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Honours Thesis

A Super Sleight of Hand

Attribute Non-Attendance in Superannuation

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Declaration

I declare that this thesis is my own work and that, to the best of my knowledge, it contains no material which has been written by another person or persons, except where acknowledgement has been made. This thesis has not been submitted for the award of any degree or diploma at the University of New South Wales Sydney, or at any other institute of higher education.

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Jonathan Nathan
6 December 2019

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Abstract

This thesis focuses on the information processing strategy of attribute non-attendance (ANA). ANA is the tendency for an individual to ignore certain product attributes when choosing between products. I estimate the probability of attribute non-attendance for Australian superannuation members choosing between investment options offered by a superannuation fund. First, it appears that superannuation members are attentive towards return and summary risk information, while inattentive to specific risk information. However, I cannot robustly say that inattention is non-zero. Second, members are willing to trade return for higher proportion of growth assets despite growth assets being a measure of increased risk and forego $725 in return objectives as a result. These results are paradoxical to the respondents' risk averse choices from a Holt-Laury instrument. This paradoxical result is attributed to the members' misinterpretation of the what growth assets represent. This has implications for the improvement superannuation choice architecture. Additionally, the results shed light on how experimental design is important when trying to replicate real world choices in a lab and how this can be used to improve the choice architecture of Australian superannuation.

Chapter 1

Introduction

Australia is currently experiencing a significant increase in the proportion of elderly in its population, prompting caution regarding the work force's ability to support an ageing population (Feng 2014). Additionally, early retirement is common in the Australian population and adds additional stress to the retirement income support system (Warren 2008). These stressors have resulted in an increased prominence and necessity of the superannuation system, Australia's self-funded retirement income system (Productivity Commission 2018). The importance of the system has resulted in reviews that consistently call for increased member engagement and developing better adequacy for members (Feng 2014). Despite the continued analysis of members' choices in superannuation (Bateman et al. 2013; Bateman et al. 2016; Langford et al. 2006; Productivity Commission 2018), none have yet to estimate the extent that individuals are paying attention when making these choices. In comparison, I find that members are attentive towards return and summary risk indicators, while having a high upper bound of inattentiveness towards specific risk indicators.

In typical choice studies of superannuation (Productivity Commission 2018; Bateman et al. 2016), it is implicitly assumed that respondents pay attention to all attributes of a portfolio when making an investment decision. However, it is possible that individuals employ a variety of information processing strategies which are not accounted for in typical choice studies. This thesis focuses on the information processing strategy of attribute non-attendance (ANA). ANA is the tendency for an individual to ignore certain product attributes when choosing between products. Failing to account for ANA relies on the implicit assumption that individuals do not exhibit bounded rationality and that all the product's attributes are considered when individuals are making decisions (Hensher et al. 2005). An implication of ANA is non-compensatory behaviour (Scarpa et al. 2009), which implies that when a change in an attribute is ignored, it cannot be compensated with a change in another attribute. This behaviour has implications for the marginal rate of substitution (MRS). In typical MRS estimates, individuals with and without non-compensatory behaviour are pooled together and produce biased results (Hensher et al. 2005). Accounting for ANA has the potential to remove that bias (Hole et al. 2014; Scarpa et al. 2009).

A current problem with the superannuation system is the lack of interest and engagement Australians have with the system (Productivity Commission 2018). This has led to continued calls for improvements in engagement and has resulted in the simplification of information provided to help improve members' choices (Godwin and Ramsay 2015). The movement towards simplification has been studied by Bateman et al. (2016) who looked at members' choice of investment options offered by a superannuation fund. The experimental data collected by Bateman et al. (2016) provides an opportunity to analyse the ANA exhibited by the respondents. Thus, this thesis extends the work of Bateman et al. (2016) by analysing ANA in the context of superannuation and its movement towards simplification and improved member engagement.

In this thesis I assess the presence of limited attention and its implications for superannuation fund members. The presence of limited attention is assessed by estimating an endogenous attribute attendance (EAA) model (Hole 2011a). The form of limited attention I study is attribute non-attendance (ANA). The EAA model allows me to estimate an upper bound on the probability that individuals are not paying attention to a product's attributes when choosing between different alternatives. Specifically, I estimate the probability of attribute non-attendance for Australian superannuation members choosing between investment options offered by a superannuation fund. The respondents' choices come from the stated choice experiment in Bateman et al. (2016), which includes staff and students from UNSW with superannuation accounts. From this I am able to estimate an upper bound on the respondents' probability of ANA for the investment options. Additionally, by estimating a suite of models nested within the Generalised Multinomial Logit model (Fiebig et al. 2010), I find that the respondents have highly varied preferences and that they are not making random choices. This suggests that the choice task garnered the attention of the respondents and the choice between alternatives is not a complex one.

The novel contributions of this thesis are threefold. First, I estimate the probabilities of ANA within the context of superannuation. A substantial literature documenting the limited attention exhibited towards product attributes exists in health insurance (Abaluck and Adams 2017), transport, marketing and health (Scarpa et al. 2009). Thus, the novelty is the estimation of attribute non-attendance in the context of superannuation members choosing between investment options offered by a superannuation fund. The results suggest that individuals have higher upper bounds of non-attendance towards specific risk attributes and lower upper bounds on return objective and summary risk attributes. Additionally, this paper has smaller contributions through the estimation of a suite of GMNL models and associated marginal rates of substitution. The GMNL estimates suggest that individual preference heterogeneity is very apparent in the respondent's choices and dominates scale heterogeneity. This implies that individuals are typically attentive to all the attributes and have varied tastes. Additionally, this results in the ANA estimates being considered as upper bounds on the probability of inattention, due to confounding between ANA and preference heterogeneity. The third contribution is the production of MRS estimates, suggesting that the respondents are likely to be foregoing $725 due to their misinterpretation of a risk indicating attribute and that risk averse students are the most likely demographic to be making the perverse trade.

Chapter 2

Theoretical Foundations

A core element of the modern Australian superannuation system involves individuals making choices between different superannuation funds and investment options within each fund. However, individuals make suboptimal choices for a number of reasons such as searching too little, confusion, excessive inertia and inattention (Grubb 2015). These behavioural anomalies have implications for an individual's welfare, such as Handel (2013) finding that can forgo \$2032 annually because of inertia in medical insurance.

The notion that individuals employ simplification when making a choice between alternatives deviates from the theory of rational decision making. As noted by Samuelson and Zeckhauser (1988), a paradox exists between the theory of the rational decision maker and empirical findings. Labels and ordering should not affect an individual's preferences. Yet they do. This anomalous behaviour is partially attributed to status quo bias and results in individuals ignoring some of the available alternatives. In a similar vein, Gabaix (2014) develops a framework of choice behaviour which incorporates limited attention where individuals ignore attributes rather than alternatives. The simple deterministic version of the model provides a common framework for most variants of limited attention (Gabaix 2017). This framework is used to illustrate attribute non-attendance in the EAA model.

2.1 A Simple Deterministic Model of Attribute Non-Attendance

The EAA model (Hole 2011a) is a variant of limited attention models which incorporates limited attention through an individual ignoring certain attributes when making a choice between alternatives. In a traditional maximisation problem, a rational consumer would maximise their utility with respect to a good. The consumer's utility is a function of the action they take (a), and a vector of the attributes of the product ($\boldsymbol{x}$),

$$\max_a U(a, \boldsymbol{x}) \tag{2.1}$$
$$\implies a^r(\boldsymbol{x}) = \arg\max_a U(a, \boldsymbol{x})$$

In the EAA model, a consumer builds a simplified model of their world and makes choices using their simplified model. The simplified model has only a few variables which are attended to and used in the decision problem. "This is how a sparse agent sails through life: for a given problem, out of the thousands of variables that might be relevant, he takes into account only a few that are important enough to significantly change his decision" (Gabaix 2014). This results in the agent maximising their utility by choosing the action which benefits them the most. By incorporating variation in the attention paid to each of the attributes, this results in an "attention augmented decision utility" (Gabaix 2014). The "attention augmented decision utility" differs from the traditional utility function (2.1) through the addition of an attention parameter ($\boldsymbol{\gamma}$). The attention parameter governs whether the agent will be attentive towards an attribute or not. For the EAA model, the attentive parameter can be specified to be a function of the socio-demographic characteristics of the agent (z),

$$U(a, \boldsymbol{x}, \boldsymbol{\gamma}) = U(a, \gamma_1(z) \cdot x_1, ..., \gamma_K(z) \cdot x_n), \tag{2.2}$$
$$\text{Where, } \gamma_k \in \{0, 1\}$$

This results in the good's attributes being perceived as a function of the true value of the attribute and the attention paid to the attribute,

$$x_k^s = \gamma_k(z) \cdot x_k \tag{2.3}$$

The agent's use of perceived values has implications for the marginal rates of substitution (MRS). The estimated marginal rate of substitution, especially willingness-to-pay (2.4) , is typically found to be substantially different when incorporating attribute non-attendance due to the pooling of attentive and inattentive individuals (Abaluck and Adams 2017; Hole 2011a; Scarpa et al. 2009; Hensher et al. 2005),

$$\frac{dCost}{dAttribute} = -\frac{\beta_{Attribute}}{\beta_{Cost}} \tag{2.4}$$

A higher willingness-to-pay is expected when individuals ignore the attribute because they have zero willingness-to-pay (i.e. $\beta_{Attribute} = 0$) and will now be excluded from the estimated MRS. Similarly, a lower willingness-to-pay is expected if respondents ignore cost. If individual ignore cost, they have an infinite willingness-to-pay (i.e. $\beta_{Cost} = 0$) and will now be excluded from the estimate (Hess et al. 2012). This implication can help shed light on the presence of inattention (Hensher et al. 2005). Thus, in this thesis the MRS between different attributes is used to provide evidence on the attribute non-attendance of the participants in the experimental dataset from Bateman et al. (2016).

2.2 A Simple Deterministic Model of Limited Attention

In comparison to the illustration of the EAA model above, a formal model of limited attention is given by Gabaix (2014). The two models of limited attention are similar through the incorporation of an attention parameter into the utility function of the agent. In comparison, the EAA model allows for the attentive parameter to be a function of individual characteristics. Whereas, Gabaix's model incorporates a default value into the perceived attribute. Thus, the simple deterministic model of limited attention from Gabaix (2017) and Gabaix (2014) provides a more rigorous frame for understanding limited attention.

The model presented by Gabaix (2014) builds upon the traditional maximisation problem by incorporating costly attention. In this model, a consumer builds a simplified model of their world and makes choices using this simplified model. This simplified model has only a few variables which are attended to and used in the decision problem. The simplified model is employed because of the high computation costs of weighing up every variable and incorporates many behavioural effects (Gabaix 2014). This results in the agent maximising their utility by choosing the action which benefits them the most, through the "attention augmented decision utility",

$$U(a, \boldsymbol{x}, \boldsymbol{\gamma}) = U(a, \gamma_1 \cdot x_1 + (1 - \gamma_1)x_1^d, ..., \gamma_Q \cdot x_n + (1 - \gamma_n)x_n^d) \tag{2.5}$$

Under this model, there are a number of implications which affect Marshallian demand, elasticity and the Slutsky matrix (Gabaix 2014). Firstly, as inattention creates a money illusion, the Marshallian demand is no longer homogeneous of degree zero (Gabaix 2014). Secondly, because of attenuated elasticities, the Slutsky matrix is not symmetric because small terms in the matrix will appear (Gabaix 2014). The implication of a non-symmetric Slutsky matrix is used by Abaluck and Adams (2017) to empirically study inattention in health care plans. Abaluck and Adams (2017) develops a framework of consideration set models which identify and estimate whether goods are chosen because they provide higher utility or are more likely to be considered. Abaluck and Adams (2017) find that the inertia present in health care plan decisions is largely attributable to attention and that a change in the search position of hotels on Expedia.com affects attention rather than utility.

A low elasticity could be mistaken because of un-attended prices which reduce estimated elasticities due to the pooling of attentive and inattentive consumers (Gabaix 2014). A number of recent studies have shown that individuals exhibit a low price sensitivity, which potentially support the existence of limited attention. Gabaix (2014) attributes the findings of Ellison and Ellison (2009) to limited attention. By studying a market of internet retailers, Ellison and Ellison (2009) look at consumer choices between different suppliers, and find that some of the prices are partially neglected by consumers and that consumers have an incomplete learning of prices. Similar to this, there are findings of price insensitivity in Mexico's privatised social security system (Hastings and Tejeda-Ashton 2008; Hastings et al. 2013; Duarte and Hastings 2012). Mexican investors responded to a simplified fee index, despite some of the responses resulting in increased fees which reflects a lack of attention towards prices (Grubb 2015). The evidence of price sensitivity can be used to support the notion of limited attention.

Chapter 3

Contextual Background

Australia's ageing population is placing the federal government under increasing pressure from the costs of servicing the needs of the elderly Australians through health, aged care and retirement incomes (Warren 2008; Productivity Commission 2018). Superannuation's importance thus stems primarily from its expected replacement of the Age Pension as the primary source of retirement income (Productivity Commission 2018). Superannuation system is complex and multilayered system consisting of multiple funds, sources of contribution and incentives (Feng 2014). To reduce the complexity of the system recent reforms have attempted to simplify the superannuation system and reduce reliance on the Age Pension (Warren 2008). The superannuation system is an important issue for the current Australian agenda as it poses a serious problem for both the government budget and the welfare of all Australians. However, with realistic and conscientious action the welfare and prosperity of Australians can be maintained and improved.

The superannuation system requires working Australians to be members of and make financial contributions to superannuation funds. Members are reimbursed through retirement income when passing an age threshold (Feng 2014). For the defined contribution plan, members' contributions are invested by the superannuation fund and retirement payments are based on the contributions, investment returns minus fees and taxes (Productivity Commission 2018). Industry funds provide superannuation for employees of an industry (Productivity Commission 2018). In this thesis, I focus on superannuation members' choice of investment options offered by an industry fund for its defined contribution plan. Based on the choice of investment option, this would affect the investment returns and thus retirement income of the fund's members and their welfare during retirement.

3.1 Australia's Shorter PDS Regime

To combat the complexity of the superannuation system[1] and disengagement of its members, new initiatives to simplify the superannuation system have been implemented. Australia's simplification of financial product disclosure statements

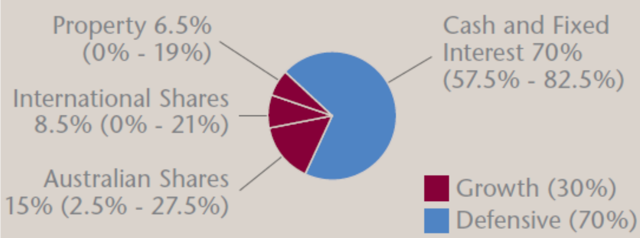
[1]For a brief history of Australia's Superannuation system see Appendix E

(PDS) aimed to counteract the PDS's lack of effectiveness in conveying key product information to consumers and their limited use (Godwin and Ramsay 2015; Gallery et al. 2013). The shorter PDS regime was introduced by the Australian Securities and Investments Commission (ASIC) in 2012. The regime required a standardization of the PDS (Commonwealth of Australia 2011). The standardisation of the PDS required funds to provide the following attributes for each investment option: (a) the name of the option, (a) a short description including suitable investors for the option, (b) the allocation of asset classes,(c) a description of the investment return objective, (d) the minimum suggested time frame for holding the investment and (e) a summary of the associated risk level (Commonwealth of Australia 2011). The summary risk level was later required by the regulator to be "the expected frequency of negative annual returns in twenty years" (Bateman et al. 2016). Thus, the shorter PDS regime requires a shorter and simpler PDS which is specific in size and content.

The change in information format is studied by Bateman et al. (2013) and Bateman et al. (2016). Firstly, Bateman et al. (2013) uses a discrete choice experiment to assess how different presentation of investment risk affect the choice of retirement plan accounts. Bateman et al. (2013) elicit the choices of experimental subjects who allocated retirement income among a safe, risky and equally mixed account, while varying the presentation of the risk information. A typical finding is that the subjects dislike risk. However, graphical presentations were associated with riskier choices relative to textual presentations. Bateman et al. (2013) also found that subjects became less attentive to risk as basic financial literacy declined, as subjects seemed unable to make risk-return trade-offs. Other socio-demographic information helped to predict risky choices, where age, retirement accumulation and belief of a future stock market crisis are associated with safer choices. Similar to Bateman et al. (2013), Bateman et al. (2016) studies how changes in the presentation and deprivation of information affects choices of investment options under the Simpler Super Regime. Using an incentivised choice experiment, Bateman et al. (2016) analysed superannuation fund members choice of investment options, using a Simpler Super Regime format for the investment options. From this experiment, it is found that the investment decision is not immune to choice architecture as respondents traded between risk and return information, and asset allocation information. Additionally, it is found that subjects exhibit preferences for a naive diversification strategy similar to Benartzi and Thaler (2007). Thus, it appears that behavioural heuristics are being employed when subjects are making their decisions in superannuation, and this can result in sub-optimal choices.

Figure 3.1: A typical Summary of an Investment Option in the UniSuper Product Disclosure Statement

INVESTMENT DETAILS FOR OUR CAPITAL STABLE INVESTMENT OPTION

Description of option/ Type of investor	Invests in a diversified portfolio, comprising largely defensive assets such as bonds and cash, and with some growth assets such as shares and property investments. Designed for investors with a medium risk tolerance who are comfortable with a medium level of expected returns.
Investment return objective*	To achieve returns (after Fund taxes and investment fees) that are at least 2.0% p.a. more than inflation (CPI).
Strategic asset allocation and ranges	
Minimum suggested timeframe for investment	Two years
Expected frequency of negative annual return	Two in twenty years
Summary risk level	Medium

The above figure is taken from UniSuper (2015) and illustrates the information provided to super fund members about each invest option. The above example illustrates the Capital Stable Investment Option.

The Simpler Super requirements are closely followed by UniSuper (UniSuper 2015). Each of the investment options provided by UniSuper met the information requirements of the regulator (Commonwealth of Australia 2011; UniSuper 2015). A typical example of this from UniSuper can be seen in figure 3.1 which illustrates the information provided for the Capital Stable Investment Option from the 2015 PDS from UniSuper. UniSuper has provided the specified attributes in a tabular form where almost each requirement, (a)-(e), is on a separate row, except that the summary risk level (e) occupies the bottom two rows. UniSuper displays the asset allocation as a pie chart, where each segment represents a different asset class. The colour of the segment differentiates between the assets being classified as either Growth or Defensive. Thus, UniSuper has clear distinctions between the different attributes from the investment funds, which the experiment in Bateman et al. (2016) proxies. This clear distinction allows for me to estimate and infer the probability that individuals are not paying attention to each of the attributes.

The superannuation system is critical to the welfare of Australians. The increasing elderly demographic is creating a fiscal strain. This has resulted in the increasing importance of superannuation to improve the self-sufficiency of the elderly population. The complexity of the system and presentation of its numerous options has been problematic and creates disengagement between Australians and their superannuation. To combat this, the Simpler Super Regime was legislated and provides the overarching context for this thesis. Whereas UniSuper's provision of investment options provides a more concise context.

The implications of the global push towards simpler financial product disclosure have yet to be analysed for the presence of limited attention and attribute non-attendance. Superannuation has been studied in terms of the impact that simplification (Langford et al. 2006), how simplified risk affects choice (Bateman et al. 2013) and how changes in availability of information impact choices (Bateman et al. 2016). In comparison, ANA has been extensively applied to a variety of fields such as travel (Hensher et al. 2005; Hensher et al. 2011), agricultural valuation (Scarpa et al. 2009), health insurance (Abaluck and Adams 2017), and health choices (Hole 2011a; Hole et al. 2013). Thus, it is a natural extension to explore limited attention in the Australian superannuation system. This thesis fills the gap and helps to shed light on the presence of limited attention by estimating the probabilities of attribute non-attendance and the marginal rates of substitution in the context of superannuation and the simpler super regime, thus extending the work of Bateman et al. (2016).

To recapitulate the idea of this thesis through an example, suppose we have Gary. Gary is a member of a superannuation fund. This superannuation fund is following the Simpler Super Regime and provides simplified information on the attributes of its investment options. Gary now has to make a choice of which investment option is going to receive his superannuation savings. Classically, economists would assume that Gary would pay attention to every single attribute of the investment options and from this we could deduce Gary's marginal rate of substitution between each attribute. However, what happens if Gary does not pay attention? If Gary doesn't pay attention to all the attributes of the investment options, this has some significant implications when comparing estimates. For instance, when looking at the marginal rate of substitution, if Gary is inattentive, the classical MRS used by economists won't apply to Gary because he isn't even thinking about the attributes used. Thus, this thesis is looking at whether Gary is paying attention to the attributes of the investment options and how this affects the welfare estimates of MRS and whether the MRS is applicable to Gary!

Chapter 4

Experimental Design & Data

The importance of limited attention within choices of superannuation products is examined through experimental individual choice data from Bateman et al. (2016), "As Easy as Pie: How Retirement Savers use Prescribed Investment Disclosures". The experiment recorded incentivised choices of staff and students from UNSW. The choices are from pairwise comparisons of 10 investment options which were sourced from UniSuper (2015). I focus on a subsample of participants from the experiment[1]. The subsample of participants all received information as required by the Simpler Super Regime. The subsample provides an opportunity to analyse the attribute non-attendance implicit in real world choices of Australians amongst superannuation funds and the resulting implications of these choices. This chapter will draw primarily from the experimental design and implementation from Bateman et al. (2016).

4.1 Design

The experiment consisted of four phases which all the participants progressed through. The first phase required participants to review each of the investment options. The second phase required the participants to make an incentivised choice from all 45 possible pairwise choices between the 10 investment options. The third phase elicited risk preferences and the fourth stage involved collecting demographic information from the participants. After the fourth stage payments were collected and the participant was finished.

[1]For further information on the experiment and treatments see Bateman et al. (2016)

4.2 First Phase - Investment Options

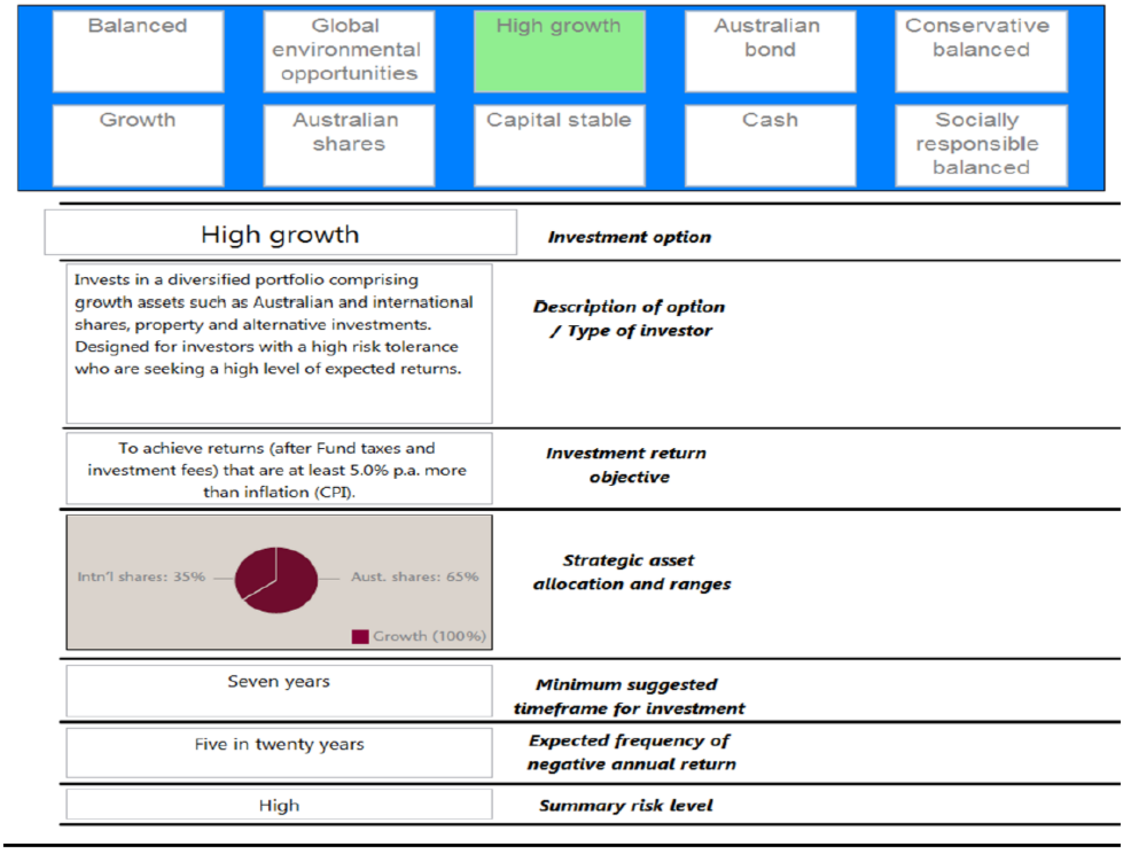
Table 4.1: Investment Option Attributes

	Return Objective	Risk Measures		Concentration Measures	Horizon		Description	
Option Title	Return[1]	$\mathbb{E}$(Negative Returns)	Risk Level	Herfindahl Index	Growth Proportion	Minimum Sug. Time Frame	Word Count	Sustainable Practices
Capital Stable	2	2	Medium	0.52	0.3	2	38	No
Socially Resp. Bal.	3	4	High	0.36	0.7	6	53	Yes
Growth	4	5	High	0.3	0.85	7	41	No
Cash	1	0	Very Low	1	0	0	45	No
Australian Bond	1.5	3	Med. to High	1	0	4	29	No
Australian Shares	5	6	Very High	1	1	7	27	No
Global Env. Opp.	5	6	Very High	1	1	7	55	Yes
Conservative Bal.	2.5	3	Med. to High	0.34	0.5	4	42	No
Balanced	3	4	High	0.27	0.7	6	41	No
High Growth	5	5	High	0.42	1	7	35	No

The above table shows the attributes of the 10 investment options provided to the respondents.

