordingly, remains consistent.

3.6 Prior Period Loss

Another possible explanation for a member's decision to change strategy could be the gains or losses their chosen investment option (or options) experienced in the period prior to the decision. For example, a member who receives negative returns in their current strategy may see this as a reason to change investment option to either a less risky or riskier strategy. I account for this by including a control variable for a negative return in the 6-month period prior to the decision to switch. That is, if a member's investment option has a negative return in the 6 months before the member changes their investment option, the variable will be equal to 1, and 0, if otherwise.[15] The prior 6-month negative variable captures the cumulative returns a member received over the 6-month period from their chosen option. For members invested in more than one investment option, returns were calculated by using the portion of funds allocated to each option as portfolio weights.

Table 3.9 shows the results of the Gompertz proportional hazard model with the control for prior period losses. When including the additional control variable the inferences I make on the basis of this analysis remain unchanged from those in Table 3.7. I note that the prior 6-month negative dummy variable has differing effects on members' first and second decisions. The hazard ratios for the first choice less risky and first choice riskier are 2.604 and 1.162 respectively, and both significant at the 1% level. When making the first decision to change investment option a negative return in the prior 6-months increases the likelihood of a decision being made. The effect is stronger when the members' first choice is to a less risky strategy, suggesting more

[15] The prior 6-month negative variable differs from the All Ords 6-month variable by using the cumulative returns the member receives from their investment option 6-months prior their decision to change option. The All Ords 6-month variable uses return of the All Ords 6-months prior to the member's decision to change option.

risk averse members may seek to reduce their risk more quickly, when experiencing negative returns, compared to less risk averse members. The response of members to a prior loss is consistent with Kahneman and Tversky (1979), the effects of a loss in the prior 6-month has a greater effect than a gain in the previous period. Furthermore, the results here are reminiscent of the VIX findings, where members appear to have two contrasting responses to the same stimuli. When experiencing negative returns one group chooses to reduce risk, the other chooses to increase risk.

When looking at the second decision I see the opposite effect for equations 2 and 5. Significant hazard ratios less than 1 (0.782 & 0.577) showing that when members experience negative returns the time to make a second decision is increased. Results for equation 4 are not significant. When I include the prior 6-month negative variable in this survival analysis I find that the stimuli influencing a member's first and second investment option decisions remains unchanged.

Table 3. 10 Own benchmark summary statistics, Shapiro Wilk & Wilcoxon test
Table 3.10 presents the summary statistics, Shapiro-Wilk tests of the null-hypothesis that the data conform to a normal distribution and Wilcoxon signed-ranktests for the investors' performance – their own benchmark. Results are presented in decimal form.

Summary Statistics				**Shapiro Wilk test**		**Wilcoxon signed-rank test**		
	Mean	Median	Stdev	Observations	z-score	Positive	Negative	z-score
2 year								
Less risky	-0.0097	-0.0099	0.0821	1,864	9.3330***	790	1,074	-6.051***
Riskier	0.1027	0.0066	0.0610	1,662	10.014***	1,009	653	7.838***
5 year								
Less risky	-0.0452	-0.0345	0.1661	1,418	9.7220***	437	981	-12.826***
Riskier	0.0245	-0.0025	0.1120	1,016	11.929***	495	521	3.737***
10 year								
Less risky	-0.0530	-0.0291	0.1680	1,066	10.325***	366	700	-11.205***
Riskier	0.0409	-0.0148	0.1960	682	9.1330***	294	388	1.663*

3.7 Investor Performance Against Their Own Benchmark

Do the decisions I have modelled in the previous section matter? In other words, do the investors benefit from the changes they made. The data allows me to address this question quite readily. I can observe the returns they received and compare these returns with what they would have received had they done nothing. In effect, I can use each investor as their own benchmark. As stated earlier, I am interested in observing whether the decision to move into a riskier or less risky strategy is moving members closer or further away from the required savings balance, through the returns received as a result of this decision. An investor's own benchmark is calculated by subtracting the returns that would have been received if no change in investment was made, from the actual returns received. For example, an investor in fund A switches to fund B, I calculate the cumulative returns they received by being in fund B and compare it with the cumulative returns they would have received if they had stayed in fund A.[16] In the event of a fund option being discontinued, members within that fund are transferred to another investment option. This change in strategy is treated as a continuation and is not included as a change in the analysis.

I present the results in Table 3.10 and comparisons are made at 2 year, 5 year and 10 year intervals post the decision to switch. I see that investors choosing more risk have positive "own benchmarks". In contrast, investors choosing less risk have negative "own benchmarks". Table 3.10 presents the summary statistics, Shapiro-Wilk and Wilcoxon signed-ranks test for the own benchmark, showing the results at 2 years, 5 years and 10 years after the decision to switch.

Column 5 of Table 3.10 displays the results of the Shapiro-Wilk test which is used to test if the sample conforms to a normal distribution (Shapiro and Wilk, 1965). In each case, I find that I can reject the null hypothesis the data conforms to a normal distribution. As such, I use the non-parametric Wilcoxon signed rank test to consider

[16] In other words the $Own\ Benchmark$ is equal to the cumulative returns of the fund they switched into (Fund B), minus the cumulative returns of the fund they switched out off (Fund A). Therefore, Own Benchmark = $Fund\ B\ cumulative\ returns - Fund\ A\ cumulative$ returns

if investors are better or worse off (that is, whether they have positive or negative own-benchmarks).

In all three time horizons I examine (2, 5 and 10 years), I find that investors are more likely to underperform their own benchmark after choosing a less risky strategy. In other words, they are worse off by changing strategies. Using the five-year horizon to illustrate this, I see that 437 investors have a positive own-benchmark result (that is, are better off); 981 have a negative own benchmark (are worse off). The Wilcoxon test indicates that this difference is statistically significant.

In contrast, I find that a higher proportion of members that changed into a riskier fund have a positive own benchmark. On average, investors are better off by taking on more risk. Using the five-year horizon to illustrate this, I see that 521 investors have a positive own-benchmark result and 495 have a negative own benchmark. The Wilcoxon test indicates that this difference is statistically significant. Figures 3.6 & 3.7 depict the distribution of the 5 year less risky and riskier own benchmark changes. Figure 3.6 clearly shows that the majority of own-benchmark outcomes are negative for those choosing less risky portfolios and, for those choosing riskier portfolios, Figure 3.7 shows the opposite.

A consideration should be given to the fact that I only observe members' behaviour within their superannuation accounts. As a result, I do not observe their entire portfolio and therefore cannot state whether their choice to move to a riskier or less risky strategy is optimal. Instead, I seek to answer whether their choice is moving them closer to or further away from the balance needed to fund their retirement lifestyle. The results show that a greater proportion of the members that elect to move into a riskier strategy and benefiting from this decision, as opposed to those moving to a less risky strategy.

Figure 3.6 Distribution of own benchmark returns for less risky choices
Figure 3.6 displays the distribution of Own-Benchmark returns for members that chose to move into a less risky investment option five years after the decision to switch.

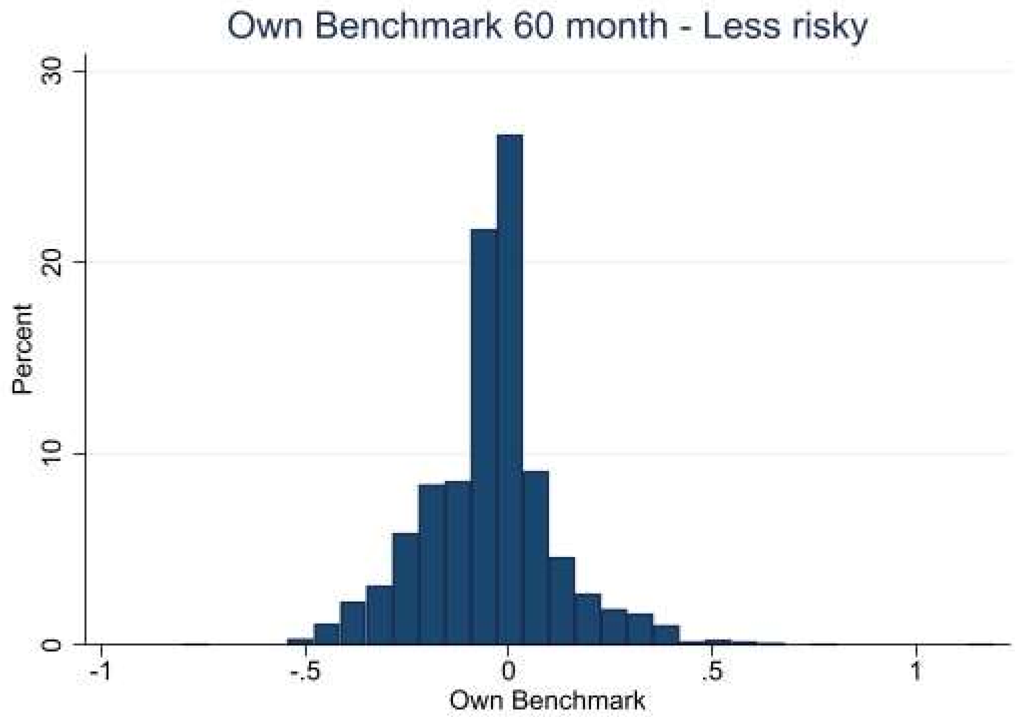
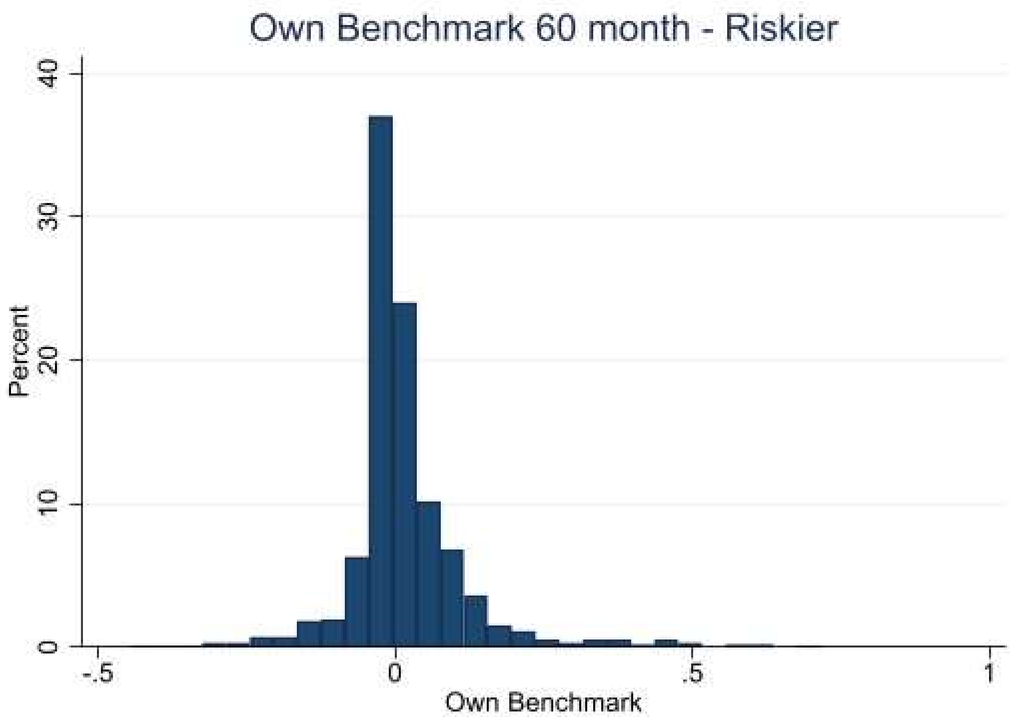


Figure 3.7 Distribution of own benchmark returns for riskier choices
Figure 3.7 displays the distribution of Own-Benchmark returns for members that chose to move into a riskier investment option five years after the decision to switch.



3.8 Conclusion

This chapter has been motivated by the growing concerns about the adequacy of Australia's retirement savings system (Super) which began in 1992. The study has been made possible through access to a unique dataset from a major Australian fund which allowed the analysis of data for over 32,000 members for a period beginning soon after super began (in July 1994).

I provide evidence of behaviour which suggests that Australian investors succumb to behavioural biases which appear contrary to their best interests. Investors exhibit two contrasting responses to increased volatility, either reduce risk or increase risk. I find contrarian behaviour consistent with behaviour documented for households in Finland (Grinblatt and Keloharju, 2000). Contrarian behaviour is consistent with investors perceiving patterns (which do not exist in informationally efficient markets). I also find behaviour consistent with investors perceiving patterns when I consider longer run past returns; this is consistent with the reliance on heuristics such as representativeness or the recency bias. I also find different age cohorts display different decision-making “cultures” (thinking about culture as a set of learned behaviours), but all age groups display a bias towards choosing a less risky strategy than a riskier strategy.