The first phase of the experiment required participants to review the attributes of the 10 provided investment options (Bateman et al. 2016). The 10 investment options were taken from the 15 investment options available to members of UniSuper with defined contribution plans (UniSuper 2015). This process was used to replicate the real-world choices superannuation members would make. To reduce the probability of participants fatiguing, the most diverse single sector options from UniSuper were chosen. The combination of different funds available to the participants are similar to Madrian and Shea (2001), where the 10 selected funds comprised of six pre-mixed options and four single section options which can be seen in table 4.1.

Figure 4.1: Information Provided to Participants during the Investment Option Review.



Note: The above figure shows an example the screen shown during the investment option review during phase 1. From the example, the participant is viewing the High Growth investment option.

Figure 4.1 shows an example of a review screen given to the participant. The screen presented to the participants can be decomposed into 2 major sections, the option review choices (1: The dark blue landscape rectangle at the top), the current review choice (2: The white table on the bottom). The participant would thus review the information of each of the 10 investment options by using the review system (1 and 2). The following attributes are clearly observed for each investment option: the name of the investment options, a brief description which includes a the most suitable investor for the option, the return objective, asset allocation and proportion of growth assets, minimum suggested time frame, expected negative annual returns and a summary risk level.

Table 4.2: Attribute Values and Descriptions

Attribute	***Full Title***	***Values***	***Mean(Median)***	***Description***
Return	Investment Return Objective	1,1.5,2,2.5,...,5	3.2(3)	To achieve returns (after fund taxes and investment fees) that are at least X% p.a. more than inflation (CPI).
$\mathbb{E}$(Negative Returns)	The expected frequency of negative annual returns in every 20 years	0,1,2,...,6	3.8(4)	The expected number of years where there are negative annual returns for every 20 years of investment.
Risk Level	Summary Risk Label	Very Low [1], Medium [2], Medium to High [3], High [4], Very High [5]	3.5(4)	A qualitative summary label indicating that the potential for the investment value to rise or fall.
HI Index	Herfindahl Index	0.27,0.28,...,1	0.621(0.47)	The Herfindahl-Index is a measure of asset allocation concentration.
Growth %	Proportion of Growth Assets	0,0.01,..,1	0.605(0.7)	The proportion of assets which are classified as Growth, with the remainder being defensive.
Time Frame	Minimum Suggested Time Frame for investment	0,1,.., 7	5(6)	The suggested number of years that the investment option is chosen to mitigate investment risks.
Word Count	...	27,28,...,55	40.6(41)	The number of words used in the description of the option.
Sustainable Practice	Socially Responsible & Environmentally Solutions	0,1	0.2(0)	An indicator of whether the fund invests in companies who engage in Sustainable Asset Management or businesses which deliver solutions to environmental challenges.

Information sourced from Bateman et al. (2016) and UniSuper (2015), unless stated otherwise.

Due to redundancies and collinearity[2], there are attributes which I cannot use to study ANA. Additional to the attributes described in table 4.1 and 4.2, we can see the option name and the written "Description of option/ Type of Investor" in figure 4.1. The inclusion of attribute based alternative specific constants has been omitted due to the worsening of the within-group collinearity when the alternative specific constants are included. This results in the omission of Option Name and using the ordinal properties of Risk Level. The description of the option includes a list of the assets invested in, a sustainability indicator, the risk-tolerance level and expected returns for a suitable investor. The list of assets is not included because of worsening within-group collinearity. Whereas the sustainability indicator is included in certain specifications[3]. The risk-tolerance of the investor is not included as it provides redundant information with the Risk Level attribute. The risk-tolerance of the suggested investor is exactly the same as the Summary Risk Level in table 4.2 and 4.1.

The Risk Level attribute has a number of problems. The attribute is coded as a continuous variable for the empirical analysis. The continuous values are used to preserve the ordinal properties of the different qualitative labels and allows me to

[2] See Appendix C for more detail.
[3] See table D.6

produce an estimate for Risk Level. However, this attribute is most likely unidentified, due to overlapping values with two other attributes found in the description of the investment option. Risk level is overlapping with both the qualitative and ordinal properties of the risk-tolerance and a qualitative indicator for expected returns (UniSuper 2015). The overlapping values are an issue due to the confounding between the qualitative expected returns and Risk levels. The estimates for Risk Level are confounded because it would be typically expected that investors would seek to maximise returns and minimise risk (Sharpe 1966). Thus, the estimates for Risk Level are likely to be unidentified because we cannot identify whether the estimated preferences are for returns or risk.

To capture the asset allocation and portfolio diversification two attributes are used. The first is Growth Proportion, which is the proportion of assets in the investment option portfolio which are classified as growth assets. The Growth attribute can be seen in each pie chart (see figure 4.1 below) and is defined as assets which include shares, infrastructure and private equity (UniSuper 2019). These assets are prone to short term fluctuations in value and are thus associated with higher risk (UniSuper 2019). The remainder of the proportion (i.e. 1-Growth) are assets which are classed as defensive (UniSuper 2019).

The second indicator of diversification is the Herfindahl Index of portfolio concentration (Bateman et al. 2016). The Herfindahl Index is 1 for a portfolio containing a single asset and decreases as the number of equally sized asset allocation increases. The Herfindahl index is calculated as,

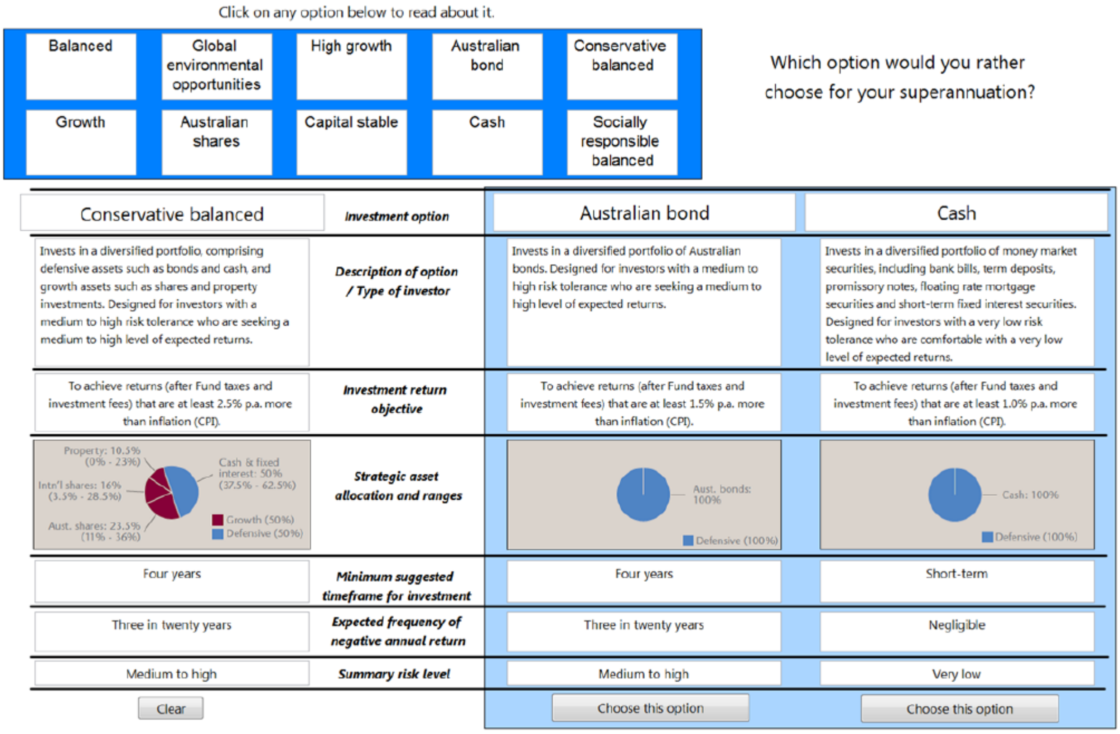
$$HI = \sum_{i=1}^{n} w_i^2 \tag{4.1}$$

Where w_i are the portfolio weights of each asset in each portfolio. The Herfindahl index is constrained between 0 and 1 by construction, where a value of 1 indicates that the portfolio contains only 1 type of asset. However, the Herfindahl index is used to proxy the asset allocations and participants were not given the Herfindahl index value. Rather participants are shown pie charts which list percentage weights (see figure 4.1).

4.3 Second Phase - Choice structure and Treatments

The second phase of the experiment required participants to choose their preferred investment option from all 45 possible pairwise combinations (Bateman et al. 2016). I use a pooled subsample of participants to determine if ANA is present in their choice of investment option. The pooled subsample of participants received "full information" relative to participants not in the subsample [4]. The "full information" subsample received the information according to figure 4.1, which adhered to the requirements of the Simpler Super Regime. This results in a sample size of 161 participants and is the largest possible homogeneous sample from Bateman et al. (2016) with which attribute non-attendance can be empirically estimated in the context of the Simpler Super Regime.

Figure 4.2: Information Provided to Participants during the Pairwise Ranking.

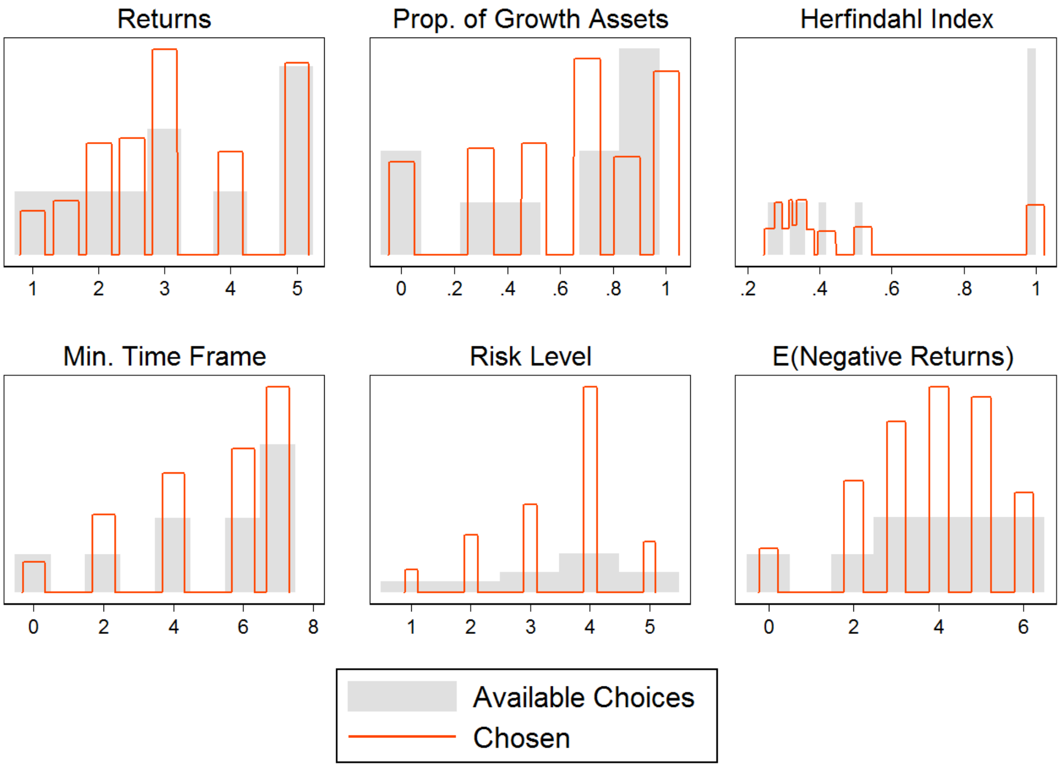


Note: The above figure shows an example pairwise choice between two investment options in phase 2. On the left-hand side, the participant is viewing the information for the "Conservative Balanced" investment option. The light blue shaded area highlights the two investment options the participants must choose between.

Figure 4.2 shows an example of a pairwise choice given to the participant. The choice screen presented to the participants can be decomposed into 3 major sections, the option review choices (1: The dark blue landscape rectangle at the top), the selected review choice (2: The white portrait on the left) and the pairwise comparison (3: The light blue rectangle on the right of the screen). A participant could thus review the information of any of the 10 investment options by using the review system (1 and 2), but made a choice between the 2 pairwise options given on the right in the light blue area (3).

[4] See figure B.1

Figure 4.3: Available Attribute Values and Chosen Attribute Values



Note: The above figure is based on the "full information" subsample. The chosen values are calculated using rectangular kernel densities of the attributes which were chosen, given the participants' choices. Whereas the Available Choices are a histogram of all the available choices the participants had.

Figure 4.3 shows a comparison of which attributes were available and which attributes were actually chosen by the full information subsample. Each plot shows a histogram of the attributes values which were available to participants over the course of their choices and a rectangular kernel density estimate showing the chosen attribute values, given the participants choice of investment options. By comparing the histogram and kernel density plot, we can observe which attributes' values are preferred, given the participants choice of investment options. From figure 4.3 we can observe that increasing attribute values are available and chosen for Expected returns, Proportion of Growth assets and the Minimum Time Frame. In comparison, a large number of single asset portfolios were available, shown by the large proportion at of available choice at a Herfindahl index of 1. Despite the abundance of single assets portfolios, there is not a clear majority of single asset portfolios being chosen. Rather, there is a large number of chosen values with a lower Herfindahl index which is indicated by the clumping around values less than 0.4. This is suggestive that participants prefer to have an equally weighted asset allocation. This preference for equally weighted allocations is suggestive of a naive diversification strategy (Benartzi and Thaler

2007).

From figure 4.3, I infer suggestions of which specifications should be used in the empirical analysis. Comparing the kernel densities and the histogram for $\mathbb{E}$(Negative returns) and Risk Level, a maximum can be seen to form at 4 for $\mathbb{E}$(Negative returns) and High[4] for Risk Level. The maxima at 4 is suggestive of quadratic preferences with respect to the attributes. The quadratic preference for the $\mathbb{E}$(Negative returns) are carried over to the modelling, whereas the Risk Level is not. A likelihood ratio test suggests that including a second order polynomial for Risk Level is unnecessary[5]. Additionally, this polynomial would also reduce the parsimony of the model and is not carried forward to the modelling.

4.4 Third Phase - Holt-Laury & DOSPERT

The third phase of the experiment required participants to complete a Holt-Laury instrument and DOSPERT survey (Bateman et al. 2016). This provides information on the risk preferences (Holt and Laury 2002) and nature of risk aversion of the participant (Weber et al. 2002). The Holt-Laury instrument requires the participants to make choices over different lotteries which allow the identification of risk attitudes (Holt and Laury 2002; Holt and Laury 2002; Harrison et al. 2005). The DOSPERT survey assesses risk in five general domains of finance (investment and gambling), health and safety, recreational, ethical and social where participants rate how likely they would engage in a domain specific risky activity (Weber et al. 2002). Thus, these instruments help to provide information and evidence on the risk preferences of the individuals.

[5]See Appendix C

Table 4.3: Holt-Laury instrument Choice between Lotteries

Decision	Lottery A			OR	Lottery B			Expected Payoff $\mathbb{E}$(A-B)
1	3 ECU	and	2.40 ECU		5.80 ECU	and	0.15 ECU	1.745 ECU
	(1 in 10)	and	(9 IN 10)		(1 in 10)	and	(9 IN 10)	
2	3 ECU	and	2.40 ECU		5.80 ECU	and	0.15 ECU	1.24 ECU
	(2 in 10)	and	(8 IN 10)		(2 in 10)	and	(8 IN 10)	
3	3 ECU	and	2.40 ECU		5.80 ECU	and	0.15 ECU	0.735 ECU
	(3 in 10)	and	(7 IN 10)		(3 in 10)	and	(7 IN 10)	
4	3 ECU	and	2.40 ECU		5.80 ECU	and	0.15 ECU	0.23 ECU
	(4 in 10)	and	(6 IN 10)		(4 in 10)	and	(6 IN 10)	
5	3 ECU	and	2.40 ECU		5.80 ECU	and	0.15 ECU	-0.275 ECU
	(5 in 10)	and	(5 IN 10)		(5 in 10)	and	(5 IN 10)	
6	3 ECU	and	2.40 ECU		5.80 ECU	and	0.15 ECU	-0.78 ECU
	(6 in 10)	and	(4 IN 10)		(6 in 10)	and	(4 IN 10)	
⋮				⋮				⋮
10	3 ECU	and	2.40 ECU		5.80 ECU	and	0.15 ECU	-2.8 ECU
	(10 in 10)	and	(0 IN 10)		(10 in 10)	and	(0 IN 10)	

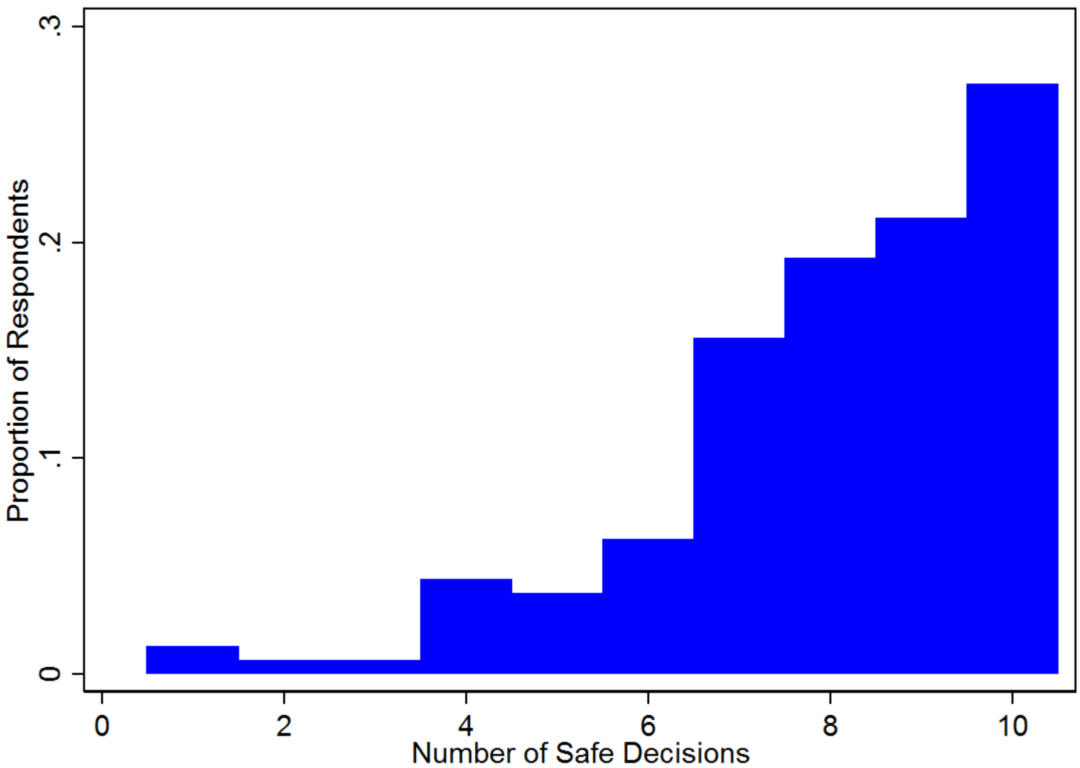
Note: 1 ECU = 1 AUD. The table shows the two available lotteries in the Holt-Laury instrument and how the expected pay-offs change as participants progress through the decisions.

I use the Holt-Laury instrument to account for risk preferences of the participants. The Holt-Laury instrument requires the participants to make 10 choices between two lotteries, and the sequence of chosen lotteries highlights the participants risk aversion. This choice can be seen in table 4.3. The participant had to sequentially choose between Lottery A or Lottery B for each decision. As the decisions progress, the expected pay-offs of each lottery change in a manner which highlights a participant's risk preferences. The first four decisions have a positive expected pay-off for choosing lottery A. After the fourth decision, the expected pay-offs become negative when choosing lottery A. Thus, a completely risk averse participant would choose lottery A in the first 4 decisions and then proceed to choose lottery B until the last decision.

The participants in the sample have a significant degree of risk aversion. Similar to

Holt and Laury (2002), Holt and Laury (2005) and Harrison et al. (2005). I find that a majority of participants prefer safer choices and are risk averse. This can be seen in figure 4.4. The histogram in 4.4 shows the proportion of participants making a certain number of safe choices. The safe choices are calculated as the number of times lottery A was chosen between decisions 1-4 and the number of times Lottery B was chosen from decisions 5-10. From the histogram, there is larger proportion of participant making more risk averse choices, with 85% of the participants choosing at least 7 safe choices and 25% of participants choosing all the safe options.

Figure 4.4: Proportion of Safe Choices From The Holt-Laury Instrument



Note: The above figure is a histogram of the number of safe choices for the participants. This is calculated as the number of times lottery A was chosen up to decision 4, and then adding the number of time lottery B was chosen after decision 4.

4.5 Fourth Phase - Socio-Demographics

The fourth phase of the experiment surveyed participants on their social-demographic characteristics. After the completion of the socio-demographic questions, the participants were paid and required to leave. Staff received a base payout of 18 and students received 9 Australian Dollars. An additional pay-off based on a random draw from the log-normal distribution of their most preferred investment option and the Holt-Laury measure. From the entire sample, Bateman et al. (2016) note that there is a possible over-representation of younger and better educated university retirement plan members. One participant has been omitted due their failure to complete a number of socio-demographic questions.

Table 4.4: Mean and (Median) Socio-demographic Characteristics

Characteristic	Pooled Sample	Full Sample
Age		
years	30.15(25)	29.05(25)
Education (years)		
Secondary	6.94(7)	6.95(7)
Tertiary	4.23(4)	4.09(4)
Children		
Number of	0.30(0)	0.28(0)
Self-Reported Health		
Out of Five	3.89(4)	3.89(4)
Monthly Purchases ($)		
Food purchased In	283(240)	275(220)
Food purchased Out	182(150)	178(150)
Telephone Bill	61(50)	56(40)
Total Consumption	780(600)	715(500)
Finances ($ '000)		
Gross Income[1]	41(25)	37(24)
Net Worth[2]	222(20)	1922(20)
Employment		
Proportion of UNSW Staff	0.43	0.33
Total		
Respondents	$n = 161$	$n = 229$

Note: The mean value of the socio-demographic characteristics is provided, and the median value is provided within parenthesis. [1]159 respondents in pooled sample and 225 in the full sample. [2]156 respondents in pooled sample and 224 in the full sample.

Table 4.4 presents comparative summary social-demographic characteristics for all the participants in the experiment and individuals within the "full information" subsample. From the table it appears that the pooled sample is older, wealthier and more educated, but a t-test of the difference in means rejects this[6]. However, the pooled sample has ∼30% more UNSW staff relative to the full sample and is the only mean which is statistically different. From this, the pooled sample does not mitigate the oversampling of younger and better educated university retirement plan members.

4.6 Limitations

A limitation of this thesis is a lack of real-world choice data. It would be preferable to conduct the analysis of limited attention on a real-world data set comprising of Australians choosing between actual superannuation funds. This real-world data set would provide greater extrapolation than the experimental dataset (Arnett 2008). However, poor quality of superannuation data collection is well known (Productivity Commission 2018). In the Productivity Commission's review of superannuation, a noted issue has been the lack of reporting by a quarter of the funds since 2004, despite the data being collected by APRA, ASIC and the ATO (Productivity Commission 2018). The lack of reporting results in a missing data on numerous important issues including the number of unique superannuation members in each segment, incomplete and inconsistent fee disclosure by funds, major gaps in areas of potential conflicts of interest and a lack of member-based data (Productivity Commission 2018). This results in data on the Australian superannuation system which is largely immune to empirical analysis.

Thus, the data I use to analyse limited attention is a pooled subsample from Bateman et al. (2016). The subsample consists of the all the participants who received attributes and information as per the Simpler Super Regime. The participants then made 45 pairwise choices from 10 investment options which were sourced from a real-world superannuation fund, UniSuper. The subsample shows a significant amount of risk aversion from the Holt-Laury instrument Bateman et al. (2016). From this, the work of this thesis can be seen as an extension of the work of Bateman et al. (2016), which studies the presence of limited attention within the participants.

[6]See table D.1 in Appendix D.

Chapter 5

Empirical Models

In this chapter, I outline the econometric models used and the behaviour that the models describe within the context of superannuation. Under the study of choice behaviour, an econometric model which describes particular choice behaviour can be constructed for a participants' choices by assuming that the probability of an investment option being chosen is a member of a parametric family of probability distributions and that the observed choices are multinomially distributed. Under these assumptions, I can obtain estimators of the underlying parameters from the econometric models (McFadden 1973). The particular choice behaviour I am interested in is ANA, which is described by the endogenous attribute (EAA) model (Hole 2011a). However, ANA may not be the only behaviour being used by the subsample of respondents and the EAA model may not describe the participants choice behaviour. To test for this, I use the Generalised Mulitinomial Logit (GMNL) (Fiebig et al. 2010) which describes a variety of choice behaviours. To test which model of choice behaviour best fits the participants' choices, I employ three criterions. Thus, I firstly derive McFadden's Conditional Logit (Clogit) (McFadden 1973) using the Random Utility Framework and develop a baseline specification of the investment options attributes. I then outline the GMNL, which nests the Clogit. I then describe the EAA model and finish with a brief summary of the information criteria.

5.1 Conditional Logit

McFadden's Conditional Logit (Clogit) (McFadden 1973), is typically considered a workhorse in choice modelling (Keane and Wasi 2012). The reliance on the Clogit is due to the ease of interpretation and computation of the model's parameters (McFadden 1973). However, the Clogit model has a drawback in the assumption of independence of irrelevant alternatives. The assumption of independence of irrelevant alternatives implies that the introduction of an additional alternative results in an equal proportional change in the probability of each alternative being chosen (McFadden 1973). This assumption holds when there are no close substitutes between investment options. However, from table 4.1, there are a number of investment options which have close substitutes. Thus, the Clogit is a problematic choice because it would not be able to identify differential substitutability or complementarity between the close investment options. The Clogit is used to establish a baseline model and set of estimates which can be built upon.