When I consider if investors are better off after making a decision to change, I find that those taking on more risk have higher returns and that those choosing less risk have lower returns. Overall, this analysis suggests that investors gravitate to a lower risk strategy (hence, lower expected returns). Given the longevity of investors’ time in super, a long run lower-risk and lower-returns profile would be consistent with lower than desirable savings balances when entering retirement.

The findings have implications for investors’ well-being in retirement, their investment advisors, fund managers and policy makers. Given that the adequacy of retirement savings is of concern in many countries, the findings in this chapter will be of interest outside of Australia. Other than saving more tomorrow, the “risk less tomorrow” strategy suggests that it may be possible to develop super products which nudge investors towards positive behaviour. Awareness of investor behaviour might help advisors and fund managers when dealing with investors.

Chapter 4 The Retirement Decisions

4.1 Introduction

This chapter looks to evaluate the factors that influence member decision-making around the time of retirement. Specifically, I look to assess how retirement savings are invested, and whether the portfolio members allocate their wealth towards change as they commence retirement.

The superannuation system was introduced to provide Australians with an effective way of saving for their retirement, with the goal that people would be able to fully (or partially) finance their retirement. Superannuation is a form of mandatory retirement savings, which has been shown to reduce procrastination, a common issue for retirement savings (Larsen and Munk 2023). As stated in chapter 1, members accumulate savings in their superannuation accounts through contributions[17], which are then invested on the members' behalf. Super funds provide members with a range of investment options, designed to cover different asset classes and risk profiles. Members have the freedom to invest their wealth across one or more of the available options.

Each super fund will have a different number of investment options for members to choose from. Huberman and Jiang (2006) show that people opting to use more than one fund typically spread their wealth evenly across them and that the number of options available does not influence an investor's propensity to allocate their wealth across funds. Typically, over a person's working life, their superannuation balance would grow through contributions, and the investment returns generated by their chosen investment option (or options). This occurs in the accumulation phase, members make contributions and grow their retirement balance without being able to withdraw any funds.[18] By changing from the accumulation phase into the pension phase, members can begin to withdraw funds. Once in pension, members have effectively started their retirement. While they are no longer able to further contribute

[17] Contributions are either concessional or non-concessional. Concessional contributions are pre-tax and include the employer mandated contributions. Non-concessional and made using after-tax income.
[18] There are some scenarios where members can gain access to their superannuation savings if they are experiencing financial hardship.

to their balance, once in pension, members can begin to withdraw their retirement savings with few restrictions. Members can withdraw up to 100% of their balance as a lump sum payment or as a retirement income stream drawing regular payments.[19] There is no maximum limit on withdrawals, however, there is a minimum annual drawdown percentage that members must adhere to.[20] The minimum drawdown is based on the members' age, and gradually increases as members' age. Appendix A shows a breakdown of the current minimum drawdown rates. Minimum drawdown rates are enforced to ensure members are using the superannuation pension system as it was intended, and not as a vessel for storing inheritance. Members are only able to access their super (by switching to the pension phase) once they reach the preservation age; the youngest age you can start to draw down from your super account. A member's preservation age is dependent on their date of birth for members born after 1 July 1964 the preservation age is 60, see Appendix B for the full list. Members that opt to draw down on their retirement savings through the pension phase can still invest their funds into one of the options offered by their chosen super fund. When they choose to draw down, members' portfolios are liquidated with equal proportion to finance the withdrawal.[21] For example, a member 70% invested in the balanced option and 30% invested in the growth option would have a portion of their portfolio liquidated to finance their pension withdrawal. 70% of the withdrawal would be financed by liquating the balanced option, the remaining 30% would come from the growth option. This would occur in line with the frequency a member is receiving a pension payment (i.e. weekly, monthly). This allows members to still receive returns while beginning to withdraw money from their super fund.

In this chapter, I am looking to examine factors that influence the level of portfolio risk superannuation members take on around the time of retirement. When looking at previous literature, it can be seen that risk tolerance influences savings and wealth accumulation. Bernheim, Skinner, and Weinberg (2001) find that when controlling for socioeconomic factors, there is still substantial heterogeneity in savings and wealth. They attribute this disparity to differences in risk tolerance. Furthermore, it has been shown that an individual's level of risk aversion plays a considerable role in portfolio

[19] For example, members can elect weekly, fortnightly, monthly or any combination of these.
[20] Drawdown rates start at 3% per annum and gradually increase until a maximum of 14% per annum.
[21] By default the investment option(s) a member is invested in are liquidated according to the investment option weightings but members can opt to specify the order their funds will be sold down.

choice composition (Frijns, Koellen, and Lehnert 2008). Within retirement savings schemes, members' approach to asset allocation, specifically equities, tends to be all or nothing (Agnew, Balduzzi, and Sundén 2003). Additionally, as couples age they reduce their allocation to stocks, and substantially reduce equity holdings after retirement (Addoum 2017; Fagereng, Gottlieb, and Guiso 2017). These findings are consistent with the literature on age and risk aversion, typically age is associated with higher levels of risk aversion, see for example Blanchett, Finke, and Guillemette (2018); Chris Brooks et al. (2018); Irandoust (2017); Malmendier and Nagel (2011); Morin and Suarez (1983). Merton (1980) shows the positive relationship between risk and return, a central tenet of finance. As members approach retirement, they reduce their risk, and therefore their expected return. However, as previously stated as members age the minimum rate they must withdraw from their super accounts increases, and lower expected returns (from lower expected risk portfolios) could hasten the depletion of retirement savings.

The unique dataset used in this chapter comes from one of Australia's largest superannuation funds and contains the portfolio choices of over 600,000 members. When looking at the members that commence retirement within the observation period, I find results that are consistent with prior literature. I use 4 different proxies for the expected risk of a portfolio: beta, a measure of systematic risk; standard deviation, a measure of total risk; the proportion of international shares in a member's portfolio; and the proportion of cash in a member's portfolio. For each dependent variable I run three regression models, the quarter before, the quarter of, and the quarter after commencing retirement, to examine how portfolio risk and factors that influence portfolio risk change with retirement. The explanatory variables included in the analysis include gender, age, total superannuation balance, financial advice status and median house price by postcode. Running these models I find evidence of members displaying increased risk aversion with age, and male members taking on higher levels of expected risk, before, during and post the decision to commence retirement, a finding that is consistent with Blanchett, Finke, and Guillemette (2018); Chris Brooks et al. (2018); Morin and Suarez (1983); Schurer (2015), and Almenberg and Dreber (2015); Barber and Odean (2001); C. Brooks et al. (2019); Charness and Gneezy (2012). The disparity between males and females could be explained by collective household decision making where couples make decisions together rather than as two individuals. However, this is not something I am able to test with the current dataset. Additionally, members seeking financial advice tend to hold lower-risk portfolios, which could be because of better diversification (and therefore lower idiosyncratic risk), or, through lower systematic risk, the results are reminiscent of Kramer (2012). Higher retirement savings balances are associated with lower risk portfolios immediately before retirement, and higher risk portfolios once retirement has commenced. The differing effect could be attributed to the selection of a retirement savings strategy, or, apprehension in the lead-up to commencing retirement. Furthermore, I see members' displaying behaviour which I liken to gambling with the house money where their portfolio choices are being influenced by increases in house prices in a prior period. A rise in the median house price over the previous 3 months is associated with a higher-risk portfolio. Lastly, a higher median house price has a positive relationship with expected portfolio risk. This is important as it shows how members' retirement portfolio allocations can be influenced by unrealised gains in property value.

The result of this chapter will be structured as follows: section 2 will outline the data used in this analysis; section 3 will examine retirement balances and retirement income guidelines; section 4 will overview the empirical methodology used in this chapter; section 5 will discuss the results of the linear regression model; and lastly, section 6 will conclude the chapter.

4.2 Data and key variables

4.2.1 Data

The unique dataset used came from a large Australian superannuation fund (different to that of chapter 2 & 3) and contained quarterly information regarding the choices that over 600,000 members made within the super fund from 2020 Q1 to 2023 Q2. There are several differences between the dataset used in chapter 4 with the dataset used in chapter 2 & 3. Firstly, this dataset contains quarterly information, as opposed to monthly, and it only contains 2.5 years of data, compared to nearly 25 years. This resulted in some of the explanatory variables included in chapter 2 & 3 becoming unsuitable for this analysis. For example, variables relating to the state of the market

(All Ords return, All Ords 12 month and VIX), were unable to be included due to the limited time series of this dataset, the quarterly returns, or quarterly volatility included very little variation.[22]

The focus of this analysis is at the point members decide to retire, importantly, the data contains information regarding their retirement status. That is, whether they were in the accumulation phase (not yet retired), or, the pension phase (retired). I observed members commencing their retirement when their status changed from accumulation to pension; as stated previously, this is when members can start drawing a pension from their retirement savings. The data also contained the total retirement balance of each member and included a breakdown of how the balance was allocated across each of the investment options available to members. As previously mentioned, superannuation members have the freedom to allocate their retirement savings to any of the investment options offered; they can also choose to invest a proportion of their wealth across several strategies. If a member changed their investment option allocation, then this information would be captured in the next quarterly observation. Furthermore, the quarterly returns of each investment option were captured. Appendix F shows a list of the investment options with the asset allocation breakdown. In addition to their investment information, the data contained demographic information such as age, gender and postcode, along with the date they joined the super fund and whether or not they were receiving advice from a financial advisor. Lastly, as the unique dataset contained the members' postcode, I was able to include the median house price in the analysis. The house price data is from CoreLogic[23], which provides the monthly median house price of each suburb across Australia.

4.2.2 Key variables

The analysis of this chapter focuses on examining the wealth allocation decisions made by individuals and the variations in portfolio risk preferences during three key periods: one quarter before the decision to initiate retirement, the actual retirement quarter, and the quarter after retirement initiation. To effectively account for portfolio risk, a proxy was necessary, and, in alignment with chapter 2, beta was employed as the dependent

[22] In total there was only 10 different quarterly values for the All Ords return, All Ords 12 month & VIX, for almost 20,000 retiring members.
[23] CoreLogic is the largest custodian of Australian property data: https://www.corelogic.com.au/

variable and proxy for expected risk. Following on from Gray and Zhong (2022), who conclude that the market risk premium (Rm – Rf) is the primary influencing factor in Australia. Furthermore, Barber, Odean, and Zheng (2005) demonstrate that in the US, beta is the only factor perceived by investors. As such, this makes beta a suitable proxy for expected portfolio risk for this analysis.

Beta is constructed for each member by regressing the monthly returns of the investment option they have selected with the All Ords Accumulation Index for 60 months before the decision to retire. For members that have allocated a portion of their wealth across multiple investment options, the weighting of each investment option is multiplied by the respective beta and summed up to determine portfolio beta, as shown by equation (1).

$$\beta = \sum_{n=1}^{N} w_i * \beta_i \,, 0 \le w_i \le 1 \sum_{n=1}^{N} w_i = 1 \qquad (1)$$

The weight invested into each investment option is represented by w_i, with r_i representing the return of investment option i. In addition to using beta as the proxy for expected risk of the portfolio, three other measures are also used to ensure robust findings: standard deviation, the proportion of international shares and the proportion of cash, each representing a potential dimension of portfolio risk. The standard deviation variable represents the standard deviation of the members' portfolio returns. The proportion of international shares and the proportion of cash variables represent the total portfolio weighting to international shares and cash respectively. These were calculated by multiplying the proportion of wealth allocated to each investment option by the proportion of international shares or cash of the respective investment options. For beta, standard deviation and the proportion of international shares, all things being equal, the higher the value the higher the expected risk of the portfolio. The proportion of cash, all things being equal, has an inverse relationship with expected portfolio risk, the higher the proportion of cash, the lower the expected risk of the portfolio. As such a negative relationship with beta, standard deviation and the proportion of international shares, and a positive relationship with the proportion of cash, shows the same relationship to risk aversion.

Chapters 2 & 3 showed how demographic factors and external stimuli can affect member decision making. In this chapter, I seek to observe how these influences impact portfolio risk around the time of retirement. As such, the following explanatory variables were included in the analysis: identified gender, age, total balance, advice status, property increase and median house price.