The Clogit model can be derived from the Random Utility Framework. The participant's utility from choosing investment option i can be split into a systematic component ($\boldsymbol{X}^{'}\boldsymbol{\beta}$) and a random component (ε_{njt}). The systematic component is an index of attributes ($\boldsymbol{X}$) and preferences weights ($\boldsymbol{\beta}$). Whereas, the random component (ε_{nit}) represents unobserved attributes of the investment option and unobserved characteristics of the participant. Using the systematic and random component, the utility received by a participant (n) from choosing investment i in pairwise choice t is,

$$U_{nit} = \boldsymbol{X}^{'}_{nit}\boldsymbol{\beta} + \varepsilon_{nit} \tag{5.1}$$

Assuming that a participant chooses an investment option because it yields a higher utility results in the probability that investment option i is chosen over investment option j from the available investment options $J = \{i, j\}$,

$$\mathbb{P}_{nit} = \mathbb{P}(U_{nit} > U_{njt}) = \mathbb{P}(\boldsymbol{X}^{'}_{nit}\boldsymbol{\beta} - \boldsymbol{X}^{'}_{njt}\boldsymbol{\beta} > \varepsilon_{njt} - \varepsilon_{nit}) \tag{5.2}$$

By assuming that ε_{njt} and ε_{nit} have extreme value (Weibull) distributions, then the probability that alternative i is chosen,

$$\mathbb{P}(Investment\ Option_{n,t} = i) = \frac{exp(\boldsymbol{X}^{'}_{i,t}\boldsymbol{\beta})}{\sum_{j}^{J} exp(\boldsymbol{X}^{'}_{j,t}\boldsymbol{\beta})} \tag{5.3}$$

5.2 Baseline Specification

The baseline specification of the design matrix $\boldsymbol{X}$ estimates the preference weights of return, the proportion of growth assets, the asset allocation via the Herfindahl Index, minimum suggested time, risk labels and expected negative returns on the probability that each investment option is chosen. The baseline specification is:

$$\begin{aligned} \boldsymbol{X} = [&Return_j,\ Growth_j,\ HI\ index_j,\ Min\ Sug.\ Time_j,\ Risk\ Level_j, \\ &\mathbb{E}(Negative\ returns)_j,\ \mathbb{E}(Negative\ returns)^2_j] \end{aligned} \tag{5.4}$$

This baseline specification is founded on Model 1 in Bateman et al. (2016) and captures similar results[1]. The attributes in the baseline specification were chosen to replicate the real-world choices that a participant would make amongst investment options offered by a superannuation fund. Hence, the attributes replicate the information provided in UniSuper PDS documents (UniSuper 2015). However, it is not possible to exactly replicate Model 1 from Bateman et al. (2016) due to the within-group collinearity created by the long-form data structure required by the EAA and GMNL models. To compensate for this, I have substituted the alternative specific risk levels used in Bateman et al. (2016) with a continuous risk level variable and a second order polynomial of $\mathbb{E}$(Negative returns)[2]. The loss of the alternative specific risk levels is important because investment risk is a key factor when choosing financial products (Sharpe 1966; Productivity Commission 2018). Thus, the baseline model endeavours to capture how participants use attributes provided by a real-world superannuation fund, while circumventing the within-group collinearity.

5.3 Generalised Multinomial Logit

The Generalised Multinomial Logit (GMNL) extends the Clogit model by incorporating a greater degree of flexibility while surmounting the assumption of independence of irrelevant alternatives. The GMNL is capable of accounting for the presence of scale heterogeneity (Fiebig et al. 2010), and the importance of assessing scale heterogeneity is that it can model common extreme behaviour such as lexicographic preferences and random choice. Previously, variance was normalised to 1 for identification, this has been recently realised as unlikely (Louviere and Eagle 2006). Thus, the addition of scale heterogeneity solves a fundamental identification problem. Additionally, the Clogit model is a special case of the GMNL. Alongside the Clogit, the GMNL nests the Mixed Logit which accounts for preference heterogeneity, the Scaled-Multinomial Logit (Scale-MNL) which accounts for scale heterogeneity and the GMNL-II which can be described as a scaled Mixed Logit.

Using the GMNL model, the utility (U) a participant n receives from choosing investment option i on occasion t is,

[1] See table 6.1 and 6.2.

[2] An interaction term between Return and Risk Level was also tested for, see table D.2.

$$U_{n,i,t} = [\sigma_n \boldsymbol{\beta} + \psi \boldsymbol{\eta}_n + (1-\psi)\sigma_n \boldsymbol{\eta}_n]\boldsymbol{X}'_{n,i,t} + \varepsilon_{n,i,t} \tag{5.5}$$

A participant's utility is a function of their scale heterogeneity (σ_n), mean preference weights ($\boldsymbol{\beta}$), how each participant deviates from the mean preference weights ($\boldsymbol{\eta}_n$, i.e. individual preference heterogeneity) and how scale heterogeneity varies in the presence of participant preference heterogeneity (ψ). From this, the preference weights can be observed to be composed of scale heterogeneity (σ_n), individual preference heterogeneity (η_n) and how preference heterogeneity varies with scale heterogeneity (ψ),

$$\beta_n = \sigma_n \beta + \psi \eta_n + (1-\psi)\sigma_n \eta_n \tag{5.6}$$

I estimate a mixed logit model using the GMNL framework to analyse variation in the participants' preferences (individual preference heterogeneity) (Fiebig et al. 2010). Preference heterogeneity is the extent of variation in preferences for a good (Price et al. 1989). To estimate the Mixed Logit model requires the normalisation of the scale heterogeneity to 1 ($\sigma_n = 1$). The Mixed Logit can be expressed using the random utility framework as,

$$U_{n,i,t} = [\boldsymbol{\beta} + \boldsymbol{\eta}_n]\boldsymbol{X}'_{n,i,t} + \varepsilon_{n,i,t} \tag{5.7}$$

$$\tag{5.8}$$

From this, the preference weights for the Mixed Logit can be seen to be composed as a mean preference weight (β) and how the participants' preferences differ from the mean preference weights by η_n (Keane and Wasi 2012),

$$\beta_n = \beta + \eta_n \tag{5.9}$$
$$\text{where, } \sigma_n = 1 \text{ and } \boldsymbol{\eta}_n \sim MVN(0, \Sigma)$$

To analyse how random the participants' choices are, I estimate the Scale-MNL using the GMNL framework (Fiebig et al. 2010). To observe the Scale-MNL we require the normalisation of ψ to 1 and the variance of the participant preference heterogeneity normalised to zero (i.e. $var(\boldsymbol{\eta}_n) = 0$) (Gu et al. 2013),

$$U_{n,i,t} = [\sigma_n \boldsymbol{\beta}]\boldsymbol{X}_{n,i,t} + \varepsilon_{n,i,t} \tag{5.10}$$

From this, the preference weights for the Scale-MNL can be seen to be composed of a mean preference weight ($\boldsymbol{\beta}$) and a scale parameter (σ_n). This heterogeneity in scale is similar to a specific heterogeneity across the preference weights (Fiebig et al. 2010). This implies that all the preference weights are scaled proportionately across participants,

$$\beta_n = \sigma_n \beta \tag{5.11}$$

$$\text{Where, } \sigma_n = \exp(\bar{\sigma} + \tau\nu_i), \;\; \nu_i \sim N(0,1) \tag{5.12}$$

To observe how the scale parameter results in random choices, we can use a simple random utility framework of a participant choosing between alternative j and i with attributes $\boldsymbol{X}$. Under the assumption of iid Type-I extreme value stochastic error terms, the probability of choosing investment i over j is (Fiebig et al. 2018),

$$\mathbb{P}(Investment\ Option = i) = \frac{exp(\sigma \boldsymbol{X}'_i \boldsymbol{\beta})}{\sum_j^J exp(\sigma \boldsymbol{X}'_j \boldsymbol{\beta})} \tag{5.13}$$

If there is a large amount of variation of scale in the participant's choices this results in a small scale which is associated with more random choices. The scale of the error term is inversely related to the error variance from (5.12). As choice behaviour becomes more variable the probability of an investment option being chose is as likely to be chosen as it is not, regardless of the attributes. This can be seen as σ approaches zero in (5.13) and the probability of choosing either attribute approaches half,

$$\lim_{\sigma \to 0} \mathbb{P}(Investment\ Option = i) = \lim_{\sigma \to 0} \frac{exp(\sigma \boldsymbol{X}'_i \boldsymbol{\beta})}{\sum_j^J exp(\sigma \boldsymbol{X}'_j \boldsymbol{\beta})} = \frac{1}{2} \tag{5.14}$$

This implies that choice behaviour is more random for some participants than others (Gu et al. 2013). To observe this, the key parameter that captures scale heterogeneity is the standard deviation of σ_n, τ. From the assumption that the scale heterogeneity is log-normally distributed with a mean of 1 for identification, and standard deviation of τ (Fiebig et al. 2010). From this, an increase in τ, the distribution of the scale becomes more skewed to the right of the mean at 1 (Fiebig et al. 2018). This implies that as τ approaches zero, the GMNL approaches a standard Logit with a scale of 1, whereas if τ is positive, the GMNL approaches the Scale-MNL.

To observe the combination of both scale and preferences heterogeneity, the GMNL-II is estimated. The GMNL-II incorporates both the Scale-MNL and the Mixed Logit in a way that can be described as a scaled mixed Logit. Both the mean estimate ($\boldsymbol{\beta}$) and variance in participants' preferences ($\boldsymbol{\eta}$) are scaled (by σ_n) (Fiebig et al. 2010). This can be expressed using a random utility framework as:

$$U_{n,i,t} = [\sigma_n(\boldsymbol{\beta} + \boldsymbol{\eta})]\boldsymbol{X}'_{n,i,t} + \varepsilon_{n,i,t} \tag{5.15}$$

The preference weights for the GMNL-II can be seen to be composed of a mixed Logit being scaled. This results in the variance of the participants' preferences to be proportional to the scale heterogeneity (σ_n). The preference weights for the GMNL-II can be expressed as,

$$\beta_n = \beta \cdot \sigma_n + \eta_n^* \tag{5.16}$$
$$\text{where, } \psi = 0 \;\&\; \eta_n^* = \eta_n \cdot \sigma_n$$

Despite the flexibility of the GMNL, it has a series of drawbacks regarding computation. It is not possible to estimate the GMNL model parameters using maximum likelihood estimation and must be estimated using simulated maximum likelihood estimation (Fiebig et al. 2010). This implies that the estimates are dependent on the random number seed, number of Halton draws, starting values and optimisation method (Gu et al. 2013). Of critical importance is the number of Halton draws, where the number of draws increases the accuracy of the estimates but also increases the computational time (Gu et al. 2013). Additionally, starting values are important to achieve convergence of the more complicated GMNL variants. Choosing different starting values may result in different estimated parameters due to the estimates being a local rather than global maxima (Gu et al. 2013). This variation can be seen between the difference between the estimates from a standard desktop using `STATA 14` and the Katana High Performance Cluster[3] using `STATA 12`[4], which is used to calculate the bootstrap marginal rates of substitution. This

[3]Katana, UNSW Sydney, https://www.hpc.science.unsw.edu.au/cluster/katana
[4]See table D.9

results in a model that is computationally intensive which produces varied results.

5.4 Endogenous Attribute Attendance Model

The main model used to analyse attribute non-attendance is the endogenous attribute attendance (EAA) model (Hole 2011a). The EAA model allows the participant to consider an attribute in an endogenous manner when choosing between investment options. This is achieved by the EAA through two stages. The first stage is a choice by the participant of which attributes to consider when comparing K attributes of the investment options. In the second stage, the participant chooses which investment option with the best attribute values given the participants preferences. The estimated parameters of the model can be used to calculate attribute attendance probabilities and estimate marginal rates of substitution which account for ANA (Hole 2011a).

The Endogenous Attribute Attendance model is parsimonious and easy to compute relative to other ANA models. The EAA model can estimate ANA from typical choice data and does not require supplementary data from introspective surveys (Scarpa et al. 2009; Abaluck and Adams 2017). Additionally, the EAA model can include all possible attribute subsets relative to other latent class model approaches which can only accommodate a limited number of attribute subsets and require normalisations of an attributes ANA to zero (Hole 2011a; Hole et al. 2013). The EAA model has relatively little computing because only one vector of attributes is estimated for each attribute (i.e. $\boldsymbol{\gamma}_k$). In comparison, other latent class models require one vector of parameters per attribute in each subset of attributes to be estimated. This greatly increases the computational requirements of other latent class models (Hole et al. 2014; Scarpa et al. 2009).

In the first stage, the participant will choose a subset (C_q) of K attributes to take into account for when they later choose their best investment option in the second stage. There are $Q = K^2$ possible subsets of attribute combinations. The participant will choose a particular subset to consider C_q ($q \in Q$). At the extremes of the subsets lies C_1, where none of the attributes are chosen and C_Q, where all the attributes are chosen. When C_1 is chosen, this implies that the choices made by the participant are random because none of the attributes are used to choose the investment option and is similar to the Scale-MNL. In comparison, C_Q implies that all the attributes are considered, and the EAA becomes a standard Logit model (Hole 2011a). The probability that an attribute k ($k \in K$) is considered is modelled as a Logit of socio-demographic characteristics ($\boldsymbol{z}_n$),

$$\frac{exp(\boldsymbol{z}_n^{'}\boldsymbol{\gamma}_k)}{1+exp(\boldsymbol{z}_n^{'}\boldsymbol{\gamma}_k)}$$

where $\boldsymbol{z}_n$ is a vector of socio demographic characteristics of the participant. $\boldsymbol{\gamma}_k$ is a vector of parameters to be estimated which are used to calculate the probability of ANA for the corresponding attribute (k). Assuming the that the ANA probabilities are independent over the attributes and using the above Logit model allows the probability that the attribute subset is going to be considered by the participant to be expressed as:

$$H_{nC_q} = \Pi_{k\in C_q}\frac{exp(\boldsymbol{z}_n^{'}\boldsymbol{\gamma}_k)}{1+exp(\boldsymbol{z}_n^{'}\boldsymbol{\gamma}_k)}\Pi_{k\notin C_q}\frac{1}{1+exp(\boldsymbol{z}_n^{'}\boldsymbol{\gamma}_k)} \tag{5.17}$$

In the second stage the participant will choose which alternative provides the highest utility, given that the participant has chosen which attributes to ignore and which to attend to. The utility that a participant, n, derives from choosing investment option i on occasion t, conditional on their choice of subset is based on the value of attribute k relating to alternative i for pairwise choice t and the preference weight given to attribute k (β^k). This can be expressed as:

$$U_{nit} = \sum_{k\in C_q} x_{nit}^k\beta^k + \varepsilon_{nit} \tag{5.18}$$

Where ε_{nit} is assumed to be IID extreme value. From the above utility, the second stage is the probability that the participant chooses alternative i over alternatives $j \in J$, conditional on their chosen subset,

$$\mathbb{P}(Investment\ Option_{nt} = i)|C_q = \frac{\sum_{k\in C_q} x_{nit}^k\beta^k}{\sum_j^J\sum_{k\in C_q} x_{njt}^k\beta^k} \tag{5.19}$$

By combining the first two stages (5.17) and (5.19), I get the unconditional probability of the observed sequence of choices:

$$P_n = \sum_{q=1}^{Q} H_{nC_q} \cdot \Pi_{t=1}^{T} \Pi_{i=1}^{J} \mathbb{P}(choice_{nt} = i)|C_q \tag{5.20}$$

The unconditional probability of the observed sequence of choices is then estimated using maximum likelihood estimation of the log-likelihood function,

$$LL = \sum_{n=1}^{N} \ln(P_n) \tag{5.21}$$

In this thesis, I specify the probability that a participant takes an attribute into account in multiple ways. Firstly, I am assuming that attention is used on visually apparent attributes of a good rather than introspective attributes the participant may use such as the Sharpe ratio, which need to be calculated by the participant. Thus, the $\mathbb{E}(NegativeReturns)$ polynomial is specified as only a single $\boldsymbol{\gamma}$ vector and will produce one probability of ANA for the entire polynomial. This models participants as attentive to the $\mathbb{E}(NegativeReturns)$ polynomial as a whole. Secondly, the probability of attendance is specified as a constant ($\boldsymbol{z}_n = [1]$) in the baseline model. This implies that the probability of non-attendance is the same for all participants (Hole 2011a). I relax this assumption in chapter 7.

Despite the ability of the EAA model to infer ANA probabilities, it has a few drawbacks. The first being that the probability of attentiveness towards and attribute can only be identified when the preference weights are not equal to zero, $\beta_k \neq 0$ (Hole 2011a; Hole et al. 2013). Additionally, The EAA model requires a number of assumptions to hold for the estimates to be valid. Firstly, the EAA model assumes that the decision behaviour used by participants when considering attributes is constant over the pairwise choices, which may not be true (Hess and Hensher 2010; Bateman et al. 2016). Another inherent assumption of the model is that the probabilities of paying attention to each attribute are independent (Hole et al. 2014). A critical drawback of the relatively simple EAA is that it can confound ANA with weak preference heterogeneity (Hess et al. 2012; Hole et al. 2013). This poses a major problem with the estimation of ANA using the EAA model, as ANA cannot be cleanly identified.

5.5 Goodness of Fit: Information Criterion

To determine which model fits the participants' choices best, we need to establish the goodness of fit between each of the models. Three information criterions are used in a "horse race" style of model selection (Fiebig et al. 2010; Keane and Wasi

2012). The three information criterion are the Akaike (AIC), consistent AIC (CAIC) and Bayesian (BIC) information criterion (Schwarz 1978; Akaike 1974; Bozdogan 1987). Each of the information criterion penalise for increases in model complexity via the number of estimated parameters. The BIC and CAIC are noted to be more reliable measures when assessing scale heterogeneity, with the BIC being the most reliable (Fiebig et al. 2010). Additionally, the BIC and CAIC have larger penalties for model complexity, and this provides a more stringent criteria for complex models. The information criteria are calculated as,

$$\text{AIC:} \; -2 \cdot LL + k \cdot 2 \tag{5.22}$$

$$\text{CAIC:} \; -2 \cdot LL + k \cdot [\ln(N) + 1] \tag{5.23}$$

$$\text{BIC:} \; -2 \cdot LL + k \cdot \ln(N) \tag{5.24}$$

where LL is the log-likelihood of the model and N is the number of observations. The criteria indicate a better fitting model by a relatively lower score when comparing models using the same data. As suggested by Gu et al. (2013), the total number of observations used to calculate the information criterion should be the number of participants multiplied by the number of choice occasions. This results in the number of observations for the information criterion's being $161 \times 45 = 7245$ in a typical application, rather than the default observation count in STATA^{TM} of $161 \times 45 \times 2 = 14\ 490$ (StataCorp 2015). Additionally, for all estimations, the standard errors are clustered at the individual level.

5.6 Summary of the models.

Thus, to assess whether the pooled subsample of participants from Bateman et al. (2016) exhibit attribute non-attendance I estimate an EAA model and a suite of GMNL models. The EAA model provides the core results to this thesis as it estimates the ANA of the participants along with preference weights (β) which account for ANA. Despite this, due to the simplicity of the EAA model the estimates of ANA may be confounded with weak preference heterogeneity (Hess et al. 2012; Hole et al. 2013). The EAA model is thus compared to the GMNL models, specifically the Mixed logit, Scale-MNL and GMNL-II, to assess model fit and relative misspecification. The Mixed Logit and GMNL-II models account for preference heterogeneity and act as a check on whether preference heterogeneity plays a strong role within the choices of the pooled sample, which would lead to confounding of the attribute non-attendance estimates.

Chapter 6

Estimation

In this chapter, I present the estimates for the Clogit, Endogenous Attribute Attendance (EAA) model and Generalised Multinomial Logit (GMNL) model using the baseline specification (5.4). The estimates use the "full information" subsample from Bateman et al. (2016) which were outlined in chapter 4. The first set of estimates include the Clogit and EAA model. These estimates are used to analyse the participants' attribute non-attendance and highlight some of the issues with using a Clogit model. The second set of estimations include the Clogit, Mixed Logit, Scale-MNL and GMNL-II specifications. The second set of estimations are used to analyse and provide evidence on other possible choice behaviours such as individual preference and scale heterogeneity. Additionally, the second set of estimates also help to identify whether the EAA model is confounding individual preference heterogeneity with attribute non-attendance (Hole et al. 2013; Hess et al. 2012). These models were estimated using STATA 14 (StataCorp 2015), with the `Clogit` command (StataCorp 2015), the `gmnl` package (Fiebig et al. 2010; Gu et al. 2013) and the `eaalogit` package (Hole 2011a). In the next chapter, I relax some of the constrictive assumptions made in this chapter and further extend the models to include socio-demographics. However, the results from this chapter are robust despite the extensions.

6.1 Attribute Non-Attendance

Table 6.1: Clogit and Endogenous Attribute Attendance Estimations, Baseline specification

	1	*2*	*3*	*4*
			EAA ($z_n = 1$)	
Attribute$_k$	Clogit:β	2^{nd} Stage:β	1^{st} Stage: γ	$\mathbb{P}$(Attendance$_k$)
Return Objective	-0.305	-1.503***	-0.195	0.549***
	(0.321)	(0.148)	(0.262)	(0.0649)
Proportion of Growth Assets	1.613	6.377***	0.657	0.341***
	(1.598)	(0.787)	(0.506)	(0.114)
Herfindahl Index	-1.620**	-3.169***	0.686*	0.335***
	(0.767)	(0.324)	(0.375)	(0.0836)
Minimum Suggested Time Frame	-0.354***	-0.925***	0.493**	0.379***
	(0.123)	(0.123)	(0.209)	(0.0492)
Risk Level	-0.371	-0.953***	-0.332	0.582***
	(0.349)	(0.139)	(0.253)	(0.0614)
$\mathbb{E}$(Negative Returns)	1.108***	2.701***	$\vdots$	$\vdots$
	(0.235)	(0.366)		
			1.142***	0.242***
			(0.280)	(0.0514)
$\mathbb{E}$(Negative Returns)^2	-0.0809***	-0.273***	$\vdots$	$\vdots$
	(0.0308)	(0.0470)		
AIC	8440.6	$\cdots$	6339.2	$\cdots$
CAIC	8495.8	$\cdots$	6441.7	$\cdots$
BIC	8488.8	$\cdots$	6428.7	$\cdots$

Note: The above table shows the estimation results for the Clogit and EAA model for the baseline specification. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The number of observations used in this estimation is 161 respondents by 45 choices each, resulting in 7245 observations.

The estimates of a Clogit and EAA model are presented in table 6.1 and are similar to Bateman et al. (2016). In column *1*, the Clogit model finds the estimated preference weights Return Objective, Growth Proportion and the risk level attributes to be statistically insignificant. This suggests that we cannot reject the null hypothesis that these attributes have no impact on a participants' preferences of investment option. The significant preference weights for the Clogit have the expected signs and are similar to Bateman et al. (2016). In column *2* the estimated preference weights for the

EAA model are all statistically significant at the 1% level, which contrasts the Clogit's insignificant estimations. All the signs the EAA model's preference weights are in line with prior expectations, except for Return Objective. The estimated preference weight for Return Objective has a negative sign, indicating that an increase in the Return Objective is associated with a decrease in the probability of an investment option being chosen. The unexpected result is attributed to participants overlooking risk and return information and are rather making choices based primarily on the asset allocations of each investment option (Bateman et al. 2016). Additionally, this result could be indicative of the intrinsic risk-return trade-off inherent in the real-world investment options provided.

The Clogit model implicitly assumes that participants pay full attention to all the investment option's attributes. In comparison, the EAA model relaxes this assumption and allows for participants to vary their attendance to each attribute. For the EAA estimates in table 6.1, the probability of attending to an attribute is modelled as a constant ($z_n = [1]$) and implies that the ANA probabilities are fixed across participants. All the coefficients in the second stage of the EAA model are statistically significant, implying that the first stage estimates (γ_k) are identified and the probability of attendance towards each attribute can be calculated as,

$$\begin{aligned} \mathbb{P}(\text{Attendance}_k) &= \Lambda^{-1}(-\hat{\boldsymbol{\gamma}}_k) \qquad (6.1) \\ \implies \mathbb{P}(\text{Non-attendance}_k) &= 1 - \mathbb{P}(\text{Attendance}_k) \end{aligned}$$

where $\Lambda^{-1}(\cdot)$ is the inverse Logit function.

From the ANA probabilities, respondents appear to be attentive towards Returns and inattentive towards specific risk attributes. The probability of attendance to each attribute is shown in column *4* of table 6.1. The probability of non-attendance is largest towards the $\mathbb{E}$(Negative Returns) attribute, where the mean participant has a 75.8% probability of not taking $\mathbb{E}$(Negative Returns) into consideration when choosing investment options. This is followed by the Growth Proportion, Herfindahl index and the Minimum Suggested Time Frame with a ∼65% probability of non-attendance to any of these attributes. In comparison, the attributes which garnered the most attention were Risk level with a 41.8% probability of ANA and Return Objective with a 45.1% probability of ANA. These estimates suggest that participants are likely to pay attention to concise summary information such as the Return objective and the Risk level. In comparison, the participants are likely to ignore specific risk indicators such as the asset allocations and the expected negative returns associated with an investment option. However, due to the unidentified nature of Risk Level, the estimated ANA is likely to be spread across the 3 entangled attributes. The limited attention to specific risk indicators is similar to the results of Ehm et al. (2013) who found that participants fail to account for different risk measures and rather employ a simple allocation rule between risk and risk-free assets.

6.2 Generalized Multinomial Logit

Table 6.2: Generalised Multinomial Logit Estimates, Baseline Specification

	1	*2*	*3*	*4*	*5*	*6*
	(Clogit)	(Scale-MNL)	(Mixed Logit)		(GMNL-II)	
Attribute (k)	(β)	(β)	(β)	(σ_β)	(β)	(σ_β)
Return Objective	-0.305	-0.335	-1.030**	1.084***	-1.176**	1.233***
	(0.321)	(0.340)	(0.480)	(0.0979)	(0.521)	(0.123)
Proportion of Growth Assets	1.613	0.893	5.008**	0.351*	5.994**	2.830***
	(1.598)	(1.760)	(2.336)	(0.189)	(2.588)	(0.321)
Herfindahl Index	-1.620**	-2.570***	-2.009*	2.482***	-2.527**	2.729***
	(0.767)	(0.849)	(1.117)	(0.302)	(1.251)	(0.350)
Minimum Suggested Time Frame	-0.354***	-0.505***	-0.531***	0.524***	-0.668***	0.606***
	(0.123)	(0.157)	(0.179)	(0.0677)	(0.210)	(0.0635)
Risk Level	-0.371	0.00418	-1.294**	-0.807***	-1.377**	1.150***
	(0.349)	(0.421)	(0.507)	(0.0892)	(0.549)	(0.224)
$\mathbb{E}$(Negative Returns)	1.108***	1.143***	2.547***	0.174	3.128***	0.419*
	(0.235)	(0.278)	(0.369)	(0.117)	(0.500)	(0.240)
$\mathbb{E}$(Negative Returns)^2	-0.0809***	-0.0810**	-0.214***	0.0704***	-0.255***	0.0329**
	(0.0308)	(0.0371)	(0.0469)	(0.00774)	(0.0617)	(0.0147)
		(τ)			(τ)	
Scale		0.948***			-0.522***	
Heterogeneity		(0.0912)			(0.0886)	
AIC	8440.6	8084.2	6279.1		6260.9	
CAIC	8495.8	8139.3	6389.5		6379.2	
BIC	8488.8	8147.3	6375.5		6364.2	
Log likelihood	-4213.3	-4034.1	-3125.6		-3115.4	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. The sign of the estimated standard deviations is irrelevant: interpret them as being positive. The number of observations used in this estimation is 161 respondents by 45 choices each, resulting in 7245 observations. The above Log Likelihood refers to the simulated Log likelihood for the non-Clogit models.

The estimates for the suite of GMNL models are presented in table 6.1 and are similar to table 6.1 and Bateman et al. (2016). The models include the Clogit (*1*), scale-multinomial Logit (Scale-MNL) (*2*), Mixed Logit (*3-4*) and GMNL-II

(*5-6*). In these estimates, participants are implicitly assumed to attend to each of the investment option's attributes. Additionally, the Mixed Logit and GMNL-II incorporate individual preference heterogeneity, and the Scale-MNL and GMNL-II incorporate scale heterogeneity. From table 6.2 the estimated preference weights (β) of the Scale-MNL are similar to the Clogit in terms of signs and significance. Whereas the models which account for preference heterogeneity are similar to the EAA model in terms of signs and significance. In addition, the sign on each attribute's preference weights is the same across the different models except for the Risk level, which is positive and insignificant for the Scale-MNL. The estimated magnitudes are similar between the Clogit and Scale-MNL and the EAA, Mixed Logit and GMNL-II. This suggests that there may be behavioural overlap within the two sets of models.

From the estimates of Scale Heterogeneity, there appears to be disagreement. The Scale-MNL has estimated a scale standard deviation (τ) of 0.948, whereas the GMNL-II has a scale standard deviation of 0.522, with both estimates being statistically significant. From a descriptive perspective, the two models disagree on the scale heterogeneity of the participants. The Scale-MNL is reporting a large estimate for the standard deviation, implying that participants are exhibiting very strong scale heterogeneity. In comparison, the GMNL-II is reporting that individuals are exhibiting substantially less scale heterogeneity in comparison to the Scale-MNL and inherently suggests that respondents are making less random choices.

By examining incremental improvements in likelihoods from simple to complex models allows me to develop a sense of the importance of scale heterogeneity (Fiebig et al. 2010). This test follows a similar intuition to the BIC and is calculated as,

$$\begin{aligned} &\text{Improvement attributable to scale heterogeneity} \\ &= \frac{\%\text{ improvement in LL from MNL to Scale-MNL}}{\%\text{ improvement in LL from MNL to GMNL-II}} \end{aligned} \tag{6.2}$$

When introducing scale and preference heterogeneity into the model, a 26.1% of the improvement in log-likelihood is achieved by the GMNL-II. From the improvement in likelihoods, only 16.3% can be attributed to scale heterogeneity alone. This along with the suggested misspecification of the Scale-MNL from the information criteria suggests that scale heterogeneity has very little presence in the choice behaviour of the participants. This is a very unexpected result, as typically the Scale-MNL dominates the Mixed Logit in terms of improvement (Keane and Wasi 2012; Fiebig et al. 2010). This is possibly attributed to the pairwise structure of the choice between investment options, as respondents only compared a few attributes across only 2 alternatives.

In comparison to the scale heterogeneity, the estimates of individual preference heterogeneity are in agreement. From the Standard deviation (σ_β) of the mean preference weights from the Mixed logit and GMNL-II, there is substantial variation in the respondents' preferences. All the estimated standard deviations are statistically significant and large relative to the means. The standard deviation and mean estimate magnitudes are also similar between the two models. In addition, the improvement in log-likelihood from just incorporating preference heterogeneity is six times larger than the improvement attributable to scale heterogeneity. This appears to suggest that the task of choosing between investment options garnered a lot of attention and resulted in varied preferences for the respondents.

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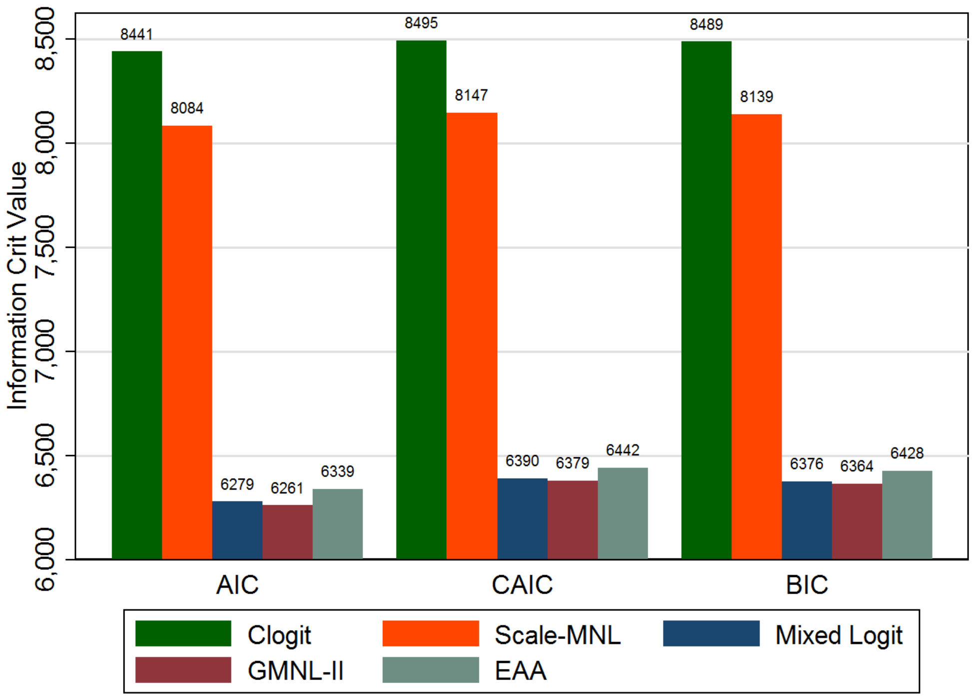
6.3 Information Criterion Comparison

Figure 6.1: Information Criterion Across Different Models Using The Baseline Specification



Note: The above figure shows the information criterion scores for the AIC, CAIC and BIC across the Clogit, Scaled MNL, Mixed Logit, GMNL-II and the EAA model. The models are estimated using the baseline specification (5.4).

Comparing information criteria scores across the Clogit, Scale-MNL and EAA model suggests that participant inattention is selective. Firstly, the information criteria suggest that the Clogit is the worst fitting model. This result is expected due to the Clogit's inflexibility and assumption of independence of irrelevant alternatives. The next best fitting model is the Scale-MNL model, which fits the data better with a 350 point improvement in the BIC over the Clogit. Albeit, this improvement in fit is dwarfed by the relative scores of the EAA with a 1711 point improvement. This suggests that the Clogit and Scale-MNL describe behaviour unlikely to be used by participants. From the poor fit we can infer that there is substantial substitutability between the investment options and that participants are not making random choices. Comparing the EAA model fit to the Scale-MNL, it appears that ANA behaviour is being used. This is suggestive that rather than the complete inattention towards attributes described by the Scale-MNL, attention is selective towards certain attributes as described by the EAA model. This supports the idea that individuals are not making random choices but are rather being selective in their inattention towards attributes and have lexicographic preferences.

Comparing information criteria across all the models, the most dominant respondent choice behaviour is individual preference heterogeneity. The information criterion scores suggest that the Clogit, Scale-MNL and EAA models are misspecified relative to the Mixed Logit and GMNL-II, with the GMNL-II having the best fit. This is an unexpected result, models which incorporate scale heterogeneity typically perform better (Keane and Wasi 2012; Fiebig et al. 2010). In these results however, the typically well performing Scale-MNL is severely misspecified. This is suggestive that there is a large amount of variation between the individual preference weights. Additionally, the EAA model is relatively misspecified in comparison to the models which account for preference heterogeneity.

Looking at how the different models fit the data, we can infer that the choice between investment options was not complex and garnered attention. As suggested by Fiebig et al. (2010), comparing the importance of scale and preference heterogeneity can identify characteristics of the choice task. The importance of Scale heterogeneity in terms of model fit is associated with tasks that are more complex and participants have little knowledge on. Thus, from the lack of scale heterogeneity within the participants' behaviour this would suggest that the task was not greatly complex, and participants were knowledgeable regarding the choice. This result is counter-intuitive, because the requirements of making an accurate assessment of a portfolio involves accommodating both risk and return (Sharpe 1966). In comparison, the relative importance of preference heterogeneity suggests that the task of choosing between investment options is a high-involvement decision. This is also an unexpected, as participants only needed to consider the Return Objective and the $\mathbb{E}$(Negative Returns) to find the most efficient portfolio through the Sharpe ratio (Bateman et al. 2016). Rather the participants have varied preferences over multiple attributes. From the fit of the models, with the information criteria preferring individual preference heterogeneity. Thus, the fits suggest that the choice between investment options received substantial attention from the respondents and was not a complex one. This can be possibly attributed to the choice between investment options, which required individuals to compare 2 sets of investment options through the pairwise structure of the choice task. This would reduce the cognitive burden and allow respondents to make active choices, while paying attention to each attribute.

Comparing information criterion also results in the EAA models being misspecified relative to the Mixed Logit and GMNL-II. This result is highly suggestive that the EAA model is confounding weak preference heterogeneity with attribute non-attendance (Hess et al. 2012; Hensher et al. 2012; Collins et al. 2013). As noted by Hess et al. (2012), modelling ANA without accounting for preference heterogeneity can result in ANA estimates which are confounded with weak preference heterogeneity. When participants have weak preferences ($\beta_k \sim 0$) for an attribute, the participant is likely to be classified as being inattentive by the EAA model when they in fact are attentive but have weak preferences in regard to the attribute (Hole et al. 2014). However, typical empirical findings suggest that the confounding between ANA and the preference heterogeneity result in inflated ANA probabilities (Hole et al. 2013; Hole et al. 2014; Hensher et al. 2012; Scarpa et al. 2009). In Hess et al. (2012) the issue of confounding between ANA and preference heterogeneity is addressed through a latent class approach by using a model which allows for classes of participants with high and low preference sensitivity. Hess et al. (2012) finds confounding between ANA and preference heterogeneity and that accounting for both behaviours results in reduced ANA probabilities. In a similar vein, Hole et al. (2013) incorporates preference heterogeneity into the EAA model and similarly finds reduced ANA probabilities. This result is also found in Scarpa et al. (2009) and Campbell et al. (2012).

Chapter 7

Discussion

The estimates in chapter 6 provide some interesting results, which are extended and checked in this chapter. Using the baseline results, I can estimate the marginal rates of substitution between the attributes and discuss the implications of ANA on willingness-to-pay. Additionally, a common idea from behavioural economics is present bias. Present Bias could be driving the inattention in the sample through the ANA, which is tested for. However, the baseline specification has a number of constrictive assumptions. The result of the EAA and Scale-MNL being relatively misspecified is unexpected and is further investigated by incorporating observable preference heterogeneity through the inclusion of socio-demographic characteristics. I then look at the supply side of the superannuation market to help determine whether fund behaviour is indicative of limited attention. I then the close the chapter with how these results affect the primary hypothesis of the thesis and what this suggests for superannuation policy.

7.1 Marginal Rate of Substitution

Incorporating attribute non-attendance is known to result in substantially different marginal rate of substitution (MRS) estimates to models which do not account for ANA (Hole 2011a; Hole 2011b; Hole et al. 2013; Hole et al. 2014; Scarpa et al. 2009; Hensher et al. 2005; Abaluck and Adams 2017; Lagarde 2012). In a random utility framework (5.1) the marginal rate of substitution is given by the negative ratio of the two desired attribute coefficients (Hole 2007). The MRS is found by taking the total derivative of utility from equation (5.1) and setting it to zero. To find the MRS, the derivative is solved for the required attributes. This yields the required change in one attribute ($\mathrm{d}X_j$) to keep utility unchanged for a change in the other attribute ($\mathrm{d}X_k$) (Hole 2007),

$$\begin{aligned} \mathrm{d}U_{njt} &= \sum_{j=1}^{n} \beta_j \mathrm{d}X_j = 0 \\ \implies \frac{\mathrm{d}X_j}{\mathrm{d}X_k} &= -\frac{\beta_k}{\beta_j}, \text{ where } k \neq j \end{aligned} \tag{7.1}$$

This calculation of the marginal rate of substitution relies on the assumption that respondent will choose the same alternative despite the change in the other attribute ($\mathrm{d}X_k$) and that the model is linear in its attributes. When the respondent can choose from multiple alternative calculating the compensating variation is suggested by Lancsar and Savage (2004) to account for the probability that an individual may switch from the currently chosen alternative to a new alternative after the change in X_k. For this thesis, I am assuming that the respondent will consistently choose the same alternative, given an increase in the other attribute, which allows me to use (7.1). Additionally, the attributes in this thesis are non-linear due to the $\mathbb{E}$(Negative Returns) polynomial. When estimating the MRS, the derivative of the polynomial requires a value to be evaluated at. The chosen value is 4, which is the most chosen value of $\mathbb{E}$(Negative Returns).

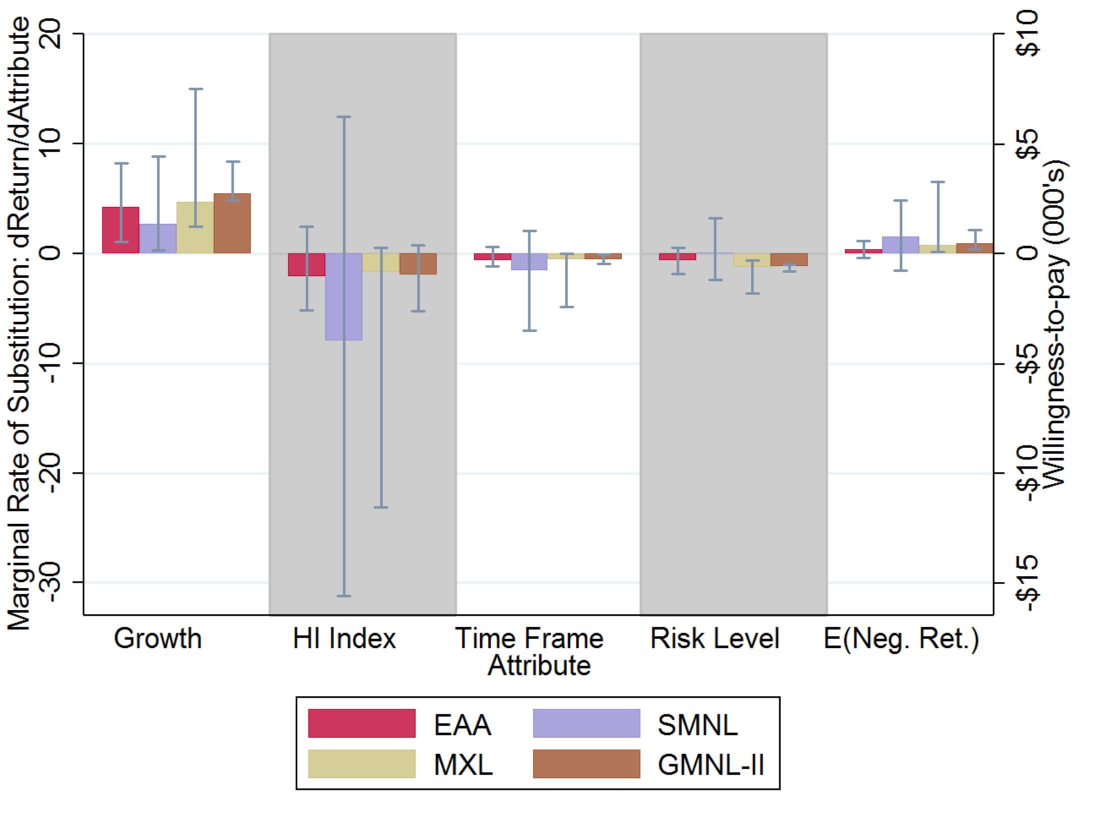
As the MRS is a random variable, it should be presented with confidence intervals (Hole 2007). The MRS is calculated as the ratio of two random variables, the MRS itself is a random variable and to calculate the confidence intervals there are four methods: the Delta method, the Fieller method, the Krinksky Rob method and bootstrapping Hole (2007). I have chosen to bootstrap the MRS estimates to provide robustness. Bootstrapping provides robustness when dealing with unobserved heterogeneity and has no assumptions on the estimates' distribution (Mooney and Duval 1993). Since bootstrapping has no distribution assumptions, normality or joint normality of the estimates is unnecessary in comparison to the other methods (Hole 2007). My preference for no distribution assumptions comes from the small sample size, as the other methods require large samples to provide accurate results (Hole 2007). Additionally, a minimum of 1000 repetitions is suggested to improve the estimates robustness of the bootstrap estimates (Andrews and Buchinsky 2000). For the Mixed Logit and GMNL-II estimates, the mean preference weights (β) are used in the MRS estimates.

The MRS estimates only provide a "local" estimate for the EAA model. In traditional MRS estimates, both attenders and non-attenders are pooled which can bias the estimates (Collins et al. 2013). The bias occurs because the non-attenders have an MRS of either zero or infinity since they do not make trade-offs with attributes they ignore. However, traditional MRS estimates will pool the zero and infinite values together with the valid MRS estimates of attenders (Scarpa et al. 2009). For example, assuming that the Return Objective and Risk Level attributes attract the most attention, the estimated MRS for return and risk level will be valid for at most $\sim$55% of the subsample who attend to both Return Objective and Risk Level and are able to make the trade-off. In comparison the estimated MRS with the Herfindahl index or proportion of Growth assets will only apply to at most $\sim$35% of the sample. Thus, The "local" estimates are only applicable to participants who are attentive.

The bootstrap MRS estimates for each combination of attributes and each model can be found in Appendix B. Similar to Hensher et al. (2012), I find that accounting for ANA and preference heterogeneity reduces the size of the percentile confidence intervals of the MRS estimates. However, in contrast to Hensher et al. (2012), I find that preference heterogeneity is a key influence on the robustness of the MRS estimates. The Clogit, EAA and Scale-MNL show a lack of robustness in being able to robustly determine the sign of the estimate. For example, the Clogit can only has four confidence intervals which are either completely positive or negative. Whereas, the EAA has 5, the Mixed Logit has 18 and the GMNL-II has 19 strictly signed intervals. By looking at the p-values which are greater than 0.9, acts as a "test of insignificance". The test of insignificance highlights the probability of an estimate being equal to 0. From the Clogit, 76% of the MRS estimates have a p-value greater than 0.9. In comparison, the EAA has 36% and the GMNL-II has no estimates with a p-value greater than 0.9. These instances of more robust and accurate results for the Mixed Logit and GMNL-II further support the notion that the key behavioural driving the respondents' choices is individual preference heterogeneity.

7.1.1 WILLINGNESS-TO-PAY

Figure 7.1: Willingness to Pay Estimates Across Different Models



Note: The above figure shows the marginal rate of substitution for $\mathrm{d}Return/\mathrm{d}Attribute_k$. The values are from the marginal rate of substitution tables in Appendix B. The willingness-to-pay values are calculated assuming an account value of $50 000.

Traditionally, stated choice and discrete choice surveys are used to estimate the willingness-to-pay ($\mathrm{d}Return/\mathrm{d}Attribute_k$) for specific attributes (Hensher et al. 2005). To infer a willingness-to-pay using the subsample from Bateman et al. (2016), I use the Return Objective to infer a nominal value for the trade-offs required to keep utility constant. This is achieved by assuming that the average account has a value of $50 000, which is typical of the superannuation literature (Productivity Commission 2018). I then infer that an increase in the Return Objective by 1 is equivalent to an increase in the account by 1% which results in an increase in $500 for the account. Using this conversion, I recover the willingness-to-pay estimates.

The MRS between Return Objective and the other attributes, along with the inferred willingness-to-pay can be seen in figure 7.1. The negative willingness-to-pay for the Herfindahl index suggests that the respondents require compensation as the asset allocation move closer to a single asset, supporting the naive diversification strategy notion (Benartzi and Thaler 2007). An increase in the minimum suggested time frame and risk level also require compensation. The required compensation for the increase in the time frame is suggestive that participants are present biased due to their impatience and prefer returns sooner rather than later (O'Donoghue and Rabin 1999). The $\mathbb{E}$(Negative Returns) may appear to be unexpected with a positive willingness-to-pay. However, the $\mathbb{E}$(Negative Returns) is evaluated at its most chosen value and a substantial number of respondents may still be receiving benefits from the increase in $\mathbb{E}$(Negative Returns) inherent in the MRS. From the estimated willingness-to-pay it appears that the respondents are showing typical traits such as risk aversion and a naive diversification strategy.

The willingness-to-pay for Growth is unexpected and suggest that respondents are losing \$725 in returns annually. The estimates from the EAA, Scale-MNL, Mixed Logit and GMNLII all suggest that a respondent is willing to pay a positive amount for an increase in the proportion of Growth assets. This is unexpected because Growth assets are associated with higher risk (UniSuper 2019). This suggests that participants are willing to pay to take on higher risk, suggesting they are risk loving or expect higher returns (Sharpe 1966). In terms of risk loving preferences, this is paradoxical because of the substantial proportion of risk averse choices from the Holt-Laury instrument. In terms of higher expected returns from the Growth Proportion, the GMNL-II's willingness-to-pay estimates suggest that respondents are willing to pay \$2725 (5.45%) for a change from a completely defensive portfolio to a completely Growth based portfolio. The largest possible gain from this change in allocations is \$2000 (4%), from a change to Australian Shares from the Cash investment option. This results in \$725 (1.45%) being unaccounted for in the change of Return Objective. One likely explanation is that respondents are misinterpreting the Growth attribute. Respondents may be assuming that growth assets are associated with returns which are not being accounted for by the Return Objective, rather than using the formal definition of Growth which indicates higher risk. This implies that the respondent's misinterpretation of Growth is costing them \$725 in foregone returns annually, while unnecessarily increasing risk.

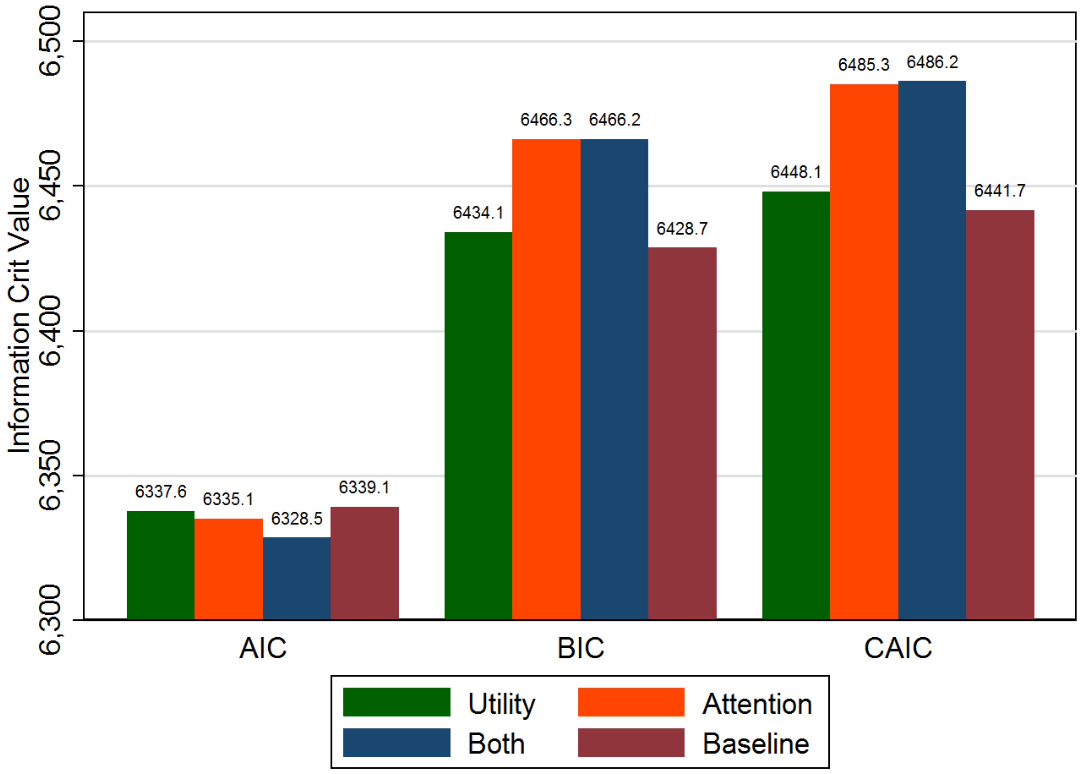
7.2 Testing Present Bias

Traditionally it has been assumed that people discount streams of utility over time in an exponential fashion. However, this ignores the tendency to favour immediate rewards and dislike immediate costs, which is not captured by exponential discounting (O'Donoghue and Rabin 1999). In comparison, present bias captures the trade-offs between current and future moments, while giving larger weight to rewards and costs the closer they are to the present (O'Donoghue and Rabin 1999). Present bias can then result procrastination due to the aversion of unpleasant tasks and their deferral to the future (Bisin and Hyndman 2014) and this may result in savings which are differed to the future. Using a national urban sample in China, Xiao and Porto (2019) find that present bias is associated with poor savings behaviour. My priors are that participants closer to the retirement age would thus be more attentive because they would receive a pay-off at a closer date, whereas younger individuals would receive the payoff much later and would be more inattentive.