Gender was included as a dummy variable, taking the value of 1 if the member was male and 0 if otherwise. When looking at the literature on gender and risk aversion it can be seen that men typically display lower (higher) levels of risk aversion (tolerance). For example, Charness and Gneezy (2012); Barber and Odean (2001) both find that men trade more than women and attribute this result to men being more risk-tolerant. C. Brooks et al. (2019) also show men being more risk tolerant, and also provide evidence that previous investment experience plays a substantial role in explaining the differences between men and women. Furthermore, within retirement savings schemes the differences in risk preferences between males and females could potentially be explained by collective household decision-making, whereby couples form portfolios as a pair, rather than as two individuals (Addoum 2017). This is not something I am able to directly observe but it could be an explanation for potential findings.

Again, following on from chapters 2 & 3 age is include in the analysis to examine its influence on the levels of portfolio risk around the time of retirement. Previous research has shown that as people age, their level of risk aversion increases (Blanchett, Finke, and Guillemette 2018; Chris Brooks et al. 2018; Irandoust 2017; Morin and Suarez 1983; Schurer 2015). Due to the preservation age,[24] the age in which I capture members retiring is largely the same. To include age in the analysis without having little variation I standardised the variable, as shown by equation (2). Where X is the age of the member, μ is the mean of age and σ is the standard deviation of age.

$$Z = \frac{(X - \mu)}{\sigma} \qquad (2)$$

As stated previously, the data captures members' total superannuation balances through time, to reduce the skewness, total balance is first log transformed before

[24] As discussed earlier, the preservation age is the age members can begin to access their superannuation savings.

being included in the analysis. Total retirement balance is used as a proxy for level of wealth, although I do not observe any assets members hold outside of their superannuation account, a higher superannuation balance still equates to higher wealth. Furthermore, as previously stated, members receive SG contributions which are a percentage of their income paid into their superannuation accounts by their employer, making total balance a suitable representation. Previous research has shown a negative relationship between level of wealth and risk aversion, as wealth increases, risk aversion decreases (Calvet and Sodini 2014; Friend and Blume 1975). Based on prior literature, I would expect to see a higher total balance being associated with a higher beta portfolio around the time of retirement.

Furthermore, the dataset contained information on whether the member was receiving financial advice during each quarter. The role of a financial advisor includes advising on investments, retirement savings, insurance products and savings habits. The level of advice a member is receiving could vary from general advice on their superannuation to comprehensive advice on all areas of their personal finances. In this analysis advice status was included as a dummy variable to capture whether or not receiving advice had a substantial impact on the level of portfolios risk of retiring members. The literature on financial advice shows that financial advisors have a substantial impact on the portfolios of their clients (Foerster et al. 2017). However, prior research is mixed on whether receiving financial advice leads to better diversified portfolios. Linnainmaa, Melzer, and Previtero (2021) show that financial advisors change returns and under diversify their clients' portfolios, while Kramer (2012) shows that investors receiving financial advice have better diversification. See also Baulkaran and Jain (2024); Durand, Newby, and Sanghani (2008).[25] By including a dummy variable in the analysis I will be able to capture how financial advice effects expected portfolio risk around retirement.

As the data include the members' postcode at the time of retirement, I included two variables to examine the impact of house prices on retirement portfolio risk. As a single

[25] Baulkaran and Jain (2024) study the behavioural biases of financial planners. They find evidence that financial planners succum to behavioural biases, and, that these biases influence their recommendations concerning retirement income. Durand, Newby, and Sanghani (2008) study the personality traits of invdidual investors. They find a positive and significant relationship between the propensity to seek financial advice and negative emotion.

postcode often contains multiple suburbs, and the data only contained the members' postcode, I used the median of the median suburbs house price, to capture the median house price of the postcode. For example, 6102 contains two suburbs, Bentley and Saint James, in this situation the median house price for 6102 would be the median of the two suburbs' median house prices. The first of the housing variables was the median house price of the postcode. Median house price was also log transformed to reduce the skewness before including it in the analysis. Lastly, property increase is a dummy variable that takes the value of 1 if there was an increase in the median house price of the members' postcode over the 3 months prior to time t, it takes the value of 0 if otherwise. Property increase has been included as a dummy variable, rather than as a return, due to the high amount heterogeneity in suburbs, and to provide an overview of the effect of property price increases. Existing literature on property prices and portfolio holdings has shown mixed results; Chetty, SÁNdor, and Szeidl (2017) show that increases in property value are associated with lower equity holdings, while Paravisini, Rappoport, and Ravina (2017) show a positive relationship between risk aversion and negative housing shocks.

Tables 4.1 & 4.2 shows the descriptive statistics for the explanatory and dependent variables. It can be seen that the average beta across all three time periods is 0.541. Table 4.2 shows that for each measure of expected portfolio risk (beta, standard deviation, proportion of international shares & proportion of cash) the average is highest in the quarter after retirement. Except for the proportion of cash, which is the lowest in the quarter after retirement. This could potentially be explained by members adopting a separate strategy for their asset allocation during retirement, to that of the asset allocation they had prior to retiring. Overall, the summary statistics show higher expected risk portfolios after a member has commenced retirement. Furthermore, through the observation period there were several increases to the cash rate, as set by the Reserve Bank of Australia. There appears to be a positive relationship between the cash rate and the average proportion of cash members hold in their portfolios around the time of their retirement, as shown by Figure 4.1. Members appear to increase the proportion of cash in their portfolios when interest rates increase.

Table 4.1 Overall summary statistics

Table 4.1 presents the summary statistics for the continuous explanatory variables, and the 4 measures of expected portfolio risk from 2021 – 2023. Age has been standardized, while total balance and median house price have been log transformed to reduce skewness. Beta, standard deviation, proportion of international shares and proportion of cash have all been winsorised at the 95% level. Results are presented in decimal form.

	Obs	Mean	Std. Dev.	Min	Max
Age_std	48,664	-0.061	1.006	-5.149	5.206
Log balance	48,664	11.886	2.407	-4.605	16.114
Median house price	48,664	13.741	0.505	11.767	15.917
Beta_win	48,664	0.541	0.218	0.218	0.845
Stdev_win	48,664	0.022	0.009	0.009	0.035
Intshares_win	48,664	0.287	0.128	0.07	0.571
Cash_win	48,664	0.348	0.171	0.00	0.663

Figure 4.1 Cash rate vs proportion of cash

This figure displays the relationship between the cash rate (as set by the Reserve Bank of Australia) and the average proportion of cash held by members in the dataset, through the observation period 2021 – 2023.

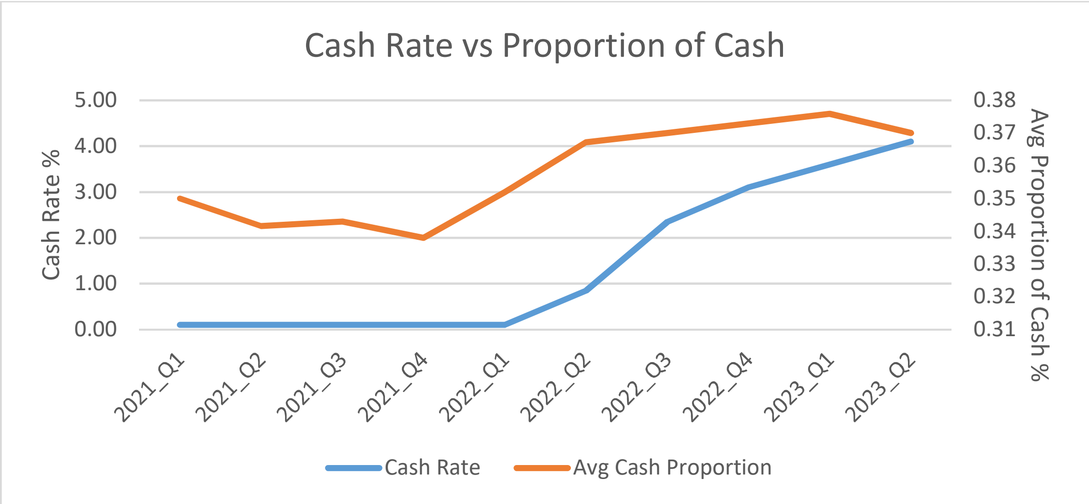


Table 4. 2 Summary statistics by retirement period

Table 4.2 presents the summary statistics for the continuous explanatory variables, and the 4 measures of expected portfolio risk, by retirement period from 2021 – 2023. Age has been standardized, while total balance and median house price have been log transformed to reduce skewness. Beta, standard deviation, proportion of international shares and proportion of cash have all been winsorised at the 95% level. Results are presented in decimal form.

Panel A. Quarter Prior Summary Statistics

	Obs	Mean	Std. Dev.	Min	Max
Age_std	17,784	-0.017	1.009	-4.967	5.206
Log balance	17,784	11.751	2.444	-4.605	15.556
Median house price	17,784	13.751	0.498	11.766	15.917
Beta_win	17,784	0.539	0.171	0.218	0.845
Stdev_win	17,784	0.021	0.007	0.009	0.035
Intshares_win	17,784	0.285	0.128	0.07	0.571
Cash_win	17,784	0.350	0.171	0.00	0.663

Panel B. Quarter Retire Summary Statistics

	Obs	Mean	Std. Dev.	Min	Max
Age_std	18,767	-0.048	1.003	-5.149	5.206
Log balance	18,767	12.997	0.955	8.274	14.874
Median house price	18,767	13.73	0.507	11.813	15.692
Beta_win	18,767	0.530	0.170	0.218	0.845
Stdev_win	18,767	0.021	0.007	0.009	0.035
Intshares_win	18,767	0.282	0.128	0.07	0.571
Cash_win	18,767	0.358	0.169	0.00	0.663

Panel C. Quarter Post Summary Statistics

	Obs	Mean	Std. Dev.	Min	Max
Age_std	12,113	-0.147	1.003	-5.149	4.479
Log balance	12,113	10.363	2.971	-4.605	16.014
Median house price	12,113	13.743	0.513	11.798	15.917
Beta_win	12,113	0.559	0.169	0.218	0.845
Stdev_win	12,113	0.022	0.006	0.009	0.035
Intshares_win	12,113	0.297	0.127	0.070	0.571
Cash_win	12,113	0.329	0.172	0.00	0.663

Table 4. 3 Correlation matrix

Table 4.3 presents the correlation matrix for the continuous explanatory variables, and the 4 measures of expected portfolio risk. Age has been standardized, while total balance and median house price have been log transformed to reduce skewness. Beta, standard deviation, proportion of international shares and proportion of cash have all been winsorised at the 95% level. Results are presented in decimal form.

Age_std	1.000						
Log balance	-0.053	1.000					
Median house price	0.134	0.057	1.000				
Beta_win	-0.046	-0.006	0.038	1.000			
Stdev_win	-0.057	0.027	0.048	0.906	1.000		
Intshares_win	-0.062	0.029	0.047	0.882	0.911	1.000	
Cash_win	0.040	0.008	-0.028	-0.973	-0.876	-0.867	1.000

Table 4. 4 Covariance matrix

Table 4.4 presents the covariance matrix for the continuous explanatory variables, and the 4 measures of expected portfolio risk. Age has been standardized, while total balance and median house price have been log transformed to reduce skewness. Beta, standard deviation, proportion of international shares and proportion of cash have all been winsorised at the 95% level. Results are presented in decimal form.

Age_std	1.000						
Log balance	-0.053	1.000					
Median house price	0.134	0.057	1.000				
Beta_win	-0.046	-0.006	0.038	1.000			
Stdev_win	-0.057	0.027	0.048	0.906	1.000		
Intshares_win	-0.062	0.029	0.047	0.882	0.911	1.000	
Cash_win	0.040	0.008	-0.028	-0.973	-0.876	-0.867	1.000

4.3 Drawdown benchmarks

Whether or not people have enough retirement savings to fully fund their retirement, is an area of concern for many Australians. To examine how retirement income guidelines work in practice, using average superannuation balances for males and females aged 60 to 64 and 3 separate portfolio returns, I model individuals drawing down on their retirement savings[26]. The findings highlight the retirement savings shortfall and the significant impact returns have on reducing the rate savings are depleted. As stated in chapter 1, individuals looking to live a "modest" lifestyle in retirement will need at least $32,417 in annual income, while individuals wanting to live a "comfortable" lifestyle, will need at least $50,981 in annual income. These figures assume that the individual owns their home (no mortgage or rent), and therefore have substantially lower expenses than in their working lives, where they may have had a mortgage. The world economic forum states that men will on average outlive their retirement savings by 10 years, and women by 12 years (World Economic Forum, 2019, p. 21), as stated in chapter 1. I Use the figures from the Association of Superannuation Funds Australia and the average superannuation balances for males and female just prior to reaching the retirement age (60-64), I model 4 scenarios with varying levels of returns to determine when retirement savings with run out, for males and females. The average balance for males and females aged 60 to 64 is $402,838 and $318,203 respectively (Australian Taxation Office, 2021), which I use as the starting point for this analysis.[27] These figures are similar to the average balances of members within my dataset, $409,219 and $483,007 for females and males respectively. I opt for the average figures across Australia to better fit the broader population of superannuation members.