To test and model present bias I incorporate the respondents' age into the EAA model through utility, attention and both utility and attention. Firstly, to model age directly into the respondents' utility, Age is modelled using an alternative specific constant. The age alternative specific constant has a base of the second investment option in each pairwise choice. This results in age being modelled into the second stage of the EAA model and attention is still assumed to be constant across the respondents. This requires the design matrix to include the baseline specification of attributes along with the addition of the age alternative specific constant (7.2). Secondly, age can be modelled through attention. This implies that age is influencing the attention paid to each attribute, which occurs in the first stage of the EAA model. To incorporate age through attention, attention is specified as function of age (7.3). Since incorporating age through utility and attention are not mutually exclusive, age can be modelled through both utility and attention which incorporates both (7.2) and (7.3). However, the incorporation of age through both utility and attention results in a very complex models due to the explosion of attention parameters (γ_k^{age}) which need to be estimated.

$$\begin{aligned}
\boldsymbol{X} =& [Return_j,\ Growth_j,\ HI\ index_j,\ Min\ Sug.\ Time_j,\ Risk\ Level_j, \\
& \mathbb{E}(Negative\ returns)_j,\ \mathbb{E}(Negative\ returns)_j^2, ASC\ Age_{jn}] \qquad (7.2) \\
\boldsymbol{Z} =& [1, Age] \qquad (7.3)
\end{aligned}$$

Figure 7.2: Information Criterion Across Different Models To test for Present Bias.



Note: The above figure shows the information criterion scores for the EAA model and the different ways of modelling Age through the first stage (Utility), second stage (Attention), and both. The baseline specification without age (5.4) is provided for comparison.

Figure 7.2 shows the information criterion between the three ways of modelling Age and the baseline specification (5.4) for comparison. The fit of the baseline specification is typically preferred by the BIC and CAIC, only just more than the utility specification. In comparison, when age is modelled through both utility and attention it results in a relatively complex model and is expectedly preferred by the AIC. From this, a clearly preferred model can't be cleanly observed. A series of likelihood ratio tests [1], suggest that it is likely that age has limited effect on the choices, except when modelled through utility. From this, it is unlikely that present bias through age is affecting the respondents. This is likely due to the structure of the experiment being a ∼60 minute session (Bateman et al. 2016). This structure is not very reflective of the large amounts of time required for superannuation members to wait to receive their superannuation income, which is rather measured in years and decades. However, by looking at the preference weights and MRS for the Minimum Suggested Time Frame attribute across the multiple specifications and models, a

[1] See table B.8

longer time frame is robustly not preferred. This dislike of higher suggested time frames could be indicative of present bias, as the time frame suggests how many years an individual would have to wait for a pay-off. From this, present biased individuals would prefer a pay-off sooner which is associated with a dislike of long waiting times (O'Donoghue and Rabin 1999). Thus, age has limited effect on present bias in the experiment, yet from the preferences in regard to the Minimum Suggested Time Frame may suggest present bias. From this, I cannot be certain if the participants are present biased or to what extent.

7.3 Preference Heterogeneity

One limitation of the baseline specification (5.4) is the omission of socio-demographic characteristics of the respondents and certain attributes of the investment options. The exclusion of these variables may be causing the wide and varied unobserved preference heterogeneity being estimated by the Mixed Logit and GMNL-II. By controlling for socio-demographic characteristics and additional attributes, some of the unobserved preference heterogeneity may be accounted for and improve the estimated ANA probabilities.

To account for the unobserved preference heterogeneity coming from the socio-demographics, I relax the assumption of constant attendance in a manner similar to section 7.2. For the EAA, I model this through three different ways, whereas I only use a single specification for GMNL model. Firstly, for the socio-demographics to affect the respondent through their utility, alternative specific constants for each socio-demographic are included with the baseline specification. Additionally, the alternative specific constants are not scaled in the Scale-MNL or the GMNL-II due to their fundamental difference to an attribute (Fiebig et al. 2010). For the EAA model, the alternative specific constants are included in a similar fashion. In the EAA model the probability of attention to each of the alternative specific constants is normalised to 1 due to the fundamental difference to an attribute. The alternative specific constants are included as,

$$\begin{aligned}\boldsymbol{X} =&[Return_j, \cdots, \ \mathbb{E}(Negative\ returns)^2_j,\ ASC\ Age_{nj},\ ASC\ Education_{nj},\\ &ASC\ Children_{nj},\ ASC\ Telephone\ Bill_{nj},\ Staff_{nj},\ ASC\ HL\ Safe\ Choices_{nj}]\end{aligned} \tag{7.4}$$

In comparison, socio-demographics can be specified through attention in the EAA model. For the EAA model, the socio-demographics are modelled through the first stage. I allow the socio demographics to affect the levels of attention paid to each attribute, similar to (7.3). The probability of attention is specified to depend on a vector of socio-demographic characteristics,

$$\boldsymbol{Z} = [Age,\ Education,\ Children,\ Telephone\ Bill,\ Staff,\ HL\ Safe\ Choices] \tag{7.5}$$

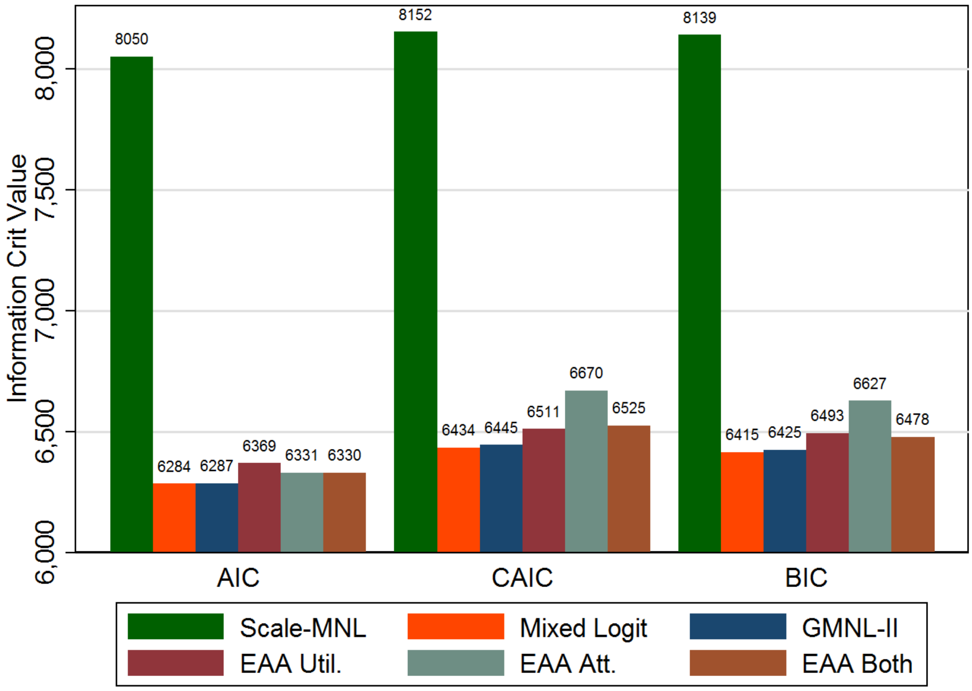
Additionally, the EAA model can incorporate the socio-demographics through both utility and attention through both (7.4) and (7.5). However, this results in a relativity complicated model due to the plethora of parameters which need to be estimated.

This specification of socio-demographics is based on Gabaix and Laibson (2006), Louviere and Eagle (2006), Bateman et al. (2013), Langford et al. (2006) and Productivity Commission (2018). Education and age are noted to lead to more optimal and attentive choices. Additionally, the other characteristics were chosen based on the findings of the suite of GMNL estimates from table D.7 which include a more extensive set of socio-demographic characteristics. This allows me to calculate the probabilities of ANA given specific values of the socio-demographic characteristics, and when the characteristics are modelled as indicator variables, they will allow me to calculate the probability of ANA for specific demographics of respondents..

From a technical standpoint, this specification is also chosen as it represents the most viable socio-demographic characteristics useable. These characteristics are recorded for most of the respondents and prevents shrinking the small subsample further. This small set of characteristics is also chosen because of convergence issues with the EAA estimates when including a more extensive set of socio-demographics. Thus, the characteristics are the largest set of socio-demographic characteristics which achieve convergence when estimating the EAA model.

7.3.1 RESULTS

Figure 7.3: Information Criterion Across Different Models including Socio-Demographics



Note: Shows the information criterion scores across the Clogit Scaled MNL, Mixed Logit, GMNL-II and the three variants of the Endogenous attribute attendance model which incorporate socio-demographic characteristics.

Despite controlling for the socio-demographic characteristics, the goodness of fit between the models is consistent with the prior results in chapter 6. Table 7.3 shows the information criterion scores for the different models which incorporate the socio-demographic characteristics. From the criteria, the models which include preference heterogeneity fit the data better. By comparing the fit between the models, we can see that the best performing EAA model includes socio-demographics through both attention and utility. This is surprising for the BIC, as the BIC has a larger penalty for increasing model complexity, and the EAA with both utility and attention is the most complex model. In comparison, the EAA using attention is the worst performing of the EAA models and is the second most complex. This suggests that the socio-demographics characteristics affect the respondents through both utility and attention and that the inclusion of characteristics through utility are important. As, expected the ANA probabilities decrease with the incorporation of increasing observable preference heterogeneity, which suggests that ANA is being confounded with preference heterogeneity[2] .

Another surprising result is that the Mixed Logit outperforms the GMNL-II in terms of fit, albeit only by a small amount. This implies that the inclusion of scale worsens the fit of the GMNL model. This result carries over to a model which includes added description variables and the socio-demographics [3]. This would suggest that when accounting for socio-demographic characteristics the scale parameter is close to one and that random choices are not being used by the respondents. Additionally, this further supports the notion that unobserved individual preference heterogeneity is a dominant behaviour when respondents making their choices, which the EAA model is confusing with ANA.

In previous work, attribute non-attendance is specified as a vector of a constant and a series of binary indicator variables (Hole et al. 2013; Hole et al. 2014). This makes it possible to distinguish between the probabilities of attention for respondents over different demographics. In this fashion, I specify the socio-demographics from (7.5) as indicator variables. This will help determine the upper bounds of ANA for different demographics,

$$\boldsymbol{Z} = [1,\ Age_{BI},\ Education_{BI},\ Staff_{BI},\ HL\ Safe_{BI}] \tag{7.6}$$

Where,

$$\begin{aligned}
&Age_{BI} = \mathbf{1}[Age_n \geq 29] \\
&Education_{BI} = \mathbf{1}[Education_n \geq 4.1] \\
&Staff_{BI} = \mathbf{1}[Staff_n = 1] \\
&HL\ Safe_{BI} = \mathbf{1}[HL\ Safe_n \geq 7]
\end{aligned}$$

This can be seen in table B.7, which shows how ANA upper bounds vary over age, education, staff status and Holt-Laury safe choices for the respondents. Most of the estimates are as expected, where the elderly, more educated students making safer HL choices are more likely to be attentive. However, from the "local" characteristic of the MRS, I can infer the demographic likely to forgo the $725 for growth assets. The demographic is risk averse students over the age of 29 with greater than 4.1 years of education. This demographic has the highest attentiveness to the Return Objective and proportion of growth assets, and due to the confounding this probability of attendance is likely to increase. From the high levels of attentiveness to both Growth and Return, this demographic is most likely to be willing-to-pay for higher growth

[2]See table B.9

[3]which can be seen in table D.6

allocations and is foregoing \$725 in Return Objective.

7.4 Superannuation Fund Obfuscation

Based on the observation that firms hide information from consumers, Gabaix and Laibson (2006) develop a model showing how firms are immune to competitive pressure in the presence of inattentive consumers and charge prices higher than marginal cost. This occurs because inattentive consumers do not completely analyse the game tree. The consumers do not take all the attributes of the product into consideration because they have not seen the information about the attributes (Gabaix and Laibson 2006). The primary variant of this model is one where the firms shrouds an attribute and the attribute's cost, which is an add-on such as colour printer ink by printer companies. Shrouding the add-on is not an equilibria strategy when the consumers are rational. The rational consumer infers that the shrouded prices are high and then choose a firm with an unshrouded price (Gabaix and Laibson 2006). However, if there are enough inattentive consumers shrouding is more profitable because a monopoly price can be charged for the shrouded add-on (Gabaix and Laibson 2006). This results in inattentive consumers only observe the unshrouded base-good and not the shrouded add-on. Thus, if there exist enough inattentive consumers, firms hide the price of their add-ons and compete solely on the base-good while charging prices above marginal cost for the add-on.

A variant of Gabaix and Laibson (2006)'s model extends to the case where consumers are naturally inattentive to multiple attributes and firms cannot shroud. The predictions of the core variant hold where a firm can charge a markup. In this variant all the attributes are observable, but consumers can exhibit ANA. The prices of the non-attended attributes will attract a markup with a price between marginal cost and monopoly price. Comparing the probability of ANA against the ratio of effort required to switch and price of the attribute, will suggest whether the firm will educate the consumers about the non-attended attribute and unshroud the non-attended attribute. From the results of the EAA estimates, this suggests that it will be easiest for superannuation funds to inform their customers on the Return Objective, while provide the lowest prices based on this attribute. In comparison, superannuation funds will not educate members on the $\mathbb{E}$(Negative Returns) and the asset allocation attributes, while charging higher prices associated with these attributes.

The results of the recent review of the superannuation market in Productivity Commission (2018) suggests that some of the predictions of Gabaix and Laibson (2006) are borne out in the Australian superannuation market. The Australian superannuation market is currently experiencing excess variety (Productivity

Commission 2018), which is noted to obscure consumers ability to find products and funds which are appropriate. The task of choosing a fund for consumers is likely demanding, as consumers must make comparisons over a number of different attributes over a number of different funds. Consumers may simplify this problem and only attend to only a few attributes (Gabaix and Laibson 2006). Thus, it appears that the large number of funds and products serves to increase costs and confusion (Productivity Commission 2018), which is a prediction of the model from Gabaix and Laibson (2006). The excess variety increases the costs of attention resulting in ANA, allowing funds to charge higher prices on the non-attended attributes. A more direct piece of evidence from Productivity Commission (2018) is through the differing levels of sophistication within superannuation, "The irony of the superannuation system is that when it should be sophisticated — particularly in managing risk and in catering for member variety — it is crudest, while being overly complex in areas that are largely irrelevant to members' needs" (Productivity Commission 2018). This suggests that superannuation firms are possibly treating risk management as a base good and lowering the price through its crudeness and charging higher markups through the largely irrelevant and complex areas. Thus, product variety is being used by for-profit funds to extract value (Productivity Commission 2018) and may be a symptom of the limited attention of superannuation members.

An alternative explanation for the excess variety is that funds are simply providing a large variety of products for a population with substantially differing preferences. The information criteria suggest that the GMNL-II and Mixed Logit provides a better fit, which supports the notion that respondents have a substantial amount of preference heterogeneity in their choice of investment options. The excess variety would then provide a multitude of choices for the varied preferences and allows for better matching between funds and consumers, and better choices. Thus, to provide a market with enough products to satisfy each members' preference would require a large product variety. Thus, the excess variety found by Productivity Commission (2018) could rather be virtuous variety as the funds are able to uniquely match the heterogeneous preference of the superannuation members with unique products.

7.5 Relation to Primary Hypothesis and Policy Suggestions

From the results of the EAA and suite of GMNL models, I cannot reject the idea that participants are paying attention to each of the attributes when making pairwise choices between investment options. From the results of the EAA model, it would suggest that there exists a substantial number of respondents who exhibit ANA and therefore limited attention. This results in substantially different MRS estimates in comparison to the traditional Clogit model. However, there has been a noted tendency for ANA models to confound weak preference heterogeneity with ANA. This confound is tested by estimating a suite of GMNL models which account for preference heterogeneity and scale heterogeneity. From the results of the information criteria, the Mixed Logit and GMNL-II results are preferred across different specifications. This suggests that preference heterogeneity is substantially present within the sample of respondents. This further suggests that the ANA estimates are confounded with weak preference heterogeneity. By accounting for observable preference heterogeneity, a decrease in the probability of attribute non-attendance can be observed, but I cannot identify to what extent the decrease will taper off. Thus, Hole et al. (2013) suggests that ANA probabilities estimated from models which do not account for preference heterogeneity are an upper bound estimate. Hence, the ANA probability estimates in this thesis can be observed as an upper bound on the ANA probabilities for the investment options. This does not rule out true zero ANA probabilities and thus, I cannot infer whether the participants in this experiment exhibit ANA due to the confounding with preference heterogeneity.

7.5.1 Policy Recommendations

From the results of this thesis, a few suggestions can be made regarding consumers' choice of investment option and superannuation fund. The suggestions derived from this thesis can be used together with the recommendations of Productivity Commission (2018) to improve the engagement of superannuation members when making choices and ensuring that members choose the best possible fund.

From the results of the suite of GMNL models, we can observe how complex the task of choosing the investment option is. As the Scale-MNL has consistently performed poorly in terms of goodness of fit relative to the Mixed Logit, the task appears to be low in complexity. Additionally, from the dominant preference heterogeneity and possibly low ANA, respondents appear to be paying attention to each of the attributes. This is an unexpected result in comparison to prior literature which finds that the Scale-MNL typically outperforms the Mixed Logit (Keane and Wasi 2012; Fiebig et al. 2010). However, this could potentially be explained by the structure of the experiment. A key difference between the prior findings and my findings is that respondents from Bateman et al. (2016) were required to make pairwise choices, rather than from a larger menu of investment options. Firstly, this reduces the number of alternatives each respondent faces on each choice occasion to 2. This reduces the number of information points needed to be considered to ~14. The reduced complexity attenuates the gap between a respondent's cognitive ability and the cognitive requirements of the task (Heiner 1983). Since the task is more easily handled by respondents, we see less of them "giving up" and making random choices.

Hence the poor performance of the Scale-MNL. From these points, I can derive a suggestion for superannuation policy development: "When Australians are making their choice of fund or investment option, they should be provided with a series of pairwise choices under the simpler super regime". As we have seen, this is likely to coerce members into making active choices. this would result in members thoroughly assessing which choice of fund or option would be most appropriate.

The suggestion of the pairwise choices needs to be accompanied by a shortlist. Despite the potential benefits of the pairwise choices, there is a very apparent downside. To cycle through all pairwise choices between just Australian super funds, and not the offered investment options, would result in $\sim$2080 pairwise choices. This would be a time-consuming endeavour, creating more disengagement with the superannuation system. However, if the pairwise choices were combined with the Productivity Commission's suggested "best in show" short list of funds (Productivity Commission 2018), this would greatly reduce the time spent on the choices. Additionally, since the short list encompasses funds which are known for value, the respondents would be making attentive and active choices over high-value funds. Thus, Participants would be able make an active choice from good funds which meet the participants specific and varied preferences, resulting in an efficient choice.

In terms of the actual choices of investment option and superannuation funds, the attribute labels need to be more descriptive of what the attribute represents. The results from the willingness-to-pay estimates suggest that the members are making perverse trade-offs due to a misunderstanding. This misunderstanding can be corrected through a relabelling of the Growth attribute from "Proportion of Growth Assets" to "Proportion of Aggressive Assets". This would suggest that the assets are inherently associated with a degree of risk, which may result in greater returns or greater losses. Thus, a conceptually simple recommendation would be to relabel the Growth assets to a name which reflects the association of the asset class with its risky properties.

Chapter 8

Conclusion

Using data from a discrete choice experiment on superannuation fund members' choice of real-world investment options. The models include a traditional Clogit model, an endogenous attribute (EAA) model, and a suite of Generalised Multinomial Logit models which allow for choice behaviour, such as scale heterogeneity and preference heterogeneity. The suite of models include a scale multinomial Logit (Scale-MNL) model, a Mixed Logit model and a scaled Mixed Logit (GMNL-II) model. From a baseline specification I find similar results to those in Bateman et al. (2016). Additionally, I consistently find that the fit of the EAA model is better than the Clogit and Scale-MNL, but worse than the fit of the Mixed Logit and GMNL-II. This suggests that the respondents exhibit varied preference heterogeneity and limited scale heterogeneity. However, the ANA probabilities are confounded with preference heterogeneity. This results in the ANA probability estimates being an upper limit which reduces with the inclusion of more observable preference heterogeneity. This suggests that when respondents are making their choices, they have varying tastes, make few random choices and are substantially attentive.

Similar to prior papers on ANA I find a substantial difference in marginal rate of substitution estimates between the Clogit and EAA model MRS estimates. However, the GMNL-II produces the most accurate and robust results. This is further evidence of confounding between the ANA estimates and preference heterogeneity. However, it is also found that individuals appear to be confused as to the definition of the Growth proportion attribute and forego $725 while increasing their risk, which is at odds with their risk averse choices from the Holt-Laury instrument. By incorporating socio-demographic characteristics, I find that unexpectedly it is risk averse students who are most likely to make the detrimental substitution. From these results we can observe a few suggestions for the further development of superannuation choice policy. Superannuation funds should be chosen from a "best in show" short list using a pairwise comparison. Additionally, funds should update the labelling of their investment option attributes to reflect the true nature of risk of the investment option, such as changing the term "Growth" to "Aggressive".

A few papers explored inattention and inertia, but none have addressed the fundamental causes of the more nuanced behavioural processing strategies that may be driving these phenomena. Typically, the literature treats inertia and inattention as given (Hensher et al. 2005; Handel 2013). Thus, an area of potentially fruitful research would be to investigate the causes and drivers of inattention and why individuals choose to adopt the behavioural processing strategies of inattention and inertia.

Despite the results of this paper, there exist a number of limitations. Firstly, a number of attributes were not able to be included due to the within-group collinearity and is likely causing omitted variable bias. Secondly, the confounding of the ANA with preference heterogeneity prevents a definitive argument being reached in terms of the central thesis of this paper. Thirdly, the policy suggestions are based on the results of this paper and the structure of the experiment. These suggestions do not include a counterfactual, which varies the entropy of the alternatives through menu size and other potential factors. Thus, future work can be directed at the development of models which incorporate ANA and preference heterogeneity and variations in choice entropy.

Assuming that attribute non-attendance is non-zero for Australian superannuation members helps to explain the current plethora of products within the superannuation market. According to Gabaix and Laibson (2006), firms increase prices when consumers are inattentive and compete on attributes which consumers are attentive to. This pattern can possibly be seen within the Australian superannuation market. However, the proliferation of products is also potentially attributable to the preference heterogeneity found and that funds could be providing a diverse range of products for a diverse range of preferences. This suggests that the simplification of superannuation product disclosure statements is successful and that the decision to choose between investment options garners attention and diverse preferences from respondents. Rather it may be the case that limited attention is more likely to exist in a different form such as status quo bias, where members have chosen their superannuation fund and are inattentive of other better superannuation funds available (Madrian and Shea 2001).

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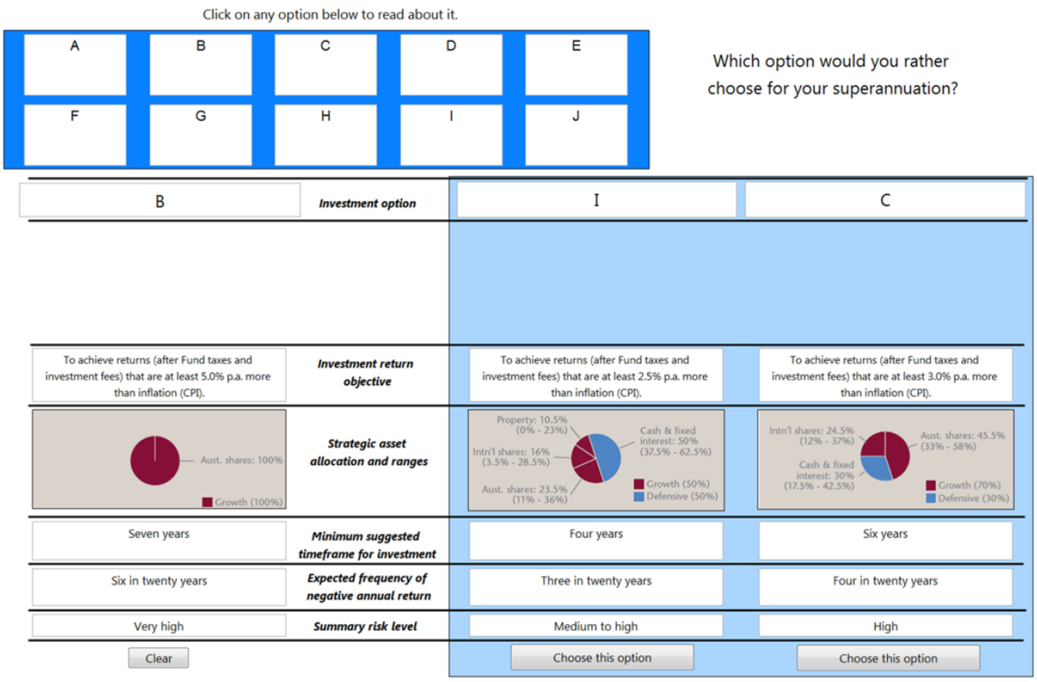
(**B**)

Appendix A

A.1 Experiment Screenshots

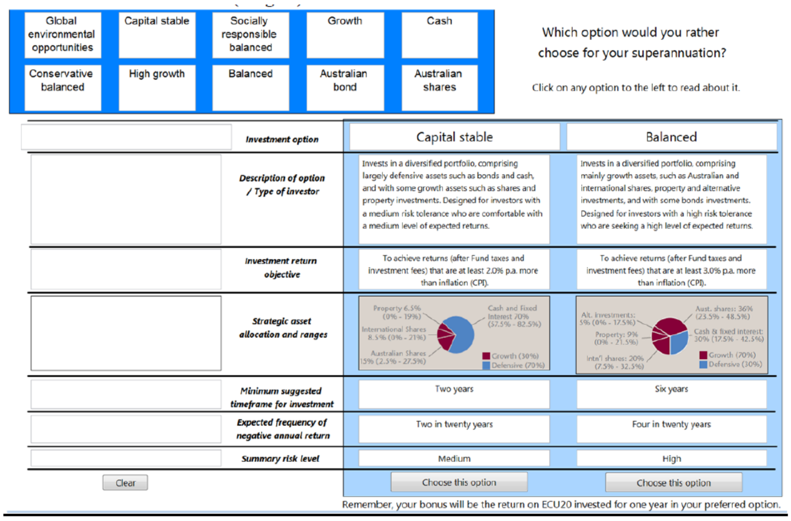
A.1.1 Treatment 1 - No Name Condition

Figure A.1: Screenshot of Treatment 1 - Choice Selection (Second Phase)



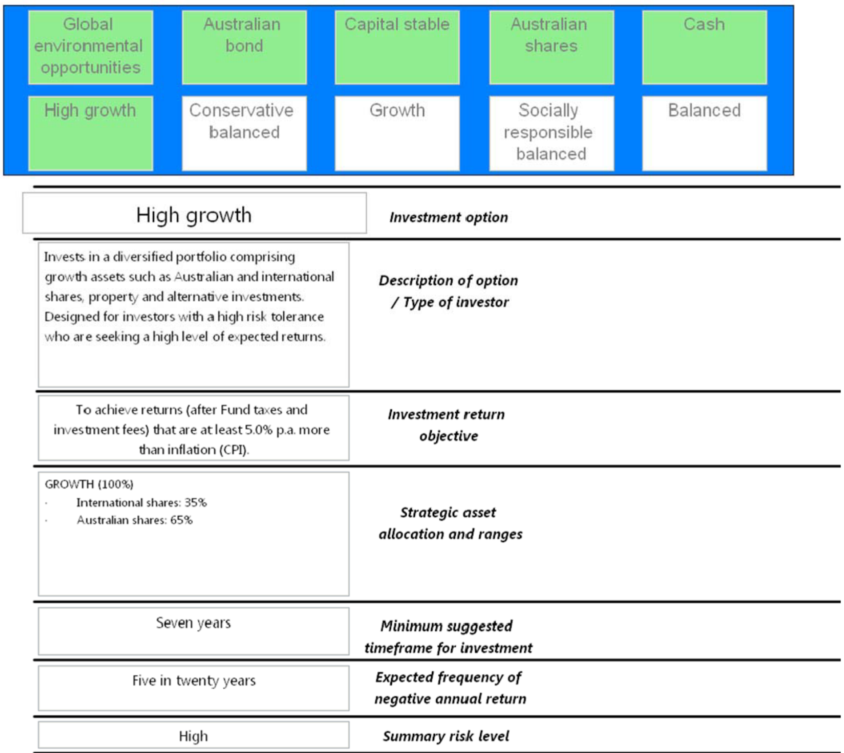
A.1.2 Treatment 2 - Full Information Condition

Figure A.2: Screenshot of Treatment 1 - Choice Selection (Second Phase)



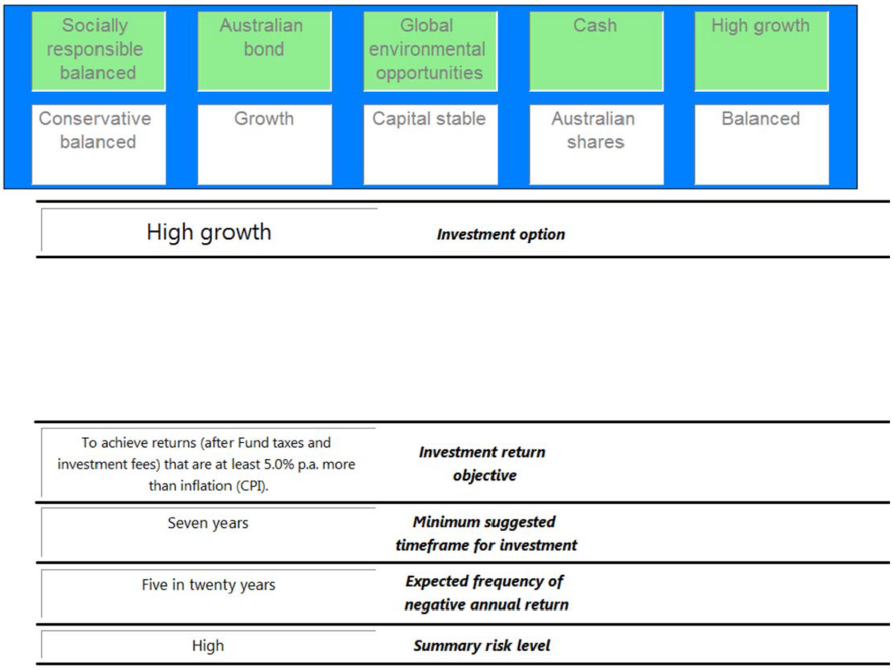
A.1.3 Treatment 3 - Table Allocation

Figure A.3: Screenshot of Treatment 3 - Information Review Stage (First Phase)



A.1.4 Treatment 4 - No Allocative information

Figure A.4: Screenshot of Treatment 4 - Information Review Stage (First Phase)



Appendix B

B.1 Treatment Summary for Bateman et al. (2016)

Table B.1: Treatment Summary

		Treatment 1[3] Name		Treatment 2 Ranking			Treatment 3 Allocation		Treatment 4 Alloc. Display	
Task										
	Pairwise Choice	✓	✓	✓	—	—	✓	✓	✓	✓
	BIBD Ranking	—	—	—	✓	—	—	—	—	—
	Complete Ranking	—	—	—	—	✓	—	—	—	—
Information Provided										
	Name	✓	—	✓	✓	✓	✓	✓	✓	✓
	Written Description	✓	✓	✓	✓	✓	✓	✓	—	✓
	Return	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Pie Chart[1]	✓	✓	✓	✓	✓	—	✓	—	✓
	List[2]	—	—	—	—	—	✓	—	—	—
	Min. Sug. Time Frame	✓	✓	✓	✓	✓	✓		✓	✓
	Negative Returns	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Risk Label	✓	✓	✓	✓	✓	✓	✓	✓	✓
Payment										
	Default or Pref. Option	—		✓			✓		✓	
	Pref. Option	✓		—			—		—	
Observations										
	Staff	26		35			6	8	0	0
	Students	34		1			33	29	30	28
	Total	60		36			39	37	30	28
Full Information Subsample		✓	—	✓			—	✓	—	✓

Note: [1] Included Growth Asset information. [2] Does not include Growth Asset information. The above table shows the different treatments and how they varied between task, information provided, payments and the number of staff and students in each treatment. [3] The treatment ran twice through the 45 pairwise options in a counterbalanced design. In one run revealing the option name omitting it in the other run.

B.2 MRS estimates

B.2.1 Clogit

1000 Replications

Table B.2: Bootstrap Marginal Rates of Substitution for the Clogit Model

Conditional Logit						
	Numerator, β_l					
Denominator, β_k	Return	Growth	HI index	Time Frame	Risk Level	$\mathbb{E}(Neg.\ returns)$
Return	—	5.293^{++}	-5.317^{++}	-1.162^{++}	-1.216^{++}	1.513^{++}
	—	[-5.135,14.298]	[-63.808,77.756]	[-11.871,15.044]	[-4.341,2.252]	[-14.589,13.235]
Growth	0.189	—	1.004^{++}	0.220^{++}	0.230^{*}	0.115^{++}
	[-0.167,0.554]	—	[-15.960,11.284]	[-3.166,2.351]	[-0.228,0.647]	[-0.841,0.776]
Herfindahl Index	-0.188^{++}	0.996^{++}	—	-0.219	-0.229^{++}	0.285^{+}
	[-2.939,0.125]	[-0.528,15.499]	—	[-0.639,-0.15]	[-3.121,0.113]	[0.125,1.315]
Time Frame	-0.861^{+++}	4.556^{+++}	-4.576^{++}	—	-1.047^{+++}	1.302^{+++}
	[-6.773,0.584]	[]-2.682,37.678]	[-6.452,-1.394]	—	[-8.415,0.538]	[0.707,3.653]
Risk level	-0.822^{+}	4.353	-4.373^{++}	-0.956^{++}	—	1.244^{++}
	[-2.919,1.170]	[-3.230,12.167]	[-64.031,57.414]	[-12.851,11.596]	—	[-10.928,12.746]
$\mathbb{E}(Neg.\ returns)$	0.661	-3.498	3.514^{*}	0.768^{**}	0.804	—
	[-0.667, 2.262]	[-12.137, 2.954]	[0.584, 7.271]	[0.273, 1.411]	[-0.660, 2.599]	—

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, $^{+++}$ $p > 0.99$, $^{++}$ $p > 0.95$, $^{+}$ $p > 0.9$. Values are bootstrapped using 1000 replications. The percentile confidence intervals are provided. When the numerator and denominator are the same attribute, the value has been Omitted. The $\mathbb{E}(Neg.\ returns)$ polynomial is evaluated at a value of 4.

B.2.2 Endogenous Attribute Attendance

1000 Replications

Table B.3: Bootstrap Marginal Rates of Substitution for the EAA Model

	Endogenous Attribute Attendance					
	Numerator, β_l					
Denominator, β_k	Return	Growth	HI index	Time Frame	Risk Level	$\mathbb{E}(Neg.\ returns)$
Return	—	4.243	-2.10	-0.615*	-0.634	0.346
	—	[1.094,8.252]	[-5.141,2.445]	[-1.189,0.592]	[-1.867,0.524]	[-0.368,1.137]
Growth	0.236	—	0.497	0.145	0.149	0.260
	[.099,0.779]	—	[-1.706,0.914]	[-0.410,0.231]	[-0.155,0.649]	[-0.954,0.479]
Herfindahl Index	-0.474	2.013	—	-0.292***	-0.301	0.164
	[-0.680,0.508]	[-0.839,2.554]	—	[-0.353,-0.084]	[-0.590,0.411]	[-0.072,0.344]
Time Frame	-1.625	6.896	-3.427	—	-1.031	0.563
	[-3.775,2.056]	[-3.617,17.989]	[-11.662,-2.8]	—	[-4.135,1.732]	[-0.334,2.363]
Risk Level	-1.577	6.691	-3.324	-0.970	—	0.545
	[2.530,1.0]	[-2.998,10.947]	[-5.757,4.605]	[-1.439,1.152]	—	[-0.465,1.301]
$\mathbb{E}(Neg.\ returns)$	2.888$^+$	-12.256	6.090$^+$	1.777$^+$	1.832$^+$	—
	[-11.832,15.336]	[-57.703,22.965]	[-23.464,40.375]	[-5.134,8.061]	[-8.921,15.815]	—

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$,$^{+++}$ $p > 0.99$, $^{++}$ $p > 0.95$, $^+$ $p > 0.9$. Values are bootstrapped using 1000 replications. The 95 percentile confidence intervals are provided. When the numerator and denominator are the same attribute, the value has been Omitted. The $\mathbb{E}(Neg.\ returns)$ polynomial is evaluated at a value of 4.

B.2.3 Scale-MNL

1000 Replications

Table B.4: Bootstrap Marginal Rates of Substitution for the S-MNL Model

Scaled MNL						
	Numerator, β_l					
Denominator, β_k	Return	Growth	HI index	Time Frame	Risk Level	$\mathbb{E}(Neg.\ returns)$
Return	—	2.652***	-7.945	-1.555	0.024^{++}	1.519*
	—	[0.319,8.860]	[-31.230,12.465]	[-7.055,2.093]	[-2.415, 3.226]	[-1.519,4.842]
Growth	0.377	—	2.996	0.586	-0.009^{+++}	0.181
	[0.113,3.139]	—	[-1.407,98.017]	[-0.236,22.143]	[-10.126,0.273]	[-0.248,2.7]
Herfindahl Index	-0.125	0.334^{+}	—	-0.195*	0.003^{+++}	-0.191
	[-3.43,0.080]	[-0.710,16.281]	—	[-0.738,-0.153]	[-3.031, 0.193]	[0.122,1.189]
Time Frame	-0.643	1.706	-5.110***	—	0.015^{++}	0.977***
	[-4.648,0.478]	[-4.234, 22.062]	[-6.522,-1.355]	—	[-4.108,1.154]	[0.686,1.611]
Risk Level	42.154***	-111.783***	334.941***	65.542***	—	-64.029***
	[-2.319, 8.464]	[-17.950,7.150]	[-10.515,61.868]	[-1.612,14.774]	—	[-16.127,2.213]
$\mathbb{E}(Neg.\ returns)$	0.658	-1.746	5.231***	1.026***	-0.016^{++}	—
	[-0.658,2.884]	[-13.692,5.834]	[0.841, 8.208]	[0.620,1.457]	[-1.591,2.549]	—

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$,$^{+++}$ $p > 0.99$, $^{++}$ $p > 0.95$, $^{+}$ $p > 0.9$. Values are bootstrapped using 1000 replications. The percentile confidence intervals are provided. When the numerator and denominator are the same attribute, the value has been Omitted. The $\mathbb{E}(Neg.\ returns)$ polynomial is evaluated at a value of 4.

B.2.4 Mixed Logit

1000 Replications

Table B.5: Bootstrap Marginal Rates of Substitution for the Mixed Logit Model

Scaled MNL

	Numerator, β_l					
Denominator, β_k	Return	Growth	HI index	Time Frame	Risk Level	$\mathbb{E}$(*Neg. returns*)
Return	—	4.716	-1.732^{++}	-0.520^{+}	-1.215	0.769 $^{+}$
	—	[2.471,15.010]	[-23.134,0.561]	[-4.892,-0.025]	[-3.613, -0.646]	[0.118,6.515]
Growth	0.212 **	—	0.367	0.110	0.258***	0.178
	[0.050,0.336]	—	[-0.089,3.267]	[0.009,0.675]	[0.143,0.464]	[-0.128,0.401]
Herfindahl Index	-0.577^{+++}	2.723^{+++}	—	-0.300^{+++}	-0.701^{+++}	0.444^{+++}
	[-8.528,42.980]	[-35.454,42.9801]	—	[-1.811,0.859]	[-10.528,7.682]	[-3.264,5.025]
Time Frame	-1.923	9.067	-3.330	—	-2.335	1.479
	[-13.807,-0.084]	[1.183,81.291]	[-7.780,3.437]	—	[-16.434,-0.363]	[0.494,8.468]
Risk Level	-0.823	3.882	-1.426	-0.428	—	0.633
	[-1.252,-0.152]	[1.987,6.824]	[-9.562,0.403]	[-1.811,-0.035]	—	[0.143,2.663]
$\mathbb{E}$(*Neg. returns*)	1.300^{++}	-6.131^{++}	2.252***	0.676^{+}	1.579^{++}	—
	[0.050,4.234]	[-21.757,-0.752]	[-0.809, 5.888]	[0.0881.649]	[0.235,4.874]	—

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$,$^{+++}$ $p > 0.99$, $^{++}$ $p > 0.95$, $^{+}$ $p > 0.9$. Values are bootstrapped using 1000 replications. The percentile confidence intervals are provided. When the numerator and denominator are the same attribute, the value has been Omitted. The $\mathbb{E}$(*Neg. returns*) polynomial is evaluated at a value of 4. The MRS values are estimated using the `mixlogit` package which is equivalent to using the `gmnl` package.

B.2.5 GMNL-II

1000 Replications

Table B.6: Bootstrap Marginal Rates of Substitution for the GMNL-II Model

GMNL-II						
	Numerator, β_l					
Denominator, β_k	Return	Growth	HI index	Time Frame	Risk Level	$\mathbb{E}(Neg.\ returns)$
Return	—	5.454***	-1.920**	-0.531***	-1.201***	0.889***
	—	[4.861,8.369]	[-5.260,0.787]	[-0.936,-0.101]	[-1.661,-0.983]	[0.358,2.128]
Growth	0.183***	—	0.352**	0.098***	0.220***	0.148 **
	[0.119,0.206]	—	[-0.147,0.629]	[0.019,0.112]	[0.159,0.254]	[-0.096,0.255]
Herfindahl Index	-0.521	2.839	—	-0.277*	-0.625	0.463
	[-1.543,1.756]	[-8.537,7.579]	—	[-0.610,0.305]	[-1.748,1.727]	[-1.079,1.164]
Time Frame	-1.880	10.255	-3.611*	—	-2.258*	1.672***
	[-9.893,-1.068]	[8.941,52.791]	[-5.619,7.789]	—	[-11.303,-1.423]	[0.704,3.693]
Risk Level	-0.833***	4.541***	-1.599**	-0.443***	—	0.740***
	[-1.017,-0.602]	[3.938,6.282]	[-3.948,0.689]	[-0.702,-0.088]	—	[0.288,1.597]
$\mathbb{E}(Neg.\ returns)$	1.125**	-6.134**	2.160**	0.598**	1.351**	—
	[0.47,2.795]	[-16.725,-3.933]	[-2.109,2.472]	[0.270,1.419]	[0.626,3.468]	—

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$,$^{+++}$ $p > 0.99$, $^{++}$ $p > 0.95$, $^{+}$ $p > 0.9$. Values are bootstrapped using 1000 replications. The 95 percentile confidence intervals are provided. When the numerator and denominator are the same attribute, the value has been Omitted. The $\mathbb{E}(Neg.\ returns)$ polynomial is evaluated at a value of 4.

B.3 ANA Estimates

Table B.7: $\mathbb{P}$(Attendance) by Socio-demographic Characteristics

	Age < 29							
	Education < 4.1				Education ≥ 4.1			
	Staff =0		Staff =1		Staff =0		Staff =1	
Attributes	HL ≥7	HL <7	HL ≥7	HL <7	HL ≥7	HL <7	HL ≥7	HL <7
Return	0.730***	0.714***	0.234***	0.221**	0.765***	0.751***	0.269	0.255**
	(0.0953)	(0.103)	(0.135)	(0.100)	(0.120)	(0.104)	(0.180)	(0.128)
Growth	0.890***	0.341***	0.0132	0.000857	0.933***	0.474***	0.0227	0.00149
	(0.255)	(0.123)	(0.0260)	(0.00226)	(0.150)	(0.169)	(0.0437)	(0.00421)
Herfindahl Index	0.361***	0.281***	0.364	0.284**	0.350***	0.271***	0.353	0.274**
	(0.207)	(0.0820)	(0.246)	(0.135)	(0.202)	(0.0960)	(0.226)	(0.123)
Time Frame	0.435***	0.388***	0.350	0.307***	0.337	0.295***	0.262	0.226**
	(0.226)	(0.0939)	(0.224)	(0.104)	(0.225)	(0.114)	(0.197)	(0.0943)
Risk Level	0.713***	0.573***	0.749***	0.617***	0.736***	0.601***	0.770***	0.644***
	(0.211)	(0.132)	(0.193)	(0.141)	(0.212)	(0.173)	(0.171)	(0.134)
$\mathbb{E}(Neg.\ returns)$	0.317	0.306***	0.150	0.143***	0.444	0.430***	0.233	0.223**
	(0.275)	(0.0744)	(0.166)	(0.0775)	(0.332)	(0.125)	(0.229)	(0.0908)
	Age ≥ 29							
	Education < 4.1				Education ≥ 4.1			
	Staff =0		Staff =1		Staff =0		Staff =1	
Attributes	HL ≥7	HL <7	HL ≥7	HL <7	HL ≥7	HL <7	HL ≥7	HL <7
Return	0.791***	0.778***	0.300**	0.284**	0.820***	0.808***	0.340***	0.323***
	(0.158)	(0.190)	(0.124)	(0.127)	(0.132)	(0.150)	(0.122)	(0.0930)
Growth	0.976***	0.719***	0.0621	0.00423	0.986***	0.817***	0.103	0.00732
	(0.0671)	(0.274)	(0.0909)	(0.0102)	(0.0361)	(0.194)	(0.132)	(0.0186)
Herfindahl Index	0.504**	0.413**	0.507***	0.416***	0.492**	0.401**	0.495***	0.404***
	(0.229)	(0.173)	(0.197)	(0.120)	(0.229)	(0.186)	(0.175)	(0.109)
Time Frame	0.660***	0.615***	0.575***	0.527***	0.561**	0.512***	0.472**	0.424***
	(0.191)	(0.163)	(0.186)	(0.134)	(0.222)	(0.184)	(0.189)	(0.125)
Risk Level	0.502***	0.352***	0.548***	0.395***	0.531***	0.379	0.577***	0.424***
	(0.283)	(0.203)	(0.211)	(0.132)	(0.290)	(0.231)	(0.180)	(0.115)
$\mathbb{E}(Neg.\ returns)$	0.260	0.249***	0.118	0.112	0.376	0.363***	0.186	0.178
	(0.238)	(0.144)	(0.121)	(0.0779)	(0.323)	(0.219)	(0.184)	(0.119)

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Values are the $\mathbb{P}$(Attendance) for each of the Attributes by binary indicator for Age, Education, Staff and the number of Safe Holt-Laury choices. The values are estimated using the baseline specification of the EAA model, and $\boldsymbol{Z}_n = [1, Age_{\geq 29}, Education_{\geq 4.1}, Staff, HL\ Safe_{\geq 7}]$.

B.4 Present Bias Likelihood Ratio tests

Table B.8: Likelihood Ration test for Present Bias

Models			
Smaller	Larger	LR Stat	P-value
Constant	Utility	3.54	0.0598
Constant	Attention	15.72	0.0154
Constant	Both	24.68	0.0009
Utility	Both	21.14	0.0017
Attention	Both	8.97	0.0027

Note: Likelihood ratio test results for Present Bias Models. The null hypothesis is that the smaller model is the true model.

B.5 ANA probabilities Over Models

Table B.9: ANA Probabilities by Different models

	$\mathbb{P}(Attendance_k)$			
Attributes(k)	Baseline	Present Bias	Socio-Demographics	Added Attributes
Return Objective	0.549***	0.881***	0.382***	0.532***
	(0.0649)	(0.0707)	(0.0587)	(0.0485)
Proportion of Growth Assets	0.341***	0.515***	0.507***	0.560***
	(0.114)	(0.158)	(0.0571)	(0.0540)
Herfindahl Index	0.335***	0.214**	0.484***	0.470***
	(0.0836)	(0.0999)	(0.0591)	(0.0876)
Minimum Suggested Time Frame	0.379***	0.184**	0.293***	0.537***
	(0.0492)	(0.0859)	(0.0729)	(0.0478)
Risk Level	0.582***	0.726***	0.425***	0.956***
	(0.0614)	(0.119)	(0.0656)	(0.0233)
$\mathbb{E}$(Negative Returns)[1]	0.242***	0.441***	0.240***	0.261***
	(0.0514)	(0.168)	(0.0451)	(0.0462)
Word Count				0.172**
				(0.0819)
Sustainable Investments				0.303***
				(0.0761)
AIC	6339.2	6337.6	6369.4	6209.5
CAIC	6441.7	6448.1	6511.3	6383.0
BIC	6428.7	6434.1	6493.3	6361.0

Note:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. [1] Include both $\mathbb{E}$(Negative Returns) and $\mathbb{E}$(Negative Returns)^2. Standard errors in parentheses. The above table shows the ANA probabilities for different models. For each model attention is assumed to be constant each participant ($z_n = [1]$).

Appendix C

A significant drawback experienced estimating the design matrix was that the data was subject to profound within group collinearity. This is caused by the limited variation between the attributes and results in perfect prediction of the chosen alternative within each individual's set of alternatives. This has prevented the modelling of potentially important alternative specific constants such as the name of the investment option and the risk label. This is a possible sources of preference heterogeneity which may be worsening the confound between attribute non-attendance and the preference heterogeneity in the EAA model.

Under the random utility framework, the agent will choose the alternative which provides the greatest utility. This choice is modelled as the agent preferring the difference between the associated attributes, resulting in the phrase "only difference in utility matter". This differencing between the investment options can occur during regression (as per a typical Clogit) or prior to regression (as done in Bateman et al. (2016)) and then the agent chooses to accept or reject the difference. This is equivalent, as the differencing will occur in either setup as per equation (5.2) or during the regression. However, taking the difference beforehand in a pairwise choice data results in a significant increase in the number of binary choice pairs. In contrast, not taking the difference results in substantially less alternatives per each individual. This is problematic when the there is little variation between the values of the attributes, and results in perfect prediction of the chosen alternative.

C.1 Collinearity

The collinearity problem associated with the experimental data in long form is caused by the amount of similarity between attributes, and when including the risk-level ASC's this results in a perfect prediction of the chosen option. Bateman et al. (2016) managed to avoid this problem by taking the difference between each of the attributes, which increase the variation in the attributes by $\sim$10 times.

C.1.1 From the Data

The raw data is given in a excel workbook, with each individual's choices presented as a matrix. The rows and columns each represent a possible alternative. Where the same column number and row number correspond to the same alternative. Each element is then coded as zero or one, and indicates which alternative was chosen of the two. This implies that the diagonal of the matrix represents the choices between the same alternative. This can be seen in the below matrix,

$$A = \begin{array}{c} \\ x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_{10} \end{array} \begin{array}{c} \begin{array}{ccccc} y_1 & y_2 & y_3 & \cdots & y_{10} \end{array} \\ \begin{bmatrix} 1 & 0 & 1 & \cdots & 1 \\ 1 & 1 & 0 & \cdots & 1 \\ 0 & 0 & 0 & \cdots & 1 \\ \vdots & \vdots & \vdots & \ddots & \\ 0 & 1 & 0 & & 0 \end{bmatrix} \end{array}$$

Each of the corresponding j_i alternatives, where $j \in \{y, x\}$, is given by the subscripts, where $Y_i = x_i$. Each element indicates whether the row alternative is preferred to the column alternative (i.e. $U(x_i) > U(y_i)$). From the matrix, it can be seen that alternative x_2 is chosen over alternative y_1 and that y_3 is chosen over x_1.

Combining this with the information on the investment attributes in Bateman et al. (2016) and taking the differences, results in data of the form which is the form used in Bateman et al. (2016) where the participant chooses whether to accept or reject the difference of the attributes as shown in the Return Column.