---

[26] The data did not contain information pertaining to members' marital status, therefore I was unable to include this in the analysis.

[27] The median balances for males and females aged 60-64 is $211,996 and $159,806 respectively (Australian Taxation Office, 2021. Which suggests the average figures present a more optimistic view of retirement balances.

Figure 4.2 Modest drawdown female projections
This figure shows the modest drawdown projections for females. The starting balance used is the average superannuation balance of females aged 60 – 64 ($318,203). All three projections show a female drawing down quarterly, according to the modest guidelines, with three different returns applied. Modest avg ret refers to members receiving the average quarterly returns of the balanced investment option. Modest actual avg al ords refers to members receiving the average quarterly All Ords return, Modest 0.5 beta refers to members receiving the returns of a 0.5 beta portfolio.

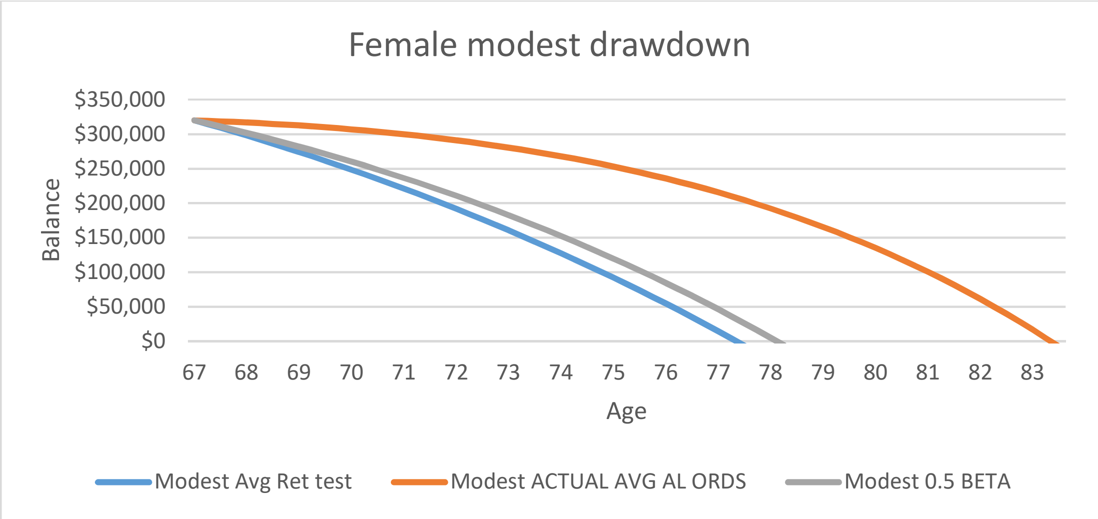
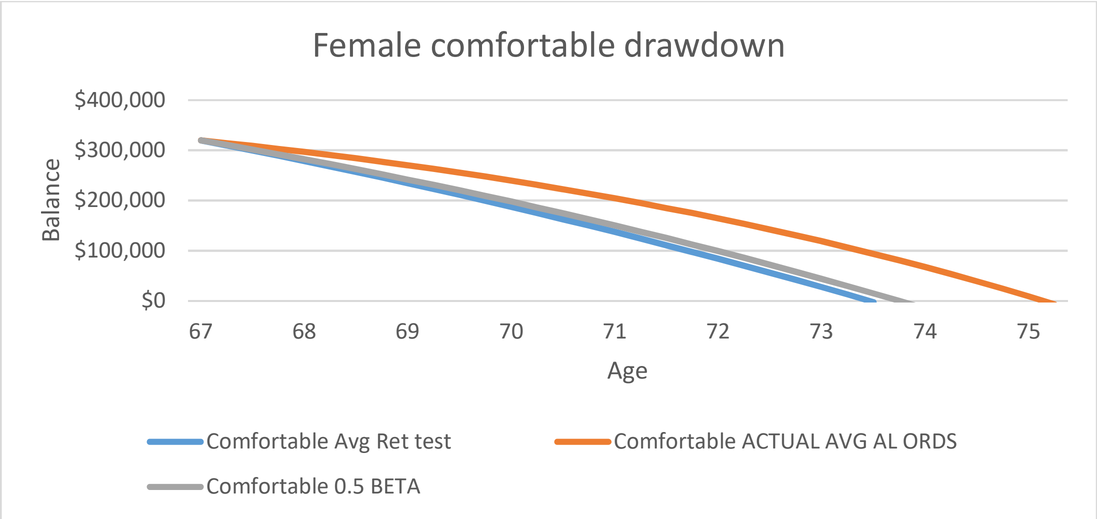


Figure 4.3 Comfortable drawdown female projections
This figure shows the comfortable drawdown projections for females. The starting balance used is the average superannuation balance of females aged 60 – 64 ($318,203). All three projections show a female drawing down quarterly, according to the comfortable guidelines, with three different returns applied. Comfortable avg ret refers to members receiving the average quarterly returns of the balanced investment option. Comfortable actual avg al ords refers to members receiving the average quarterly All Ords return, Comfortable 0.5 beta refers to members receiving the returns of a 0.5 beta portfolio.



I model 4 separate scenarios: a male with an average superannuation balance drawing down according to the modest guidelines; a male with an average superannuation balance drawing down according to the comfortable guidelines; a female with an average super balance drawing down according to the modest lifestyle guidelines; a female with an average super balance drawing down according to the comfortable lifestyle guidelines. Each scenario is based on a member retiring at age 67, and for each of these modelled scenarios I construct three portfolios: the average All Ords return[28]; the average returns members receive from the default investment option; and the returns of a portfolio with a beta of 0.5.[29] Each modelled scenario is run quarterly, at the end of each quarter, the respective portfolio returns are applied, and the quarterly retirement income is deducted. The retirement income guidelines present annual figures, to achieve the quarterly figures, the total annual figure is divided by 4.[30] In addition to this, the retirement income guidelines are increase by an inflation rate of 2.5%. According to the Reserve Bank of Australia, the price inflation target is between 2 and 3 percent.

Figure 4.2 presents the results of a female with an average balance ($318,203) drawing down $32,417 per annum, as per the modest lifestyle guidelines. I see that for females receiving the average All Ords returns, the average retirement savings balance lasts for approximately 16 years until the age of 83. For the 0.5 beta portfolio the average female drawing down according to the modest guidelines runs out of money at age 78, and for the default fund portfolio, savings run out around age 77. When looking at a female with an average balance drawing down according to the comfortable retirement lifestyle, as shown in Figure 4.3, I find they run out of retirement savings much sooner. For the All Ords portfolio, 0.5 beta portfolio and the default fund portfolio the age at which members run out is 75, 74 and 73 respectively. Assuming a retirement age of 67, this modelled scenario results in between 6 and 8 years of retirement income.

[28] The average All Ords return is average quarterly return of the All Ords accumulation index from 1994 – 2019.

[29] Table 1 & 2 show the average beta for members in the dataset is approximately 0.541.

[30] For example the total annual retirement income according to the modest lifestyle guidelines is $32,417, therefore the quarterly figure would be approximately $8,104.

Figure 4. 4 Modest drawdown male projections

This figure shows the modest drawdown projections for males. The starting balance used is the average superannuation balance of males aged 60 – 64 ($402,838). All three projections show a male drawing down quarterly, according to the modest guidelines, with three different returns applied. Modest avg ret refers to members receiving the average quarterly returns of the balanced investment option. Modest actual avg al ords refers to members receiving the average quarterly All Ords return, Modest 0.5 beta refers to members receiving the returns of a 0.5 beta portfolio.

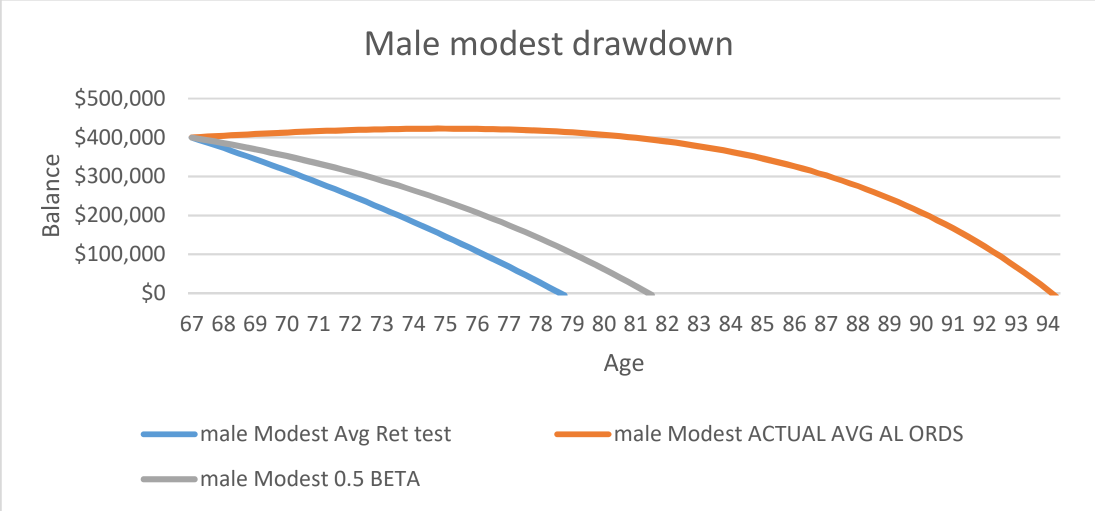
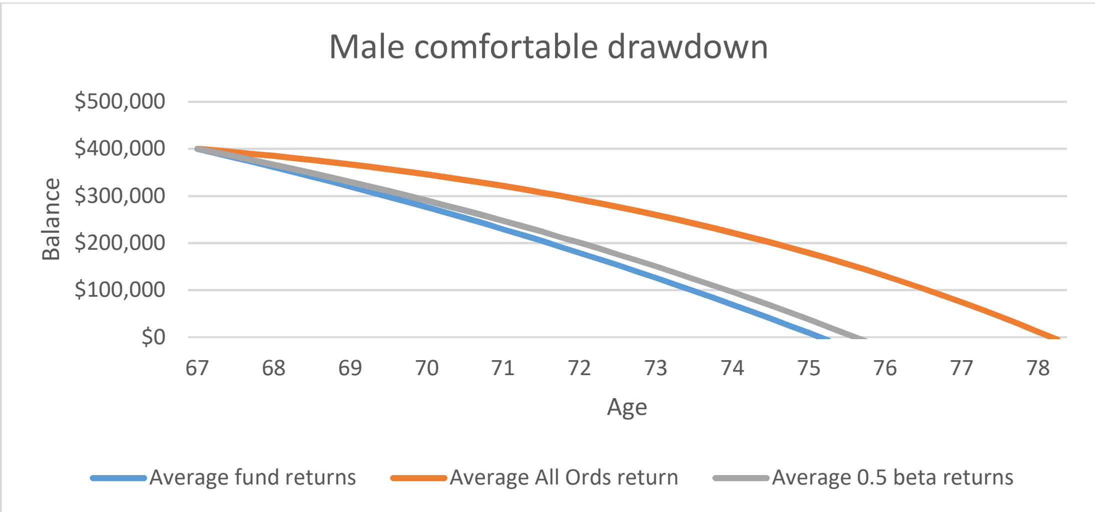


Figure 4. 5 Comfortable drawdown male projections

This figure shows the comfortable drawdown projections for males. The starting balance used is the average superannuation balance of males aged 60 – 64 ($402,838). All three projections show a male drawing down quarterly, according to the comfortable guidelines, with three different returns applied. Comfortable avg ret refers to members receiving the average quarterly returns of the balanced investment option. Comfortable actual avg al ords refers to members receiving the average quarterly All Ords return, Comfortable 0.5 beta refers to members receiving the returns of a 0.5 beta portfolio.



Males have on average a higher superannuation balance in the years before reaching the retirement age ($402,838). However, when looking at Figure 4.4 & Figure 4.5 a similar pattern emerges. When drawing down according to comfortable retirement guidelines, the average balance provides between 8 and 11 years of retirement. While a modest lifestyle can be funded by the average male superannuation balance for between 11 and 27 years. It should be noted that a "modest" lifestyle, as described by the Association of Superannuation Funds Australia only provides a standard of living which is just greater than the Age Pension.[31] Furthermore, it is important to remember that the modelling assumes no variation from the average returns and does not include any account fees, which may exist in practice. The average life expectancy for males in 81.3 years and 85.4 years for females (Australian Bureau of Statistics, 2021), based on the 4 scenarios modelled, only 2 portfolios provided enough retirement income to fully fund retirement until people die, assuming a retirement age of 67. Both of which require the member to drawdown at a rate which only allows for a modest level of living.