Table C.1: Example of the Initially Differenced Pairwise Choices used in Bateman et al. (2016)

userID	y_j	Chosen$_j$	x_j	Return	Risk Level	Return$_y$	Return$_x$	$\cdots$
4002	High growth	0	Glob. Env. Opp.	0	Vhigh	5	5	$\cdots$
4002	Balanced	1	Conservative balanced	-0.5	MedToHigh	4	2.5	$\cdots$
4002	High growth	0	Conservative balanced	-2.5	MedToHigh	5	2.5	$\cdots$
4002	High growth	0	Balanced	-2	High	5	3	$\cdots$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	
4003	Soc. resp. bal.	1	Capital stable	-1	Medium	3	2	$\cdots$
4003	Growth	0	Capital stable	-2	Medium	5	2	$\cdots$
4003	Cash	1	Capital stable	1	Medium	1	2	$\cdots$
4003	Australian bond	0	Capital stable	0.5	Medium	1.5	2	$\cdots$
4003	Australian shares	0	Capital stable	-3	Medium	5	2	$\cdots$
4003	Glob. Env. Opp.	0	Capital stable	-3	Medium	5	2	$\cdots$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	

This matches the description of the covariates and risk level ASCs provided in Bateman et al. (2016), to save space a multinomial of the Risk Level is used rather than each ASC for the Risk Level. This allows Bateman et al. (2016) to avoid the problem of collinearity because the risk level originally associated with option x_j is now associated with the difference between the attributes.[1]. This introduces a lot more variation into the attributes of the data set and prevents the perfect prediction of the risk level because there are more varied attribute values associated with each risk level.

When the data is in long form, there is less variation in the attribute values while traditionally being very similar. From this, it becomes easy to predict the value of the risk level within each group (individual). However, when using the differences and only the risk level associated with x_j, there are a lot of less similar choices which prevents the perfect prediction of the risk level. For example, the attributes from the below table when differenced experience a large increase in variation. There is a lot more variation in the attributes associated with each risk level. This eliminates the collinearity, because the risk levels can't be perfectly predicted from the other attributes because of the large increase in differenced attributes that each individual is choosing over. For example, when the table 4.1 is differenced as per Bateman et al. (2016) for use in their estimation, it becomes:

[1]The risk level is only from the x_j option, and not the difference. This results in the risk ASC associated with the x_j alternative being included in the regression, rather than a difference of the risk levels between x_j and y_j.

Table C.2: Differenced Investment Option Attributes

	Return Objective	Risk Measures	Concentration Measures	Horizon	
Option Title	Return	Risk Label	HI index	Asset Growth	Time Frame
Capital Stable Differences					
Capitalstable-Capitalstable	0	2	3.05	3.41	3.27
Capitalstable-Sociallyresponsiblebalanced	-1	2	3.21	3.54	2.87
Capitalstable-Growth	-2	2	3.27	3.53	2.72
Capitalstable-Cash	1	2	2.57	2.57	3.57
Capitalstable-Australianbond	0.5	2	2.57	2.57	3.57
Capitalstable-Australianshares	-3	2	2.57	2.57	2.57
Capitalstable-Globalenvironmentalopportunities	-3	2	2.57	2.57	2.57
Capitalstable-Conservativebalanced	-0.5	2	3.23	3.52	3.07
Capitalstable-Balanced	-1	2	3.3	3.54	2.87
Capitalstable-Highgrowth	-3	2	3.15	3.47	2.57
Sociallyresponsiblebalanced Differences					
Sociallyresponsiblebalanced-Capitalstable	1	4	-0.16	-0.13	0.4
Sociallyresponsiblebalanced-Sociallyresponsiblebalanced	0	4	0	0	0
Sociallyresponsiblebalanced-Growth	-1	4	0.06	-0.01	-0.15
Sociallyresponsiblebalanced-Cash	2	4	-0.64	-0.97	0.7
Sociallyresponsiblebalanced-Australianbond	1.5	4	-0.64	-0.97	0.7
Sociallyresponsiblebalanced-Australianshares	-2	4	-0.64	-0.97	-0.3
Sociallyresponsiblebalanced-Globalenvironmentalopportunities	-2	4	-0.64	-0.97	-0.3
	⋮				

C.1.2 Diagnostics

Within-group collinearity can be diagnosed. To diagnose within group, Gould (2013) suggests estimating a panel regression of the problematic variable on all the other covariates, with the set to the individual. Using the differenced data from the fourth treatment in Bateman et al. (2016), this results in the below regression. The R^2 within is less than one, suggesting that there is no problematic collinearity amongst the ASC for Very High and the other attributes (Gould 2013).

$$
\begin{aligned}
\text{ASC V High}_{njt} = &\beta_1 \cdot \Delta\text{Return} + \beta_2 \cdot \Delta\text{Growth} + \beta_3 \cdot \Delta\text{Time Frame} && \text{(C.1)} \\
&+ \delta_4 \cdot \text{ASC V Low} + \delta_5 \cdot \text{ASC Medium} + \delta_6 \cdot \text{ASC High} + \cdots && \text{(C.2)} \\
& && \text{(C.3)}
\end{aligned}
$$

Figure C.1: Panel Regression on differenced data

```
       panel variable:  userID (balanced)

Random-effects GLS regression                   Number of obs     =      2,610
Group variable: ids                             Number of groups  =         58

R-sq:                                           Obs per group:
     within  = 0.0000                                         min =         45
     between = 0.0000                                         avg =       45.0
     overall = 0.8311                                         max =         45

                                                Wald chi2(18)     =   12748.58
corr(u_i, X)   = 0 (assumed)                    Prob > chi2       =     0.0000

------------------------------------------------------------------------------------
             vh_l |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------------+-----------------------------------------------------------------
              xyr |  -.2243651   .0144701   -15.51   0.000    -.2527261   -.1960042
           xygrth |   1.285465   .0526337    24.42   0.000     1.182305    1.388625
            xydiv |   .4454561   .0171788    25.93   0.000     .4117863    .4791259
             xytf |  -.0070057   .0041896    -1.67   0.094    -.0152172    .0012058
           1.vl_l |   -.397465   .0203379   -19.54   0.000    -.4373265   -.3576035
          1.med_l |  -.3661759   .0148818   -24.61   0.000    -.3953438    -.337008
            1.h_l |  -.4882271   .0119424   -40.88   0.000    -.5116338   -.4648204
                                          .
                                          .
                                          .
```

Where any term starting with xy indicates a differenced value between the two investment options and i.vl_l i.med_l i.h_l i.vh_l are the risk ASCs for the x_j of the choice. However, transforming the data into long form, as shown below, and then estimating the same xtreg results in an R-sq within of 1. This implies that there is problematic collinearity.

Figure C.2: Panel Regression on non-differenced data

```
     xtset userID
       panel variable:  userID (balanced)


.
.  xtreg i_Vhigh c.return c.risk  c.Growth c.HI_index c.TF i_VeryLow i_Medium i_High, fe

Fixed-effects (within) regression               Number of obs     =      5,220
Group variable: userID                          Number of groups  =         58

R-sq:                                           Obs per group:
     within  = 1.0000                                         min =         90
     between =      .                                         avg =       90.0
     overall = 1.0000                                         max =         90

                                                F(8,5154)         =          .
corr(u_i, Xb)  =      .                         Prob > F          =          .

------------------------------------------------------------------------------
     i_Vhigh |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      return |  -2.213956          .        .       .            .           .
        risk |   1.092501          .        .       .            .           .
      Growth |   1.906757          .        .       .            .           .
    HI_index |   2.06e-09          .        .       .            .           .
          TF |  -1.713728          .        .       .            .           .
   i_VeryLow |  -3.759962          .        .       .            .           .
    i_Medium |  -2.592367          .        .       .            .           .
      i_High |   2.332247          .        .       .            .           .
       _cons |   5.973918          .        .       .            .           .
-------------+----------------------------------------------------------------
     sigma_u |          0
     sigma_e |          0
         rho |          .   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0: F(57, 5154) = .                       Prob > F =      .
```

For instance, if we sub in 0 into each of the independent ASC's we get,

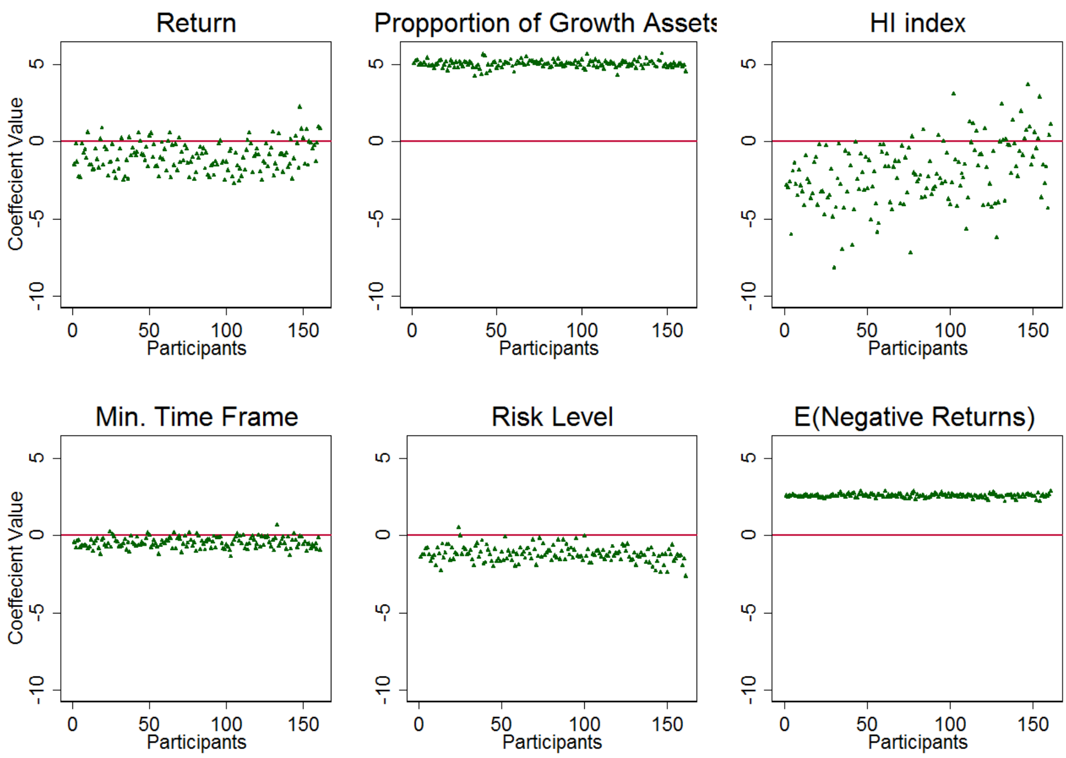
$$\begin{aligned}\text{ASC V High}_{njt} =& 5.973918(1) - 2.213956(Return) + 1.092501(Risk) \\ & + 1.906757(Growth) + \sim 0(HI\ index) - 1.713728(TF) + ...\end{aligned}$$

Since, we have a possible choice between ASC V High$_{njt}$ and ASC Med High$_{njt}$. If return is 5, then this instantly implies that ASC V High$_{njt}$ is 1. If return is not 5 this instantly implies that ASC V High$_{njt}$ is 0 which can be seen in table **??**, by subbing in the values into the above equation. Thus, even if all the ASC's are zero, except for the base and the dependent variable we can perfectly predict the outcome based on Return.

Appendix D

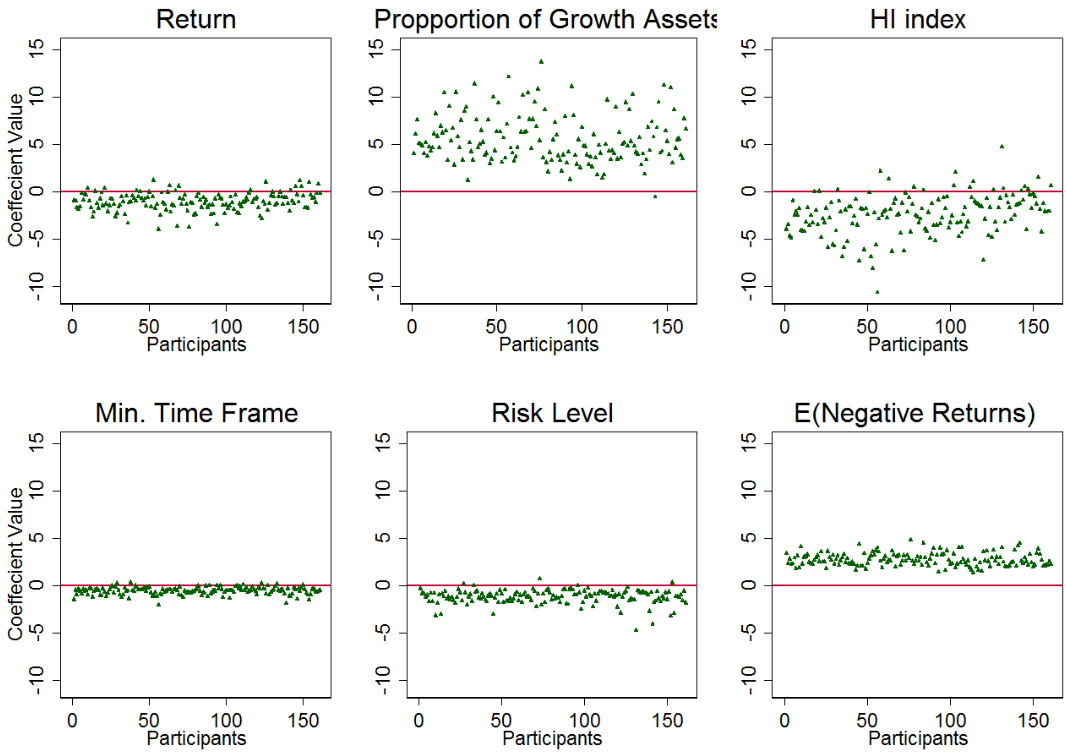
D.1 Additional Output for Regressions

Figure D.1: Utility weighting (β) Estimates For Each of The Respondents from the Mixed Logit.



Note: The above figure shows the mean estimates of the attributes by each of the participants. These estimates come from the Mixed Logit model.

Figure D.2: Utility weighting (β) Estimates For Each of The Respondents from the GMNL-II model.



Note: The above figure shows the mean estimates of the attributes by each of the participants. These estimates come from the Mixed Logit model.

D.2 T-test of means for Socio-demographics

Table D.1: Mean and (Std. Error) Socio-demographic Characteristics, with T-test of Difference in Means

Characteristic	*Pooled* Mean (Std. Error)	*Full* Mean (Std. Error)	*Difference* mean (Std. Error)	T-Statistic $\mathbb{P}(\Delta \neq 0)$
Age				
years	30.155	29.052	1.103	0.928
	(11.898)	(11.044)	(1.188)	(0.354)
Education (years)				
Secondary	6.944	6.952	-0.008	-0.245
	(0.321)	(0.300)	(0.032)	(0.807)
Tertiary	4.230	4.087	0.142	0.703

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Table D.1 – *Continued from previous page*

Characteristic	*Pooled* Mean (Std. Error)	*Full* Mean (Std. Error)	*Difference* mean (Std. Error)	T-Statistic $\mathbb{P}(\Delta \neq 0)$
	(1.950)	(1.996)	(0.203)	(0.482)
Children				
Number of	.304	0.275	0.029	0.343
	(0.852)	(0.794)	(0.085)	(0.732)
Self-Reported Health				
Out of Five	3.888	3.891	-0.003	-0.028
	(0.929)	(0.889)	(0.094)	(0.978)
Monthly Purchases ($)				
Food purchased In	283.262	275.149	8.113	0.346
	(234.197)	(219.190)	(23.462)	(0.730)
Food purchased Out	182.268	177.686	4.582	0.307
	(148.213)	(141.145)	(14.948)	(0.759)
Telephone Bill	61.087	56.262	4.825	0.790
	(62.235)	(55.152)	(6.111)	(0.430)
Total Consumption	780.249	715.428	64.821	0.906
	(717.581)	(663.831)	(71.572)	(0.366)
Finances ($ '000)				
Gross Income[1]	41	374	3.776	0.897
	(3146)	(2796)	(4208.916)	(0.370)
Net Worth[2]	222	191	31.191	0.564
	(44.3)	(33.01)	(55.270)	(0.573)
Employment				
Proportion of UNSW Staff	0.429	0.328	0.101	2.023
	(0.496)	(0.470)	(0.050)	(0.044)

Note: The mean value of the socio-demographic characteristics is provided along with the difference in means and two sample t-test. The p-value shown is for the hypothesis that the difference between the means does not equal zero.

D.3 Controlling for Risk-Return Interactions

Table D.2: Generalised Multinomial Logit Baseline Estimates, with interaction between Return and Risk Level

1	*2*	*3*	*4*	*5*	*6*	*7*
$\mathbb{P}$(Invest. Opt$_j$=1)	(Clogit)	(Scale-MNL)	(Mixed Logit)	(GMNL-II)	(EAA)	
Coefficient						
Estimate (β)						$\mathbb{P}$(Attendance$_k$)
Return Objective	1.238	2.256	-0.788	-1.180	1.359***	0.149*
	(1.586)	(1.866)	(2.165)	(2.368)	(0.198)	(0.0889)
Proportion of Growth Assets	1.421	0.440	5.151**	5.370**	2.923***	0.579***
	(1.630)	(1.868)	(2.366)	(2.407)	(0.311)	(0.102)
Herfindahl Index	-1.263	-2.025**	-1.800	-2.509**	-3.458***	0.200***
	(0.818)	(0.885)	(1.143)	(1.207)	(0.260)	(0.0487)
Minimum Suggested Time Frame	-0.507**	-0.771***	-0.489*	-0.530	-1.047***	0.320***
	(0.207)	(0.280)	(0.289)	(0.326)	(0.0729)	(0.0832)
Risk Level	0.930	2.200	-1.037	-1.450	2.008***	0.509***
	(1.378)	(1.670)	(1.877)	(2.038)	(0.143)	(0.136)
$\mathbb{E}$(Negative Returns)	0.299	-0.217	2.489**	2.824**	2.205***	0.487***

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Table D.2 – *Continued from previous page*

1	*2*	*3*	*4*	*5*	*6*	*8*
$\mathbb{P}$(Invest. Opt$_j$=1)	(Clogit)	(Scale-MNL)	(Mixed Logit)	(GMNL-II)	(EAA)	
	(0.832)	(0.982)	(1.153)	(1.218)	(0.251)	(0.0777)
$\mathbb{E}$(Negative Returns)^2	0.0336	0.111	-0.199	-0.236	-0.252***	0.487***
	(0.116)	(0.136)	(0.159)	(0.170)	(0.0357)	(0.0777)
Return×Risk Level	-0.391	-0.649	-0.0328	-0.00711	-0.396***	0.350***
	(0.387)	(0.442)	(0.523)	(0.566)	(0.0324)	(0.0733)
Scale Heterogeneity						
τ		0.949***		-0.451***		
		(0.0925)		(0.110)		
Standard Deviation (σ_β)						
Return Objective			0.976***	0.672***		
			(0.0802)	(0.0476)		
Proportion of Growth Assets			-1.127***	-0.954***		
			(0.250)	(0.317)		
Herfindahl Index			2.524***	-2.484***		

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Table D.2 – *Continued from previous page*

1	*2*	*3*	*4*	*5*	*6*	*8*
$\mathbb{P}$(Invest. Opt$_j$=1)	(Clogit)	(Scale-MNL)	(Mixed Logit)	(GMNL-II)	(EAA)	
			(0.207)	(0.292)		
Minimum Suggested Time Frame			0.404***	0.490***		
			(0.0374)	(0.0364)		
Risk Level			0.930***	0.993***		
			(0.0902)	(0.125)		
$\mathbb{E}$(Negative Returns)			0.394***	-0.0103		
			(0.0934)	(0.0382)		
$\mathbb{E}$(Negative Returns)^2			0.0365***	0.0539***		
			(0.00714)	(0.00458)		
Return$\times$Risk Level			0.155***	0.198***		
			(0.0162)	(0.0163)		
AIC	8441.7	8083.8	6278.6	6286.0	6278.6	
CAIC	8474.4	8120.5	6343.9	6355.4	6339.8	
BIC	8466.4	8111.5	6327.9	6338.4	6324.9	
pseudo loglikelihood	-4212.9	-4032.9	-3123.3	-3126.0	-3124.3	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. The sign of the estimated standard deviations is irrelevant: interpret them as being positive. The number of observations used in this estimation is 161 respondents by 45 choices each, resulting in 7245 observations. The above Log Likelihood refers to the simulated Log likelihood for the non-Clogit models. For each of the applicable models, the ASC variables are not scaled as per Gu et al. (2013)

D.4 Comparison of different order polynomials of Clogit

Table D.3: Estimates of the Investment Option Attributes incorporating further Polynomials for Risk and $\mathbb{E}$(Negative Returns)

1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
		Clogit			Mixed Logit		EAA
	Linear	Poly. $\mathbb{E}$(Neg ret)	Poly. $\mathbb{E}$(Neg ret) & Risk Level	Linear	Poly. $\mathbb{E}$(Neg ret)	Poly. $\mathbb{E}$(Neg ret) &Risk Level	Poly. $\mathbb{E}$(Neg ret) & Risk Level
Mean (β)							
Return Objective	0.473***	-0.305	-0.493	0.834***	-1.085**	-1.012*	-1.684***
	(0.183)	(0.321)	(0.358)	(0.290)	(0.474)	(0.518)	(0.166)
Proportion of Growth Assets	-2.388***	1.613	2.538	-4.683***	5.114**	5.221**	5.504***
	(0.699)	(1.598)	(1.766)	(1.142)	(2.335)	(2.554)	(0.359)
Herfindahl Index	-3.538***	-1.620**	-1.263	-6.759***	-1.879*	-1.853	-3.827***
	(0.318)	(0.767)	(0.818)	(0.488)	(1.108)	(1.181)	(1.085)
Minimum Suggested Time Frame	-0.607***	-0.354***	-0.370***	-1.098***	-0.564***	-0.500***	-0.859***
	(0.0845)	(0.123)	(0.126)	(0.139)	(0.183)	(0.189)	(0.0856)
Risk Level	0.515***	-0.371	0.263	0.999***	-1.317**	-1.154	1.138*
	(0.192)	(0.349)	(0.758)	(0.326)	(0.515)	(1.148)	(0.626)
$\mathbb{E}$(Negative Returns)	0.473***	1.108***	0.944***	0.895***	2.578***	2.506***	2.221***
	(0.0953)	(0.235)	(0.284)	(0.155)	(0.373)	(0.455)	(0.275)
$\mathbb{E}$(Negative Returns)^2		-0.0809***	-0.0533		-0.218***	-0.201***	-0.217***
		(0.0308)	(0.0402)		(0.0475)	(0.0627)	(0.0373)
Risk level^2			-0.109			-0.0107	-0.375***
			(0.107)			(0.161)	(0.0908)
Standard Deviation (σ_β)							
Return Objective				1.104***	1.007***	1.185***	
				(0.109)	(0.0812)	(0.0798)	
Proportion of Growth Assets				2.305***	-1.516***	-1.859***	
				(0.354)	(0.364)	(0.132)	
Herfindahl Index				2.159***	2.200***	2.351***	
				(0.355)	(0.279)	(0.205)	
Minimum Suggested Time Frame				0.465***	0.559***	0.509***	
				(0.103)	(0.0396)	(0.0302)	
Risk Level				0.886*	-0.942***	0.640***	
				(0.507)	(0.0637)	(0.0552)	
$\mathbb{E}$(Negative Returns)				-0.238*	0.437***	0.288***	
				(0.124)	(0.0479)	(0.0635)	
$\mathbb{E}$(Negative Returns)^2					0.0959***	0.107***	
					(0.00921)	(0.0115)	
Risk level^2						0.0797***	
						(0.0101)	
AIC	8445.6	8440.6	8441.7	6296.1	6292.0	6262.9	6314.2
CAIC	8493.0	8495.8	8504.8	6390.8	6402.4	6389.1	6371.4
BIC	8487.0	8488.8	8496.8	6378.8	6388.4	6373.1	6357.4

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. The sign of the estimated standard deviations is irrelevant: interpret them as being positive. The number of observations used in this estimation is 161 respondents by 45 choices each, resulting in 7245 observations.

Likelihood Ratio Tests

The first likelihood ratio test is between models *3* and *4*, where it is assumed that model *3* is preferred to model *4*. The likelihood ratio chi statistic is 0.85 and results in a p-value of 0.36. From this, we cannot reject the null hypothesis that model *3* is better than model *4*. The second likelihood ratio test is between model *5* and *6*, assuming that *5* is nested in *6*. The likelihood ratio chi statistic is 8.13 and results in a p-value of 0.0171. From this, we reject the null hypothesis that model *5* is better than model *6*. The third likelihood ratio test is between model *6* and *7*, assuming that *6* is nested in *7*. The likelihood ratio chi statistic is 33.10 and results in a p-value of 0.0. From this, we reject the null hypothesis that model *6* is better than model *7*.