The findings highlight how high returns can substantially slow the rate at which savings deplete. Furthermore, using average balances and retirement income drawdown guidelines form the Association of Superannuation Funds Australia, there is a clear retirement savings shortfall. The average male or female is unlikely to be able to fully fund their retirement, and therefore, will need to rely on the aged pension.

4.4. Methodology

To explore how superannuation members allocate their wealth the quarter before, the quarter of and the quarter after retirement an appropriate empirical methodology is required. I run a regression model to examine the findings. The variables included in the regression model include: gender, age, financial advice status, total super balance, property increase and median house price. The model can be seen below:

$$y = \beta_0 + \beta_1 gender + \beta_2 age + \beta_3 advice + \beta_4 balance + \beta_5 propertyinc + \beta_6 medianprice + \varepsilon_i \quad (3)$$

[31] The full age pension rate for a single is $27,664 per annum (Services Australia, 2024). As such, the modest guidelines equate to less than $100 extra per week.

Where y represents the expected portfolio risk proxy (either beta, standard deviation, proportion of international shares or proportion of cash). Furthermore, to examine how the same group of explanatory variables influences a change in expected portfolio risk from pre-retirement to post retirement, I run another regression model where the dependent variable is the change in expected portfolio risk. For example, the dependent variable for the beta model would be the beta from the pre-retirement quarter – the beta from the post retirement quarter. This model can be seen below:

$$y_{i,t} - y_{i,t+1} = \beta_0 + \beta_1 gender_{i,t} + \beta_2 age_{i,t} + \beta_3 advice_{i,t} + \beta_4 balance_{i,t} + \beta_5 propertyinc_{i,t} + \beta_6 medianprice_{i,t} + \varepsilon_{i,t} \quad (4)$$

Where $y_{i,t}$ represents the pre-retirement measure of expected risk (beta, standard deviation, proportion of international shares or proportion of cash) and $y_{i,t+1}$ represents the post retirement measure of expected risk.

4.5. Results

I seek to examine how superannuation members investment their balances during pre and post retirement, and to examine how commencing retirement effects this allocation decision. Figure 4.6, Figure 4.7 and Figure 4.8 display the average asset of allocations of member in the quarter before, the quarter of and the quarter after commencing retirement. The average asset allocation of members was calculated by multiplying the proportion of the member's portfolio that was allocated to each investment option by the proportion of that investment option by each asset class. For example, a member that is 100% invested in the balanced option, would have an asset allocation equal to that of the balanced investment option. If they were 50% in balanced and 50% in cash, then their allocation would be a weighted combination of the two options asset allocations. As discussed in Chapter 2, Agnew et al. (2003) show that equity allocations are strongly bimodal, either 100% equity or 0% equity. Again I find results that are not consistent with Agnew et al. (2003), as can be seen in below. Interestingly, the average allocation to equities, both Australian and international shares increases after retirement (from 22.61% & 29.24% to 23.15% & 30.78% respectively. Consistent with this, the average proportion allocated to cash and fixed interest drops from pre-retirement to post retirement. On the surface it suggests that members opt for riskier asset allocations post commencing retirement. To further examine the portfolio allocations of retiring members I will discussion the results of each explanatory variable in the regression model, as presented in Table 4.6.

Figure 4. 6 Pre-retirement asset allocation
This figure shows the average asset allocation of members in the quarter before they commence retirement.

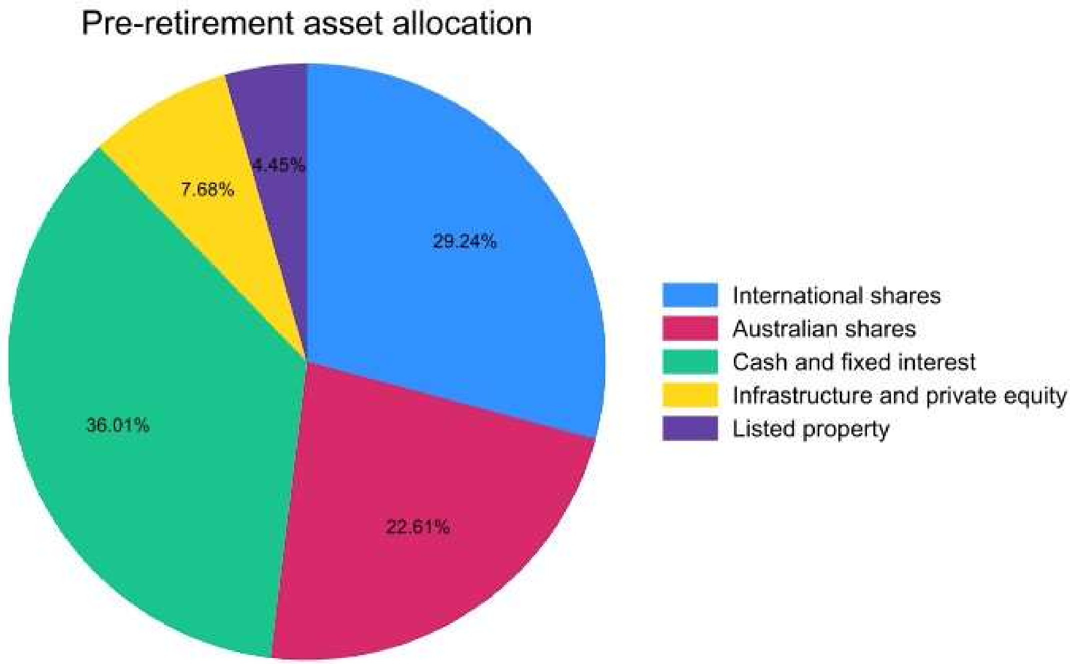


Figure 4. 7 Retirement asset allocation
This figure shows the average asset allocation of members in the quarter they commence retirement.

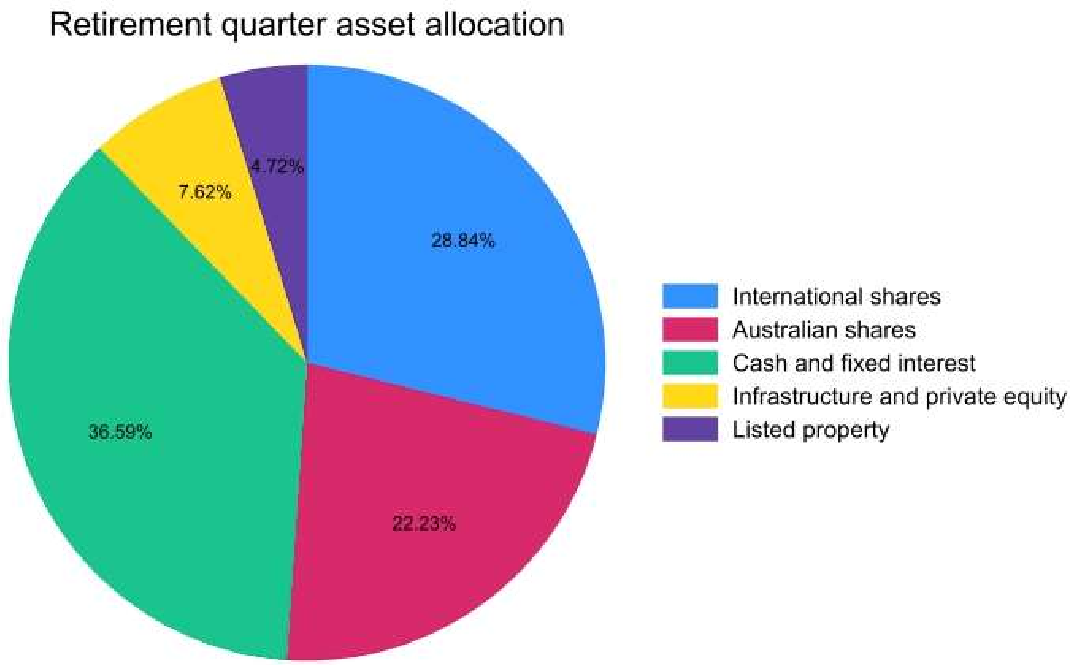


Figure 4. 8 Post retirement asset allocation
This figure shows the average asset allocation of members in the quarter after they commence retirement.

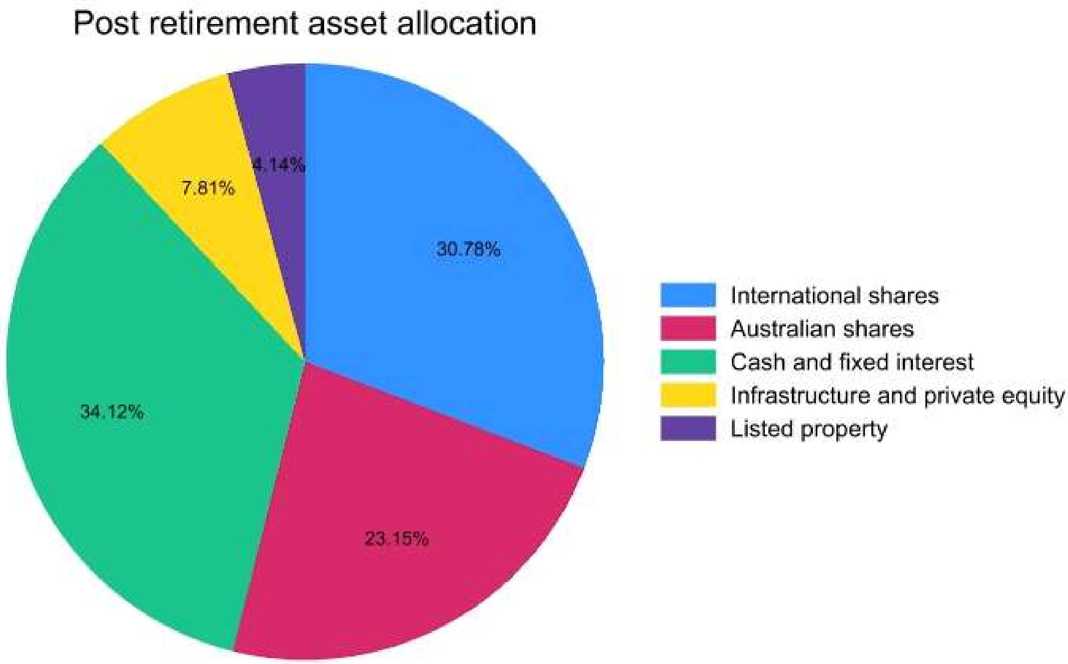


Table 4. 6 Bimodal equity allocations

Table 4.6 displays the bimodal equity allocations of members in the quarter before, the quarter of and the quarter after the decision to retire. Results are presented in %.

	Pre-retirement	Retirement	Post retirement
All equity	1.23	0.98	1.65
No equity	2.67	2.25	2.82

Table 4. 7. Regression model

Table 4.7 presents the results of the regression model for the three retirement periods. Panels A, B, C & D represent the models with dependent variables beta, standard deviation, proportion of international shares and proportion of cash respectively. Age has been standardized, while total balance and median house price have been log transformed to reduce skewness. Beta, standard deviation, proportion of international shares and proportion of cash have all been winsorised at the 95% level. Gender is a dummy variable taking the value of 1 if the member is male and 0 if otherwise. Property increase is a dummy variable taking the value of 1 if there was an increase in the median house price in the members' postcode over the previous quarter and 0 if otherwise. Coefficients and t-statics (in brackets) are displayed. ***, ** and * denote significance at the 1%, 5% and 10% level respectively.