D.5 Controlling for Socio-Demographic Characteristics

Table D.4: Endogenous Attribute Attendance Estimations, Incorporating Socio-Demographics

1	*2*	*3*	*4*	*5*	*6*
	EAA				
	($z_n = 1$)			($z_n = \boldsymbol{Z}$)	
Attributes	None:β	Utility:β	$\mathbb{P}$(Attendance$_k$)	Attention:β	$\mathbb{P}$(Attendance$_k$)
Return Objective	-1.503***	-1.018***	0.382***	-1.578***	0.582***
	(0.148)	(0.113)	(0.0587)	(0.123)	(0.0760)
Proportion of Growth Assets	6.377***	7.296***	0.507***	5.828***	0.102
	(0.787)	(0.481)	(0.0571)	(0.703)	(0.0801)
Herfindahl Index	-3.169***	-4.541***	0.484***	-3.207***	0.331***
	(0.324)	(0.471)	(0.0591)	(0.313)	(0.0622)
Minimum Suggested Time Frame	-0.925***	-0.381***	0.293***	-1.026***	0.383***
	(0.123)	(0.0606)	(0.0729)	(0.0706)	(0.0573)
Risk Level	-0.953***	-1.668***	0.425***	-1.110***	0.540***
	(0.139)	(0.144)	(0.0656)	(0.105)	(0.0700)
$\mathbb{E}$(Negative Returns)	2.701***	2.563***	$\vdots$	2.961***	$\vdots$
	(0.366)	(0.181)		(0.273)	
			0.240***		0.229***
			(0.0451)		(0.0711)
$\mathbb{E}$(Negative Returns)^2	-0.273***	-0.241***	$\vdots$	-0.274***	$\vdots$
	(0.0470)	(0.0236)		(0.0399)	
ASC Age		0.00284			
		(0.00326)			
ASC No. Children		0.0290			
		(0.0548)			
ASC Phone Bill		-0.000171			
		(0.000515)			
ASC Staff		0.190**			
		(0.0874)			
ASC HL Risk Safe Choices		-0.0152			
		(0.0103)			
AIC	6339.2	6369.4		6330.5	
CAIC	6441.7	6511.3		6669.7	
BIC	6428.7	6493.3		6626.7	
pseudo loglikelihood	-3156.6	-3166.7		-3122.3	
N	$\cdots$ 7245 = 161 Individuals $\times$ 45 Choices $\cdots$				

Note: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The above table shows the estimation results for three variation of the EAA model. The variations include the baseline specification (*2*), a constant attention with socio-demographics affecting utility (*3*) and socio-demographics affecting attention (*4*). For the Attribute Non-Attendance, the mean value is used for the socio-demographics modelled through attention (*5*) The attentive parameter for $\mathbb{E}$(Negative Returns) and $\mathbb{E}$(Negative Returns)^2 are modelled to be jointly attended. The number of observations used in this estimation is 161 respondents by 45 choices each, resulting in 7245 observations.

Table D.5: Generalised Multinomial Logit Baseline Estimates Including Socio-demographic Characteristics

1	*2*	*3*	*4*	*5*
$\mathbb{P}$(Invest. Opt$_j$=1)	(Scale-MNL)	(Mixed Logit)	(GMNL-II)	
Coefficient Estimate (β)				
Return Objective	-1.743***	-1.613**	-1.684**	
	(0.447)	(0.675)	(0.736)	
Proportion of Growth Assets	6.674***	8.449***	7.575**	
	(2.000)	(3.098)	(3.291)	
Herfindahl Index	-0.156	-0.898	-1.442	
	(0.963)	(1.408)	(1.464)	
Minium Suggested Time Frame	-0.236*	-0.296	-0.572**	
	(0.142)	(0.204)	(0.230)	
Risk Level	-1.407***	-1.884***	-1.687**	
	(0.474)	(0.704)	(0.711)	
$\mathbb{E}$(Negative Returns)	2.148***	3.084***	3.240***	
	(0.357)	(0.510)	(0.604)	
$\mathbb{E}$(Negative Returns)^2	-0.156***	-0.244***	-0.266***	
	(0.0388)	(0.0539)	(0.0623)	
ASC Age	0.00637*	0.00215	0.00152	
	(0.00384)	(0.00354)	(0.00348)	
ASC No. Children	-0.0277	0.0239	0.0450	
	(0.0445)	(0.0572)	(0.0542)	
ASC Phone Bill	-0.000104	-0.0000223	-0.000312	
	(0.000703)	(0.000490)	(0.000469)	
ASC Staff	-0.0336	0.148*	0.150*	
	(0.0959)	(0.0893)	(0.0908)	
ASC HL Risk Aversion	-0.0498***	-0.0273**	-0.0200	
	(0.0129)	(0.0127)	(0.0125)	
Scale Heterogeneity				

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Table D.5 – *Continued from previous page*

1	*2* (Scale-MNL)	*3* (Mixed Logit)	*4* (GMNL-II)
τ	0.970***		0.507***
	(0.0980)		(0.103)
Standard Deviation (σ_β)			
Return Objective		1.113***	1.538***
		(0.0827)	(0.163)
Proportion of Growth Assets		3.024***	2.257***
		(0.257)	(0.421)
Herfindahl Index		2.135***	2.696***
		(0.259)	(0.425)
Minium Suggested Time Frame		0.344***	0.505***
		(0.0353)	(0.108)
Risk Level		-0.962***	0.279***
		(0.104)	(0.0451)
$\mathbb{E}$(Negative Returns)		0.180***	0.612***
		(0.0691)	(0.0713)
$\mathbb{E}$(Negative Returns)^2		0.0806***	0.0788***
		(0.0118)	(0.0142)
AIC	8049.5	6283.8	6287.0
CAIC	8152.1	6433.7	6444.8
BIC	8139.1	6414.7	6424.8
pseudo loglikelihood	-4011.8	-3122.9	-3123.5

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. The sign of the estimated standard deviations is irrelevant: interpret them as being positive. The number of observations used in this estimation is 156 respondents by 45 choices each, resulting in 7020 observations. The above Log Likelihood refers to the simulated Log likelihood for the non-Clogit models. For each of the applicable models, the ASC variables are not scaled as per Gu et al. (2013)

D.6 Adding Attributes from the Description & ASC's

Table D.6: Baseline Estimates with Added Description Attributes and Socio-demographic Characteristics

1	*2*	*3*	*4*	*5*
$\mathbb{P}$(Invest. Opt$_j$=1)	(EAA)	(Scale-MNL)	(Mixed Logit)	(GMNL-II)
Coefficient				
Return Objective	1.494***	-40.42***	22.23***	31.88***
	(0.107)	(2.477)	(1.450)	(1.625)
Proportion of Growth Assets	2.428***	205.0***	-113.6***	-162.8***
	(0.269)	(12.51)	(7.386)	(7.837)
Herfindahl Index	-3.129***	102.7***	-63.34***	-89.87***
	(0.409)	(6.518)	(3.872)	(4.141)
Minimum Suggested Time Frame	-0.932***	12.31***	-8.020***	-11.29***
	(0.0668)	(0.761)	(0.474)	(0.483)
Risk Level	-2.513***	-41.12***	22.43***	32.23***
	(0.206)	(2.481)	(1.452)	(1.506)
$\mathbb{E}$(Negative Returns)	2.708***	34.34***	-16.42***	-24.01***
	(0.168)	(2.065)	(1.243)	(1.351)
$\mathbb{E}$(Negative Returns)^2	-0.419***	-4.475***	2.351***	3.422***
	(0.0258)	(0.274)	(0.170)	(0.173)
Wordcount	0.0692***	0.571***	-0.329***	-0.482***
	(0.00755)	(0.0363)	(0.0264)	(0.0274)
Sustainable Investments	-1.514***	-16.07***	9.601***	13.83***
	(0.173)	(1.019)	(0.701)	(0.666)
ASC Age	0.00428	0.00641*	0.000285	-0.000440
	(0.00394)	(0.00383)	(0.00401)	(0.00436)
ASC No. Children	0.0384	-0.0272	0.0736	0.0612
	(0.0743)	(0.0442)	(0.0752)	(0.0664)
ASC Phone Bill	0.000256	-0.000115	0.000268	0.000191
	(0.000508)	(0.000701)	(0.000633)	(0.000563)
ASC Staff	0.103	-0.0369	0.155	0.172*

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Table D.6 – *Continued from previous page*

1	*2* (EAA)	*3* (Scale-MNL)	*4* (Mixed Logit)	*5* (GMNL-II)
	(0.0910)	(0.0967)	(0.0991)	(0.0991)
ASC HL Risk Aversion	0.0102	-0.0502***	-0.0199	-0.0186
	(0.0128)	(0.0130)	(0.0131)	(0.0142)
Scale Heterogeneity				
τ		0.978***		0.460***
		(0.102)		(0.0928)
Standard Deviation (σ_β)				
Return Objective			-0.974***	0.716***
			(0.0647)	(0.0644)
Proportion of Growth Assets			1.636***	4.239***
			(0.163)	(0.373)
Herfindahl Index			2.390***	3.122***
			(0.250)	(0.534)
Minimum Suggested Time Frame			0.594***	0.502***
			(0.0576)	(0.0403)
Risk Level			0.925***	1.027***
			(0.0851)	(0.0992)
$\mathbb{E}$(Negative Returns)			0.516***	0.885***
			(0.0488)	(0.0571)
$\mathbb{E}$(Negative Returns)^2			0.0689***	0.0964***
			(0.00736)	(0.0119)
Wordcount			-0.0351***	0.0478***
			(0.0125)	(0.0113)
Sust			0.836***	0.502*
			(0.157)	(0.296)
AIC	6209.5	8050.9	6172.5	6207.7
CAIC	6383.0	8169.2	6354.0	6397.0

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Table D.6 – *Continued from previous page*

1	*2* (EAA)	*3* (Scale-MNL)	*4* (Mixed Logit)	*5* (GMNL-II)
BIC	6361.0	8154.2	6331.0	6373.0
pseudo loglikelihood	-3082.8	-4010.5	-3063.3	-3079.8

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. The sign of the estimated standard deviations is irrelevant: interpret them as being positive. The number of observations used in this estimation is 161 respondents by 45 choices each, resulting in 7245 observations. The above Log Likelihood refers to the simulated Log likelihood for the GMNL nested models. For each of the applicable models, the ASC variables are not scaled as per Gu et al. (2013)

D.7 Controlling for Additional Socio-Demographic Characteristics in the GMNL models

Table D.7: Generalised Multinomial Logit Baseline Estimates

1 $\mathbb{P}$(Invest. Opt$_j$=1)	*2* (Clogit)	*3* (Scale-MNL)	*4* (Mixed Logit)	*5* (GMNL-II)
Coefficient Estimate (β)				
Return Objective	-1.171**	-4.429***	-1.962***	-0.369**
	(0.491)	(0.370)	(0.692)	(0.164)
Proportion of Growth Assets	5.431**	20.69***	10.03***	2.243***
	(2.225)	(1.758)	(3.171)	(0.822)
Herfindahl Index	-0.0426	5.487***	-0.477	-3.647***
	(1.004)	(0.790)	(1.431)	(0.591)
Minimum Suggested Time Frame	-0.147	0.469***	-0.336	-0.777***
	(0.149)	(0.129)	(0.204)	(0.128)
Risk Level	-1.289**	-4.786***	-2.266***	-0.445*
	(0.524)	(0.402)	(0.723)	(0.230)
$\mathbb{E}$(Negative Returns)	1.729***	4.610***	3.289***	2.374***
	(0.357)	(0.319)	(0.535)	(0.235)
$\mathbb{E}$(Negative Returns)^2	-0.134***	-0.385***	-0.279***	-0.191***
	(0.0374)	(0.0354)	(0.0557)	(0.0338)
ASC Age	0.00218	0.00195	0.00796*	0.00822*

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Table D.7 – *Continued from previous page*

1	*2* (Clogit)	*3* (Scale-MNL)	*4* (Mixed Logit)	*5* (GMNL-II)
	(0.00481)	(0.00372)	(0.00478)	(0.00486)
ASC Tertiary Education	0.0519**	0.0244	0.0251	0.0154
	(0.0229)	(0.0173)	(0.0221)	(0.0220)
ASC No. Children	0.0292	0.0793	0.0977*	0.120*
	(0.0655)	(0.0501)	(0.0580)	(0.0635)
ASC SR health	0.0255	-0.0225	-0.0158	-0.00628
	(0.0355)	(0.0270)	(0.0377)	(0.0356)
ASC Food(in)	-0.000304*	-0.000199	-0.000336	-0.000297
	(0.000159)	(0.000307)	(0.000305)	(0.000318)
ASC Food(out)	-0.000269	-0.000352	-0.000250	-0.000220
	(0.000274)	(0.000260)	(0.000293)	(0.000309)
ASC Phone Bill	0.000692	0.000808*	0.000873*	0.00101*
	(0.000832)	(0.000429)	(0.000526)	(0.000546)
ASC Total Consumption	-0.0000372	-0.0000306	-0.0000933	-0.000109
	(0.0000690)	(0.0000567)	(0.0000679)	(0.0000721)
ASC Gross Income	-0.00000308**	-0.00000170	-0.00000198	-0.00000163
	(0.00000142)	(0.00000133)	(0.00000162)	(0.00000161)
ASC Net Worth	0.000000177***	3.64e-08	-4.98e-08	-5.05e-08
	(5.19e-08)	(4.94e-08)	(7.70e-08)	(7.74e-08)
ASC Staff	0.134	0.130	0.177*	0.139
	(0.0975)	(0.0835)	(0.105)	(0.103)
ASC HL Risk Aversion	-0.0409***	-0.0336***	-0.0283*	-0.0146
	(0.0137)	(0.0115)	(0.0147)	(0.0152)
Scale Heterogeneity				
τ		0.248***		0.383***
		(0.0262)		(0.0373)
Standard Deviation (σ_β)				

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Table D.7 – *Continued from previous page*

1	*2* (Clogit)	*3* (Scale-MNL)	*4* (Mixed Logit)	*5* (GMNL-II)
Return Objective			0.845***	1.091***
			(0.0721)	(0.0631)
Proportion of Growth Assets			3.387***	-2.463***
			(0.301)	(0.206)
Herfindahl Index			2.376***	2.228***
			(0.206)	(0.170)
Minimum Suggested Time Frame			0.429***	0.525***
			(0.0683)	(0.0564)
Risk Level			-0.725***	0.624***
			(0.0664)	(0.0680)
$\mathbb{E}$(Negative Returns)			-0.793***	-0.691***
			(0.103)	(0.0751)
$\mathbb{E}$(Negative Returns)^2			0.0335***	0.0732***
			(0.0106)	(0.0175)
AIC	8146.1	6793.9	6092.0	6060.4
CAIC	8223.1	6874.9	6197.3	6169.8
BIC	8204.1	6854.9	6171.3	6142.8
pseudo loglikelihood	-4054.1	-3376.9	-3020.0	-3003.2

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. The sign of the estimated standard deviations is irrelevant: interpret them as being positive. The number of observations used in this estimation is 156 respondents by 45 choices each, resulting in 7020 observations. The above Log Likelihood refers to the simulated Log likelihood for the non-Clogit models. For each of the applicable models, the ASC variables are not scaled as per Gu et al. (2013)

D.8 Adding a Return×Risk Level term

Table D.8: Generalised Multinomial Logit Baseline Estimates with interaction Return×Risk level

1 $\mathbb{P}$(Invest. Opt$_j$=1)	*2* (EAA)	*3* (Scale-MNL)	*4* (Mixed Logit)	*5* (GMNL-II)
Coefficient				
Return Objective	1.359***	2.256	-0.788	-1.180

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Table D.8 – *Continued from previous page*

1	*2* (EAA)	*3* (Scale-MNL)	*4* (Mixed Logit)	*5* (GMNL-II)
	(0.198)	(1.866)	(2.165)	(2.368)
Proportion of Growth Assets	2.923***	0.440	5.151**	5.370**
	(0.311)	(1.868)	(2.366)	(2.407)
Herfindahl Index	-3.458***	-2.025**	-1.800	-2.509**
	(0.260)	(0.885)	(1.143)	(1.207)
Minium Suggested Time Frame	-1.047***	-0.771***	-0.489*	-0.530
	(0.0729)	(0.280)	(0.289)	(0.326)
Risk Level	2.008***	2.200	-1.037	-1.450
	(0.143)	(1.670)	(1.877)	(2.038)
$\mathbb{E}$(Negative Returns)	2.205***	-0.217	2.489**	2.824**
	(0.251)	(0.982)	(1.153)	(1.218)
$\mathbb{E}$(Negative Returns)^2	-0.252***	0.111	-0.199	-0.236
	(0.0357)	(0.136)	(0.159)	(0.170)
Return×Risk Level	-0.396***	-0.649	-0.0328	-0.00711
	(0.0324)	(0.442)	(0.523)	(0.566)
Scale Heterogeneity				
τ		0.949***		-0.451***
		(0.0925)		(0.110)
Standard Deviation (σ_β)				
Return Objective			0.976***	0.672***
			(0.0802)	(0.0476)
Proportion of Growth Assets			-1.127***	-0.954***
			(0.250)	(0.317)
Herfindahl Index			2.524***	-2.484***
			(0.207)	(0.292)
Minimum Suggested Time Frame			0.404***	0.490***
			(0.0374)	(0.0364)

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Table D.8 – *Continued from previous page*

1	*2* (EAA)	*3* (Scale-MNL)	*4* (Mixed Logit)	*5* (GMNL-II)
Risk Level			0.930***	0.993***
			(0.0902)	(0.125)
$\mathbb{E}$(Negative Returns)			0.394***	-0.0103
			(0.0934)	(0.0382)
$\mathbb{E}$(Negative Returns)^2			0.0365***	0.0539***
			(0.00714)	(0.00458)
Return×Risk Level			0.155***	0.198***
			(0.0162)	(0.0163)
AIC	6278.6	8083.8	6278.6	6286.0
CAIC	6397.0	8154.8	6404.8	6420.1
BIC	6382.0	8145.8	6388.8	6403.1
pseudo loglikelihood	-3124.3	-4032.9	-3123.3	-3126.0

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. The sign of the estimated standard deviations is irrelevant: interpret them as being positive. The number of observations used in this estimation is 156 respondents by 45 choices each, resulting in 7020 observations. The above Log Likelihood refers to the simulated Log likelihood for the non-Clogit models. For each of the applicable models, the ASC variables are not scaled as per Gu et al. (2013)

D.9 Katana Estimates

Table D.9: Generalised Multinomial Logit Baseline Estimates from Katana HPC

1 $\mathbb{P}$(Invest. Opt=i)	*2* (Clogit)	*3* (Scale-MNL)	*4* (Mixed Logit)	*5* (GMNL-II)
Coefficient Estimate (β)				
Return Objective	-0.305	-0.315	-0.875*	-1.141**
	(0.321)	(0.329)	(0.466)	(0.486)
Proportion of Growth Assets	1.613	0.836	5.120**	6.223**
	(1.598)	(1.694)	(2.320)	(2.464)
Herfindahl Index	-1.620**	-2.504***	-1.964*	-2.192**

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Table D.9 – *Continued from previous page*

1	*2* (Clogit)	*3* (Scale-MNL)	*4* (Mixed Logit)	*5* (GMNL-II)
	(0.767)	(0.817)	(1.096)	(1.109)
Minimum Suggested Time Frame	-0.354***	-0.490***	-0.490***	-0.607***
	(0.123)	(0.151)	(0.178)	(0.187)
Risk Level	-0.371	0.00748	-1.170**	-1.370***
	(0.349)	(0.405)	(0.503)	(0.516)
$\mathbb{E}$(Negative Returns)	1.108***	1.109***	2.574***	2.955***
	(0.235)	(0.269)	(0.366)	(0.490)
$\mathbb{E}$(Negative Returns)^2	-0.0809***	-0.0787**	-0.207***	-0.243***
	(0.0308)	(0.0357)	(0.0467)	(0.0602)
Scale Heterogeneity				
τ		0.936***		-0.488***
		(0.0893)		(0.0965)
Standard Deviation (σ_β)				
Return Objective			1.218***	1.272***
			(0.0922)	(0.121)
Proportion of Growth Assets			-0.928***	2.046***
			(0.268)	(0.198)
Herfindahl Index			2.148***	-2.056***
			(0.230)	(0.185)
Minium Suggested Time Frame			0.565***	0.537***
			(0.0493)	(0.0425)
Risk Level			-0.655***	-0.672***
			(0.0641)	(0.0658)
$\mathbb{E}$(Negative Returns)			0.289***	0.194***
			(0.0734)	(0.0336)
$\mathbb{E}$(Negative Returns)^2			0.0860***	0.0567***

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Table D.9 – *Continued from previous page*

1	*2* (Clogit)	*3* (Scale-MNL)	*4* (Mixed Logit)	*5* (GMNL-II)
			(0.0110)	(0.00647)
AIC	8440.6	8084.2	6283.7	6259.2
CAIC	8495.8	8147.	6394.1	6367.6
BIC	8488.8	8139.2	6380.1	6353.6
loglikelihood	-4213.3	-4034.1	-3127.8	-3114.6

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. The sign of the estimated standard deviations is irrelevant: interpret them as being positive. The number of observations used in this estimation is 161 respondents by 45 choices each, resulting in 7245 observations. The above Log Likelihood refers to the simulated Log likelihood for the non-Clogit models. For each of the applicable models, the ASC variables are not scaled as per Gu et al. (2013)

Appendix E

E.1 Superannuation's History

The first financial product disclosures in the 1990's was not parsimonious but were complex documents which were difficult to compare. The Australian regulators established financial product disclosures statements (PDS) on the foundations that disclosures would improve individual decision making (Gruen and Wong 2010). The establishment of the PDS was founded on the recommendations of the financial system enquiry of the 90's which approved a regulatory approach of Financial markets which was based on information disclosure and market conduct (Bateman et al. 2016). However, this approach resulted in complex and confusing documents which were attributed to a high-level regulatory approach, a focus on compliance and disclosure and a lack of guidance (Bateman et al. 2016).

The mid 2000's saw a slew of developments around the choice architecture of superannuation. In the US, Madrian and Shea (2001) analysed the effect of default 401k enrolments and found that most individuals opted for the default fund, rather than make an active choice. From this, Madrian and Shea (2001) suggested the simplification of the choice process would alleviate sub-optimal savings choices. A key change to superannuation choice architecture was the Choice of Funds legislation. This legislation was implemented in 2005 and resulted in employees having the right to nominate any fund for their contributions (Commonwealth of Australia 2004). As noted by, the policy changes since the introduction of the Superannuation Guarantee in 1992 had resulted in a complex system (Warren 2008). This was compounded as individuals were not engaging with the superannuation system as policy makers originally envisioned (Feng 2014; Productivity Commission 2018). To combat the complexity and disinterest, new initiatives to simplify the superannuation system were proposed. In 2006, changes to Australia's retirement system were proposed through "A Plan to Simplify and Streamline Superannuation". The change was aimed at improving the living standards of retirement with the augmentation of superannuation and rewarding individuals for additional contributions (Warren 2008).

The introduction of the Choice of Funds legislation in 2005, provided the opportunity for welfare gains for superannuation members and was studied by Langford et al. (2006). Under the old legislation, employees were only able to change their superannuation fund if they were to change employees, however the Choice of Fund legislation now allowed employees to elect any fund (Commonwealth of Australia 2004). Comparing a sample of retail and industry funds prior to the change, the potential gains in better investment outcomes from the introduction of fund choice was studied by Langford et al. (2006). Given a choice, investors show no response to historical performance or fees and that employees who contribute to the fund selected by the employer are likely better off. Employees are better off as employers are choosing funds with low fees. This investment strategy of selected funds with low fees is supported by Malkiel (2007) and results in maximised wealth in the long-term. Thus, Langford et al. (2006) questions the effectiveness of allowing employees more choice and rather this change needs to be coupled with reform to financial planning which is causing investors to choose high fee funds.

The late 2000's saw a global theme of simplifying superannuation and its equivalents. On an international level, a common set of principles were developed by a number of international organisations to increase consumer protection in financial services which focused on improving the comparability between products, while countries individual countries experienced trends towards short form disclosure (Bateman et al. 2016; Godwin and Ramsay 2015). The U.S. was not immune to the lack of attention shown by investors towards PDSs, with two thirds of investors completely ignoring mutual fund PDS documentation prior to investment (Beshears et al. 2011). In response, the U.S. simplified the PDSs for mutual funds by requiring an optional "Summary Prospectus", which provided key information on investment objectives, risk and performance. The effect of the implementation of the summary prospectus had on investor choices was analysed by Beshears et al. (2011). Using a portfolio allocation experiment Beshears et al. (2011) found that the prospectus reduced the amount of time spent on the decision but had no effect on the actual choices made by the subjects. However, the subject's sub-optimal choices implied that they were potentially confused or inattentive regarding loads and fees (Beshears et al. 2011). Additionally, the portfolio allocation allowed Beshears et al. (2011) to test the naive diversification strategy of equal allocation (Benartzi and Thaler 2007). Beshears et al. (2011) find that despite the provision of the summary prospectus there is no change to the subjects' preference for a naive diversification strategy.

E.2 The 2018 Review of Efficiency and Competitiveness in Superannuation

The Productivity Commission was tasked by the federal government in 2017 to assess the efficiency and competitiveness of the superannuation system. The assessment has taken the form of the 3-stage review of the superannuation system by the Productivity Commission, which resulted in recommendations to improve the superannuation system to better suit its members. A major finding has been that there exists inadequate competition between superannuation funds and additionally that behavioural biases contribute to member disengagement (Productivity Commission 2018). This lack of competition has resulted in members having multiple accounts which incur more fees, a significant proportion of under-performing funds, excessive fees and insurance unnecessarily eroding balances (Productivity Commission 2018). In its review, the Productivity commissioned two separate choice experiments for stage 2 and stage 3. The stage 2 choice experiment was designed to provide evidence of how people would make choices between superannuation products, when supplied with a short list of superannuation funds (Productivity Commission 2017). The stage 3 choice experiment explores the relative value attached to member services through willingness to pay estimates in a stated preference survey (Productivity Commission 2018).

Of particular interest to this thesis is the Members Choice survey from the second stage of the superannuation review. The Members Choice survey included a stated choice preference experiment on superannuation funds. The choice experiment elicited how members might behave when choosing a superannuation product from a shortlist of good superannuation products (Productivity Commission 2017). The experiment consisted of a control group and 10 different treatment groups. Every treatment group was presented with a short list of suggested funds. The 10 treatment groups varied between menu sizes of 4 to 8 superannuation funds with differing attribute values. Another variation was the attribute values being presented in dollar values or percentage points, which were all based on a super balance of $50 000. The available funds were based on a selection of MySuper products available in the market. The provided attributes were Return, Risk, return target and fees (Productivity Commission 2017). The results suggest that many respondents were making choices which minimised fees and maximised returns, and that there exists a substantial number of participants who minimise risk. However, the results also show that there is robust heterogeneity in choices which suggests that other unobserved characteristics of the fund are important, or that respondents are making poor choices (Productivity Commission 2017).