	Pre-retirement	**Retirement**	**Post retirement**
Panel A - Beta	(1)	(2)	(3)
Gender	0.02487***	0.02604***	0.02077***
	(9.77900)	(10.53230)	(6.81009)
Age_std	-0.01131***	-0.00885***	-0.00809***
	(-8.89004)	(-7.13992)	(-5.23907)
Log balance	-0.00165***	0.00771***	0.00171***
	(-3.17890)	(5.90946)	(3.31875)
Advice	-0.05214***	-0.04554***	-0.04359***
	(-20.55502)	(-18.43665)	(-14.19036)
Property increase	0.00234	0.01792***	0.00100
	(0.79194)	(5.64514)	(0.22286)
Median house price	0.01573***	0.02115***	0.00338
	(6.10300)	(8.56415)	(1.12595)
Constant	0.35274***	0.13285***	0.50149***
	(9.80962)	(3.71184)	(11.98853)
Panel B – StDev	(1)	(2)	(3)
Gender	0.00090***	0.00089***	0.00088***
	(9.10815)	(9.09307)	(7.52753)
Age_std	-0.00048***	-0.00035***	-0.00041***
	(-9.65560)	(-7.11875)	(-6.82658)
Log balance	0.00003	0.00049***	0.00013***
	(1.43065)	(9.58460)	(6.55686)
Advice	-0.00117***	-0.00090***	-0.00102***
	(-11.87036)	(-9.27221)	(-8.63159)
Property increase	0.00040***	0.00109***	0.00030*
	(3.49367)	(8.68125)	(1.76652)
Median house price	0.00156	0.00092***	0.00031***
	(0.40351)	(9.41792)	(2.69970)
Constant	0.00469	0.00139	0.01610***
	(0.17613)	(0.98267)	(9.99262)

(Continued next page)

	Pre-retirement	**Retirement**	**Post retirement**
Panel C – Int Shares	(1)	(2)	(3)
Gender	0.01623***	0.01691***	0.01606***
	(8.49791)	(9.06489)	(6.97297)
Age_std	-0.01013***	-0.00786***	-0.00821***
	(-10.59754)	(-8.40740)	(-7.03816)
Log balance	0.00063	0.00965***	0.00272***
	(1.60682)	(9.79850)	(6.96092)
Advice	-0.02932***	-0.02521***	-0.02475***
	(-15.38890)	(-13.52977)	(-10.66772)
Property increase	0.00620***	0.01807***	0.00234
	(2.78851)	(7.54576)	(0.69164)
Log median house price	0.01594***	0.01785***	0.00563**
	(8.23446)	(9.58304)	(2.48102)
Constant	0.05991**	-0.10030***	0.19086***
	(2.21876)	(-3.71564)	(6.04065)
Panel D - Cash	(1)	(2)	(3)
Gender	-0.03015***	-0.03093***	-0.02734***
	(-11.20757)	(-12.01497)	(-8.18482)
Age_std	0.01057***	0.00731***	0.00809***
	(7.84966)	(5.65830)	(4.77794)
Log balance	0.00214***	-0.00531***	-0.00179***
	(3.90116)	(-3.90147)	(-3.15823)
Advice	0.06004***	0.05122***	0.04942***
	(22.37704)	(19.92013)	(14.69322)
Property increase	-0.00448	-0.02024***	-0.00427
	(-1.43093)	(-6.12740)	(-0.87336)
Log median house price	-0.01263***	-0.01770***	0.00053
	(-4.62926)	(-6.87938)	(0.16228)
Constant	0.48333***	0.67465***	0.33174***
	(12.70689)	(18.09904)	(7.24245)
Observations	17,784	18,767	12,113

4.5.1 Gender

Gender is included in the analysis as a dummy variable, taking the value of 1 if the member is male, and 0 if otherwise. As discussed earlier, based on prior research I would expect to find male members displaying lower levels of risk aversion, through higher measures of expected risk. I find consistent results across all models when examining the influence of gender on portfolio risk. When the dependent variable of the model is beta, standard deviation or the proportion of international shares, I observe positive and significant coefficients. For the proportion of cash, I see significant and negative coefficients. These results are consistent given the proportion of cash is used as a function of risk aversion (which is the other end of the risk spectrum to the aforementioned measures of risk tolerance). Furthermore, the findings are consistent with literature on gender differences in risk tolerance, I find males having a higher risk tolerance in the quarter before, during and just after their decision to retire. A result that is consistent with Almenberg and Dreber (2015); Barber and Odean (2001); C. Brooks et al. (2019); Charness and Gneezy (2012). Additionally, the coefficients are similar in size regardless of the time period. Using the models with beta as the dependent variable as an example, the coefficients are 0.02487, 0.02604 and 0.02077 for the quarter before the quarter of and the quarter after retirement respectively. This shows that the gender differences I observe likely do not change from pre to post retirement. A potential explanation for this could be collective household decision making, whereby husbands and wives make decisions as a couple, rather than as two individuals, optimising their collective portfolio. This would be consistent with Addoum (2017) who finds that the retirement of husbands and wives is followed by an increase and decrease in equity allocations respectively. Overall, these findings are of interest given Figures 4.2, 4.3, 4.4 & 4.5, which shows that members drawing down their pension from a lower risk portfolio tend to run out of retirement savings sooner. The magnitude of which is greater for women, given on average that have lower superannuation savings balances upon retirement.

4.5.2 Age

Given that the majority of people across Australia retire around the age of 65,[32] I first standardise age before including it in the analysis, as discussed above. The impact of

[32] For example, the average retirement age in Australia during 2020 was 64.3 (Australian Bureau of Statistics, 2021).

age is again, consistent across all models; negative and significant for models with a dependent variable measuring risk tolerance, and, positive and significant for models using the proportion of cash as the dependent variable. These findings are what I would expect, given the literature on gender and risk aversion. The results show that as people age, their risk tolerance declines, which is consistent with Blanchett, Finke, and Guillemette (2018); Chris Brooks et al. (2018); Morin and Suarez (1983); Schurer (2015). When I examine the coefficients, I find that the effect of age is strongest in the quarter before the decision to retire. Using beta as an example, I see a coefficient of -0.1131 in the quarter before retirement, compared to -0.00885 and -0.00809 in the quarter of and after retirement. The negative coefficient indicates that the older a member is the more they reduce their portfolio beta, with the effect being the strongest for the quarter prior to retirement. I see a similar pattern across models using standard deviation, the proportion of international shares and the proportion of cash as the dependent variable. The results suggest that age has the strongest effect on portfolio risk before a person decides to retire, and possibly commit to their chosen retirement strategy. Although, a longer time series is needed to further examine this finding. The results show that the impact of age on an individual's level of risk aversion is consistent with retirement portfolio allocations, as members approach retirement, and therefore age, their level of risk aversion increases.

4.5.3 Financial advice

As previously stated, members can receive guidance on investments, retirement savings, insurance products and even savings habits by seeking financial advice. The use of a financial advisor has a substantial impact on the portfolio individual investors choose to hold (Foerster et al. 2017; Kramer 2012; Linnainmaa, Melzer, and Previtero 2021). The dataset contains information concerning whether the member engaged the use of a financial adviser, as such, I included a dummy variable which is equal to 1 if the member received financial advice, and 0 if otherwise, to capture the effect of receiving financial advice. I find that members receiving advice, all things being equal, have lower risk portfolios in the quarter before, the quarter of and the quarter after commencing retirement. The results are negative and significant for models using beta, standard deviation and the proportion of international shares, and, positive and significant for the models using the proportion of cash. Furthermore, the size of the effect of receiving financial advice is consistent, regardless of whether it is the quarter before, during or after commencing retirement. The results are reminiscent of Kramer (2012), who found that people receiving financial advice hold portfolios with lower idiosyncratic risk, as a result of better diversification. I observe a negative relationship between the use of a financial advisor and total portfolio risk (as measured by standard deviation), however, I also observe a negative relationship between receiving financial advice and systematic risk (as measured by beta). Therefore I are unable to discern if the findings are entirely consistent as the reduced total risk may be caused by the reduced systematic risk. People engage financial advisors to help them navigate the vast array of retirement options and to develop a retirement strategy to maximise outcomes. I find that when people receive financial advice they opt for lower risk portfolios, a result that could be driven by better diversification, or simply lower systematic risk portfolios.

4.5.4 Retirement balance

When looking at the influence the retirement balance has on an individual's level of portfolio risk, I see that the effect changes depending whether the member has commenced retirement. I see a negative and significant coefficient for Table 4.6 Panel A column 1 (-0.00165) and positive and significant coefficients for columns 2 and 3 (0.00771 and 0.00171 respectively). This shows the differing effect total balance has on portfolio risk. In the quarter prior to retirement, total balance has an inverse relationship with portfolio risk, the higher the retirement savings balance prior to retirement, the lower the risk of the chosen portfolio. This effect is reversed once the member commences retirement, as shown by Panel A columns 2 and 3. Existing literature on the wealth effect shows that as wealth increases, investors allocate a great proportion of their portfolio towards risky assets (Calvet and Sodini 2014), and, higher wealth is associated with lower levels of risk aversion (Cohn et al. 1975). My findings indicate that prior to the decision to retire, a higher retirement savings balance is associated with less risk, in contrast to the existing literature. However, once a member commences retirement, this effect is reversed, higher wealth is associated with higher portfolio risk. This finding that is consistent with the wealth effect literature. I find that a members' retirement balance, a measure of their retirement wealth, has a differing effect on the riskiness of a members' portfolio. As previously stated, it should be noted that I am only able to observe the wealth members hold within their superannuation account, as I am unable to observe assets they may hold separately. However, a higher retirement balance still equates to higher total wealth, regardless of assets held outside of superannuation.

4.5.5 House prices

I include two variables in the analysis which allow me to capture the effect of house prices and changes in house prices on the riskiness of a member's portfolio. The median house price is included as a proxy for household wealth; property increase is a dummy variable taking the value of 1 if the median house price increased over the previous 3 months, or 0 if otherwise. When looking at property increase for the quarter when the member commences retirement, I see it is both positive and significant for beta, standard deviation and the proportion of international shares, while being negative and significant for the proportion of cash. I liken this effect to Thaler and Johnson (1990), who found that people increased the risks they were willing to take when they received a gain in a prior period. Members that receive a gain (an increase in the median house price) in the previous 3 months opt for a higher risk portfolio. The median house price appears to have a similar effect on portfolio risk, with positive and significant coefficients across beta, standard deviation and the proportion of international shares, for all observations points except the quarter after (beta) and the quarter prior (standard deviation). The results show that all things being equal, the higher the median house price, the higher the level of expected portfolio risk a member is willing to take around the time of commencing retirement. This result is not consistent with Chetty, Sándor, and Szeidl (2017), who find that increases in property value are associated with lower stockholdings. However, the results are perhaps consistent with Paravisini, Rappoport, and Ravina (2017) find that investors become more risk averse after decreases in house prices, the same inverse relationship between house prices and risk aversion is shown in Table 4.6. Overall, I see recent increases to house prices having a gambling with the house money effect, and, higher property values being associated with higher risk portfolios.

Table 4.8 Change in expected risk pre to post retirement
Table 4.8 presents the results of the regression model using the change in the expected risk from the quarter before retirement to the quarter after retirement. Columns 1 to 4 represent the models with the change in each of the four dependent variables. Age has been standardized, while total balance and median house price have been log transformed to reduce skewness. Beta has been winsorised at the 95% level. Gender is a dummy variable taking the value of 1 if the member is male and 0 if otherwise. Property increase is a dummy variable taking the value of 1 if there was an increase in the median house price in the members' postcode over the previous quarter and 0 if otherwise. Coefficients and t-statistics (in brackets) are displayed. ***, ** and * denote significance at the 1%, 5% and 10% level respectively.

	Beta	Stdev	Int	Cash
	(1)	(2)	(3)	(4)
Gender	-0.007	-0.00041**	-0.00411	-0.02321***
	(-1.607)	(-2.35819)	(-1.59729)	(-7.19341)
Age_std	0.011***	0.00046***	0.00467***	0.01363***
	(5.036)	(5.39850)	(3.63054)	(8.44680)
Log balance	-0.002**	-0.00000	-0.00042	0.00352***
	(-1.995)	(-0.11299)	(-0.80373)	(5.36287)
Advice	-0.038***	-0.00111***	-0.02002***	0.00679**
	(-8.623)	(-6.44718)	(-7.80843)	(2.11113)
Property increase	0.069***	0.00292***	0.04213***	0.02959***
	(13.591)	(14.58182)	(14.08312)	(7.87752)
Median house price	-0.022***	-0.00083***	-0.00757***	-0.03235***
	(-4.883)	(-4.78776)	(-2.90546)	(-9.88908)
Constant	0.454***	0.01678***	0.17565***	0.51863***
	(7.311)	(6.90376)	(4.83367)	(11.36840)
Observations	12,113	12,113	12,113	12,113

4.5.6 Change Analysis

To further examine how the group of explanatory variables above and control for the same member I run a regression model using the change in expected portfolio risk between the pre and post retirement quarter as the dependent variable. For example, using beta, the dependent variable would be equal to the member's portfolio beta pre-retirement less the member's portfolio beta post retirement. The same group of explanatory variables are included in the regression analysis. Table 4.7 presents the results of the change analysis. As mentioned for this analysis, the dependent variable is the difference in expected risk pre and post retirement. As such, a positive and significant coefficient would equate to increases in that variable leading to differences between the pre and post retirement expected risk.

When looking at age, I find that age has a positive association with the change in their portfolio risk between the quarter before and the quarter after retirement. The coefficients for the age variable are positive and significant for all measures of expected risk, showing a positive association between age and expected risk.

Property increase is a dummy variable taking the value of 1 if the median house price increased over the previous three months. The relationship between property increases and changes to portfolio risk is positive and significant. These findings are reminiscent of the gambling with the house money effect discussed earlier. Potentially, members make more changes to their retirement portfolios when experiencing a prior period gain, in the form of increased property prices. However, the effect is the opposite when examining the influence of median house price. Where increases in median house price are associated with less change in expected portfolio risk.

Lastly, the advice variable is perhaps the most interesting finding. The coefficients are positive and significant for beta, standard deviation and the proportion of international shares, and negative for the proportion of cash. These results show that for beta, standard deviation and the proportion of international shares, financial advice is associated with fewer changes from pre to post retirement. While financial advice has a positive association with changes for the proportion of cash.

4.6. Conclusion

This chapter was motivated by the adequacy of retirement savings being an issue of concern in many countries. This chapter examined how members allocate their retirement savings in the quarter before, the quarter of and the quarter after commencing retirement. Using a unique dataset from a large Australian superannuation fund I observe over 18,000 members commencing their retirement between quarter 1 2021 and quarter 2 2023.

I first modelled scenarios of males and females with an average superannuation balance ($402,838 & $318,203 respectively) drawing down according to the Association of Superannuation Funds Australia lifestyle guidelines. Based on the assumptions stated earlier, only two scenarios provided sufficient retirement income, both of which required the member to drawdown at a modest rate,[33] assumed consistent returns and assumed no account fees. Using different portfolios and returns highlighted how receiving lower returns can hasten the rate at which retirement savings are depleted. Emphasising the importance of optimal retirement strategy.

Using four measures of expected portfolio risk (beta, standard deviation, the proportion of international shares and the proportion of cash), I find evidence of investors displaying increased risk aversion with age, behaviour that is consistent with the literature in this area. Males also appear to display higher levels of risk tolerance pre and post retirement, which is also consistent with prior research. However, this could be attributed to households displaying collective decision making. Lastly, I observe the behavioural bias known as gambling with the house money, where prior period gains lead to investors opting for higher risk portfolios.

The results of this chapter are focused on the portfolio decisions of people pre and post commencing retirement. Retirement savings shortfalls are an issue in many countries around the world, as a result, the findings of this chapter are not limited to an Australian context. Further research could expand on this chapter by examining how members change their retirement allocations from their initial choice.

[33] As stated earlier the modest guidelines provide for a standard of living just above that of the minimum standard of living provided by the age pension.

Chapter 5 Conclusion

This dissertation examines the investment decision making of superannuation members at three critical points of their time in super. Firstly, their initial choice, the first investment option or options members choose to allocate their retirement savings towards, upon joining a superannuation fund. Secondly, their time in super after making the initial choice. Lastly, the period immediately prior to, during and after the decision to commence retirement. The investment decision making I have examined is focused on how members choose to allocate their retirement wealth, and the factors and stimuli that influence their decisions. Overall the findings indicate that behavioural biases can have a detrimental impact on members' retirement outcomes.

When exploring members' initial choice I find that over 86% of the members make no further changes to their investment allocation after the initial choice. This highlights the importance of this first decision and its potential implications. I find that on average members underperform the highest risk and return strategy and the All Ords Accumulation index. Given the retirement savings shortfall in Australia and globally, it appears that on average, a member's initial choice is moving them further away from an adequate retirement balance. Furthermore, when looking at the determinants of the initial choice, that is, the factors and stimuli that influence decision making, I find evidence of five latent classes. FMM reveals members displaying contrasting responses to increases in expected market volatility, with four classes opting to reduce risk while one classes elects to increase risk. Additionally, I see classes displaying contrarian behaviour, increasing their level of risk when the market is declining and reducing their risk when the market is increasing. Lastly, I find evidence of members anchoring on historical market states.

Exploring the length of time members spent invested in a strategy before leaving to either a riskier or less risky option, allowed me to perform two separate analyses. Firstly, I created and own benchmark where I compared the returns the members received from switching strategy, to the returns they would have received had they made no changes. This analysis reveals that on average, members choosing less risky strategies were worse off than those electing riskier strategies. Secondly, I utilise survival analysis to model the factors and stimuli that influence a member's decision to change strategy. I find evidence of the same contrasting response as the initial choice analysis, where members exhibit a "reduce risk or increase risk response" when faced with signals of increased market volatility. Members behave as if they perceive patterns in prices, while younger members tend to change strategy at a faster rate and all ages display a bias towards less risky strategies.

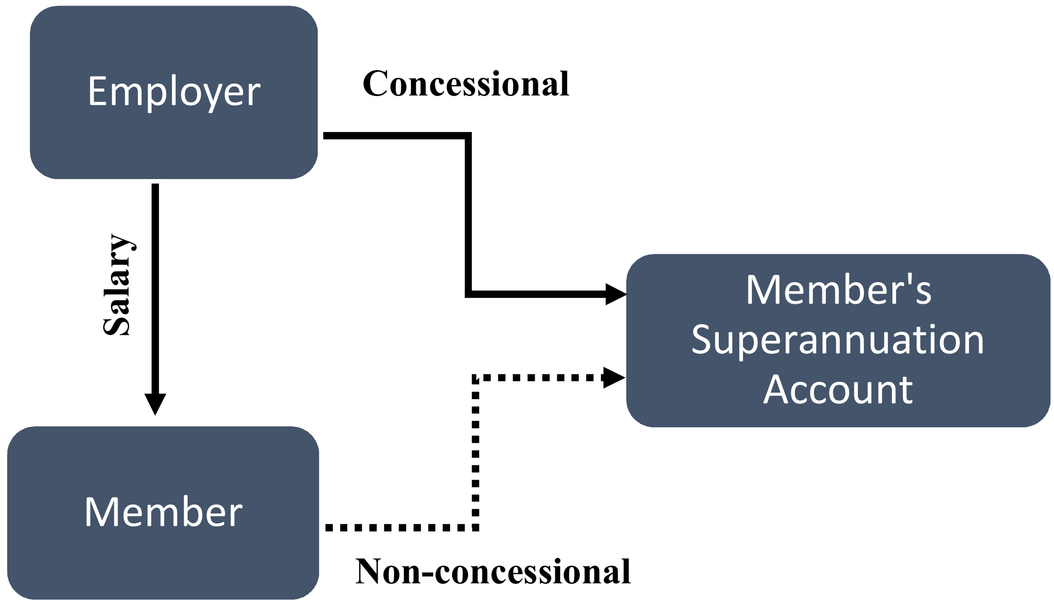
Finally, I explore how members allocate their retirement wealth the quarter before, the quarter of and the quarter after commencing retirement. Using four measures of expected portfolio risk, I find a positive relationship between age and risk aversion. I see males displaying higher levels of risk tolerance, as evidenced by the higher expected risk of their retirement portfolios. I also see members gambling with the house money, whereby the gains made in a prior period lead to members electing higher risk portfolios.

This dissertation has used data from two Australian superannuation funds to explore how behavioural biases influence decision making within retirement savings schemes. The focus of this dissertation has been on the investment allocations of superannuation members and therefore the findings are not limited to an Australian context, but also to any country where retirement savings are of concern. Overall, the findings of this dissertation reveal that members within retirement savings schemes succumb to behavioural biases, and, that these biases may detrimentally impact their ability to adequately finance their retirement lifestyles. Strategies and policies could be put in place to help members avoid these biases (risk less tomorrow) and better save for their retirement. Lastly, this research could be expanded by using data that allows the observation of a person's complete financial position.

Appendices

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).



Appendix B. Breakdown of investment options

Appendix B presents the breakdown of each of the investment options available to members at the end of May 2019. The investment options are ordered from the lowest to the highest risk option. This order was set by the superannuation fund. Please note two options with the same risk rating are deemed to have the same risk level by the superannuation fund.

Investment Option	Asset Breakdown	Risk rating
Cash	100% Cash	(1)
Diversified Conservative	10% Cash 20% Equities 15% Real assets 10% Alternatives 45% Fixed income	(2)
Bonds	100% Fixed income	(3)
MyWASuper	2% Cash 36% Equities 18% Real assets 16% Alternatives 28% Fixed income	(4)
Diversified Moderate	2% Cash 38% Equities 18% Real assets 15% Alternatives 27% Fixed income	(4)
Diversified High Growth	58% Equities 21% Real assets 16% Alternatives 5% Fixed income	(5)
Sustainable Future	60% Equities 40% Fixed income	(6)
Property & Infrastructure	100% Real assets	(7)
Australian Shares	100% Equities	(8)
Global Shares	100% Equities	(8)

Appendix C. Break of investment options selected

Panel A of Appendix C shows the breakdown of investment options selected throughout the observation period of 1994 - 2019. Combination refers to members that allocated their retirement savings across more than one of the investment options. For example, 3.81% of members selected the Cash option, while 19.40% of members selected more than one investment option to allocate their wealth across. As stated earlier, members had the option to invest a proportion of their wealth across multiple investment options, Panel B shows summary statistics for the number of investment options across which members chose to allocate their wealth. For example, if a member chose to allocate 50% of their wealth into Diversified High Growth and 50% into Australian Shares, the number of investment options they selected would be equal to two.

Panel A:

	%	Cumulative %
Cash	3.81	3.81
Diversified Conservative	12.23	16.04
Bonds	0.31	16.35
My WA Super	18.16	34.50
Diversified Moderate	38.69	73.20
Diversified High Growth	5.79	78.98
Sustainable Future	0.44	79.43
Property & Infrastructure	0.55	79.97
Australian Shares	0.36	80.33
Global Shares	0.26	80.60
Combination	19.40	100.00

Panel B: Summary Statistics for Number of Investment Options Chosen

Mean	1.53
St.Dev	1.30
Min	1.00
Max	8.00

Appendix D. Minimum pension drawdown rates

Appendix D shows the minimum drawdown rates for members in the pension phase, which is dependent on their age as at July 1.The minimum drawdown rate refers to the percentage of a member's superannuation account balance they must withdraw per annum. For example, members' aged 65-74 must withdraw 5% of their account balance per annum.

Age on July 1	Minimum drawdown rate %
< 65	4.00%
65 - 74	5.00%
75 - 79	6.00%
80 - 84	7.00%
85 - 89	9.00%
90 - 94	11.00%
> 95	14.00%

Appendix E. Preservation age

Appendix E displays the preservation for members dependent on their date of birthday. The preservation age is the age at which members can access the superannuation balances.

Date of birth	Preservation age (years)
Before 1 July 1960	55
1 July 1960 – 30 June 1961	56
1 July 1961 – 30 June 1962	57
1 July 1962 – 30 June 1963	58
1 July 1963 – 30 June 1964	59
After 30 June 1964	60

Appendix F. Investment option breakdown – Retirement dataset

Appendix F presents the breakdown of each of the investment options available to members throughout the 2021 – 2023 for the dataset used in chapter 4. PE refers to private equity.

Investment Option	**Asset Breakdown**
Conservative	65% Cash & fixed interest 10% Infrastructure & PE 9% Domestic shares 9% Property 7% International shares
Conservative Balanced	46% Cash & fixed interest 19% Domestic shares 17% International shares 9% Infrastructure & PE 9% Property
Balanced	30% International shares 28% Cash & fixed interest 28% Domestic shares 11% Infrastructure & PE 3% Property
Sustainable Balanced	39% International shares 28% Cash & fixed interest 24% Domestic shares 9% Infrastructure & PE
Growth	40% International shares 34% Domestic shares 14% Cash & fixed interest 9% Infrastructure & PE 3% Property
High Growth	49% International shares 43% Domestic shares 5% Infrastructure & PE 3% Property
Sustainable High Growth	56% International shares 38% Domestic shares 6% Infrastructure & PE
Cash	100% Cash
Australian Bond	100% Fixed income
Australian Income	100% Fixed income
Listed Property	100% Listed property
Australian Shares	100% Domestic shares
International Shares	100% International shares
Global Environmental Opportunities	100% International shares
Australian Dividend Income	100% Domestic shares
Global Companies Asia	100% International shares

References

Addoum, Jawad M. 2017. "Household Portfolio Choice And Retirement." The review of economics and statistics 99 (5): 870-883. https://doi.org/10.1162/REST_a_00643.

Agnew, Julie, Pierluigi Balduzzi, and Annika Sundén. 2003. "Portfolio Choice and Trading in a Large 401(k) Plan." The American economic review 93 (1): 193-215. https://doi.org/10.1257/000282803321455223.

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

Almenberg, Johan, and Anna Dreber. 2015. "Gender, stock market participation and financial literacy." Economics letters 137: 140-142. https://doi.org/10.1016/j.econlet.2015.10.009.

Ashton, R. H., & Kennedy, J. (2002). Eliminating recency with self-review: the case of auditors '‘going concern’ judgments. *Journal of Behavioural Decision Making*, 15(3), 221-231.

Association of Superannuation Funds Australia. 2023. “ASFA Retirement Standard. Detailed budget breakdown, September quarter 2023”. chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://www.superannuation.asn.au/wp-content/uploads/2023/12/2311-ASFA_Retirement_Standard_Budgets_September-23_quarter.pdf

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

ASX, 2020. ASX Australian Investor Study 2020. *https://www2.asx.com.au/blog/australian-investor-study*

Australian Bureau of Statistics, 2021, Housing: Census, ABS. *https://www.abs.gov.au/statistics/people/housing/housing-census/2021#cite-window1*

Australian Bureau of Statistics, 2021, *Life tables*, ABS. *https://www.abs.gov.au/statistics/people/population/life-tables/latest-release.*

Australian Bureau of Statistics, 2021, Retirement and Retirement Intentions, Australia, ABS. https://www.abs.gov.au/statistics/labour/employment-and-unemployment/retirement-and-retirement-intentions-australia/latest

Australian Taxation Office, 2021. Taxation statistics 2020-21, Snapshot table 5, ATO. https://data.gov.au/data/dataset/taxation-statistics-2020-21/resource/ebbd32e3-4556-41e1-a8b9-33387457d518?view_id=849734b7-c2b8-4b09-ae53-9ce25ef797fd

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.

Barber, B., & Odean, T. (2008). All that Glitters: The Effect of Attention and News on the Buying Behaviour of Individual and Institutional Investors. *The Review Of Financial Studies*.

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.

Barber, Brad M., Yi-Tsung Lee, Yu-Jane Liu, Terrance Odean. 2007. “Is the Aggregate Investor Reluctant to Realise Losses? Evidence from Taiwan”. *European Financial Management* 13 (3): 423-447.

Baulkaran, Vishaal, and Pawan Jain. 2024. "Behavioural Biases of Financial Planners: The Case of Retirement Funding Recommendations." Journal of Behavioural Finance: 1-14. https://doi.org/10.1080/15427560.2024.2305412.

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

Bernheim, B. Douglas, Jonathan Skinner, and Steven Weinberg. 2001. "What Accounts for the Variation in Retirement Wealth among U.S. Households?" The American economic review 91 (4): 832-857. https://doi.org/10.1257/aer.91.4.832.

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.

Blanchett, David, Michael Finke, and Michael Guillemette. 2018. "The Effect of Advanced Age and Equity Values on Risk Preferences." The journal of behavioural finance 19 (4): 434-441. https://doi.org/10.1080/15427560.2018.1431884.

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 Behaviour & Organization* 112: 112-126.

Brooks, C., I. Sangiorgi, C. Hillenbrand, and K. Money. 2019. "Experience wears the trousers: Exploring gender and attitude to financial risk." Journal of Economic Behaviour and Organization 163: 483-515. https://doi.org/10.1016/j.jebo.2019.04.026.

Brooks, Chris, Ivan Sangiorgi, Carola Hillenbrand, and Kevin Money. 2018. "Why are older investors less willing to take financial risks?" International review of financial analysis 56: 52-72. https://doi.org/10.1016/j.irfa.2017.12.008.

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.

Calvet, Laurent E., and Paolo Sodini. 2014. "Twin Picks: Disentangling the Determinants of Risk-Taking in Household Portfolios." The Journal of finance (New York) 69 (2): 867-906. https://doi.org/10.1111/jofi.12125.

Charness, Gary, and Uri Gneezy. 2012. "Strong Evidence For Gender Differences In Risk Taking". Journal Of Economic Behaviour & Organization 83 (1): 50-58.

Chetty, R. A. J., LÁSzlÓ SÁNdor, and Adam Szeidl. 2017. "The Effect of Housing on Portfolio Choice." The Journal of finance (New York) 72 (3): 1171-1211. https://doi.org/10.1111/jofi.12500.

Chiah, M., Chai, D., Zhong, A. and Li, S. (2016). A Better Model? An Empirical Investigation of the Fama-French Five-factor Model in Australia. *International Review of Finance*, 16(4), pp.595 -638.

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.

Clare, R. (2017). Superannuation account balances by age and gender. Retrieved from https://www.superannuation.asn.au/ArticleDocuments/359/1710_Superannuation_acc ount_balances_by_age_and_gender.pdf.aspx?Embed=Y

Cohn, Richard A., Wilbur G. Lewellen, Ronald C. Lease, and Gary G. Schlarbaum. 1975. "INDIVIDUAL INVESTOR RISK AVERSION AND INVESTMENT PORTFOLIO COMPOSITION." The Journal of finance (New York) 30 (2): 605-620. https://doi.org/10.1111/j.1540-6261.1975.tb01834.x.

Da Silva Rosa, R., & Durand, R. (2008). The role of salience in portfolio formation. *Pacific- Basin Finance Journal*, *16*(1-2), 78-94.

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.

De Bondt, W.F.M. and R.H. Thaler (1985). Does the Stock Market Overreact?. *Journal of Finance 40*, 793-805.

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., Limkriangkrai, M. and Smith, G. (2006). In America's thrall: the effects of the USmarket and US security characteristics on Australian stock returns. *Accounting and Finance*, 46(4), pp.577-604.

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

Durand, Robert B., Rick Newby, and Jay Sanghani. 2008. "An Intimate Portrait of the Individual Investor." Journal of Behavioural Finance 9 (4): 193-208. https://doi.org/10.1080/15427560802341020.

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.

Fagereng, Andreas, Charles Gottlieb, and Luigi Guiso. 2017. "Asset Market Participation and Portfolio Choice over the Life-Cycle." The Journal of finance (New York) 72 (2): 705-750. https://doi.org/10.1111/jofi.12484.

Fama, E.F., 1970. "Efficient Capital Markets: A Review of Theory and Empirical Work". *Journal of Finance 25*, 383-417.

Foerster, Stephen, Juhani T. Linnainmaa, Brian T. Melzer, and Alessandro Previtero. 2017. "Retail Financial Advice: Does One Size Fit All?" The Journal of finance (New York) 72 (4): 1441-1482. https://doi.org/10.1111/jofi.12514.

Friend, Irwin, and Marshall E. Blume. 1975. "The Demand for Risky Assets." The American economic review 65 (5): 900-922.

Frijns, Bart, Esther Koellen, and Thorsten Lehnert. 2008. "On the determinants of portfolio choice." Journal of economic behaviour & organization 66 (2): 373-386. https://doi.org/10.1016/j.jebo.2006.04.004.

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.

Grinblatt, M., & Keloharju, M. (2009). Sensation Seeking, Overconfidence, and Trading Activity. *The Journal Of Finance*, *64*(2), 549-578.

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 Economics55*, 43-67.

Huberman, G. U. R., and W. E. I. Jiang. 2006. "Offering versus Choice in 401(k) Plans: Equity Exposure and Number of Funds." The Journal of finance (New York) 61 (2): 763-801. https://doi.org/10.1111/j.1540-6261.2006.00854.x.

Irandoust, Manuchehr. 2017. "Factors Associated With Financial Risk Tolerance Based on Proportional Odds Model: Evidence From Sweden." Financial counseling and planning 28 (1): 155-164. https://doi.org/10.1891/1052-3073.28.1.155.

Kahneman, Daniel, and Amos Tversky. "Prospect Theory: An Analysis of Decision under Risk." *Econometrica* 47, no. 2 (1979): 263.

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.

Kliger, D., & Kudryavtsev, A. (2010). The availability heuristic and investors' reaction to company-specific events. The Journal of Behavioural Finance, 11(1), 50-65.

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.

Kramer, Marc M. 2012. "Financial Advice and Individual Investor Portfolio Performance." Financial management 41 (2): 395-428. https://doi.org/10.1111/j.1755-053X.2012.01185.x.

Kuhnen, C.M. and B., Knutson, 2005. “The Neural Basis of Financial Risk Taking”. *Nueron47*, 763-770.

Larsen, Linda S., and Claus Munk. 2023. "The Design and Welfare Implications of Mandatory Pension Plans." Journal of financial and quantitative analysis 58 (8): 3420-3449. https://doi.org/10.1017/S0022109023000029.

Lee, B., O'Brien, J., & Sivaramakrishnan, K. (2008). An analysis of financial analysts'optimism in long-term growth forecasts. *The Journal of Behavioural Finance*, 9(3), 171-184.

Lee, D., H. Chan, R.W. Faff, P. S. Kalev, 2003. Short-term contrarian investing – is it profitable?...Yes and No. *Journal of Multinational Financial Management*, 385-404.

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

Linnainmaa, Juhani T., Brian T. Melzer, and Alessandro Previtero. 2021. "The Misguided Beliefs of Financial Advisors." The Journal of finance (New York) 76 (2): 587-621. https://doi.org/10.1111/jofi.12995.

Lo, A., and C. MacKinlay, 1990. When are Contrarian Profits due to Stock Market Overreaction?, *Review of Financial Studies 3*, 175-250.

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

Malmendier, Ulrike, and Stefan Nagel. 2011. "DEPRESSION BABIES: DO MACROECONOMIC EXPERIENCES AFFECT RISK TAKING?" The Quarterly journal of economics 126 (1): 373-416.

Markiewicz, L., & Weber, E. (2013). DOSPERT's Gambling Risk-Taking Propensity Scale Predicts Excessive Stock Trading. *Journal of Behavioural Finance*, *14*(1), 65-78.

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 Behaviour 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.

Müller, G, R.B. Durand and R.A. Maller, 2011. “The Risk-Return Tradeoff: A COGARCH Analysis of Merton’s Hypothesis”. *Journal of Empirical Finance 18*, 306-320.

Nielson, L., & Harris, B. (2010). Chronology of superannuation and retirement income in Australia – Parliament of Australia. Retrieved from https://www.aph.gov.au/About_Parliament/Parliamentary_Departments/Parliamentary_Library/pubs/BN/0910/ChronSuperannuation

Nofsinger, J. R., & Varma, A. (2013). Availability, recency, and sophistication in the repurchasing behaviour of retail investors. Journal of Banking & Finance 37(7): 2572- 2585.

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.

Paravisini, Daniel, Veronica Rappoport, and Enrichetta Ravina. 2017. "Risk Aversion and Wealth: Evidence from Person-to-Person Lending Portfolios." Management science 63 (2): 279-297. https://doi.org/10.1287/mnsc.2015.2317.

Parliamentary Budget Office. 2019. "Australia's Ageing Population: Understanding The FiscalImpacts Over The Next Decade."

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.

Pepe, Margaret Sullivan, and Motomi Mori. 1993. "Kaplan—Meier, Marginal Or Conditional Probability Curves In Summarizing Competing Risks Failure Time Data?". *Statistics In Medicine* 12 (8): 737-751.

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.

Russell, T., & Thaler, R. (1985). The Relevance of Quasi Rationality in Competitive Markets. *The American Economic Review, 75*(5), 1071-1082.

Samuelson, W., & Zeckhauser, R. (1988). Status quo bias in decision making. *Journal Of Risk And Uncertainty*, *1*(1), 7-59.

Schurer, Stefanie. 2015. "Lifecycle patterns in the socioeconomic gradient of risk preferences." Journal of economic behaviour & organization 119: 482-495. https://doi.org/10.1016/j.jebo.2015.09.024.

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

Services Australia, 2024. How much Age Pension you can get - Age Pension - Services Australia. https://www.servicesaustralia.gov.au/how-much-age-pension-you-can-get?context=22526.

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 Behavioural Economics to Increase Employee Saving. Journal Of Political Economy, 112(S1), S164-S187.

Thaler, Richard H., and Eric J. Johnson. 1990. "Gambling with the House Money and Trying to Break Even: The Effects of Prior Outcomes on Risky Choice." Management science 36 (6): 643-660. https://doi.org/10.1287/mnsc.36.6.643.

Tversky, A., & D. Kahneman (1971). Belief in the Law of Small Numbers. *PsychologicalBulletin 76*, 105-110.

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

Wachter, Jessica A., and Motohiro Yogo. 2010. "Why Do Household Portfolio Shares Rise in Wealth?" The Review of financial studies 23 (11): 3929-3965. https://doi.org/10.1093/rfs/hhq092.

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.

World Economic Forum, 2019. Investing in (and for) Our Future (World Economic Forum,Geneva).