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Abstract

We assess alternative presentations of investment risk using a discrete choice experiment which asked subjects to rank three investment portfolios for retirement savings across nine risk presentation formats and four underlying risk levels. Using Prospect Theory utility specifications we estimate individual-specific parameters for risk preferences in gains and losses, loss aversion, and error propensity variability. Our results support presentations that describe investment risk using probability tails. Risk preferences and error propensity were found to vary significantly across sociodemographic groups and levels of financial literacy. Our findings should assist regulatory efforts to disclose risk information to the mass market.

Keywords: Discrete choice, investment risk, Prospect theory
JEL classification: G23, G28, D14

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1 Introduction

Individuals face many financial decisions in their lifetime. These decisions range from the relatively simple such as choosing bank accounts and credit cards, to the more complex involving investment products and retirement planning. The latter is especially important, as it directly affects the spending ability and quality of life during retirement. Under the increasingly prevalent Defined Contributions (DC) retirement income arrangements, retirement planning imposes a sequence of decisions on ordinary people, including choice of retirement fund, investment option, take-up of financial advice, retirement age and type of retirement benefit. There is evidence that people find it difficult to make good financial decisions, due to poor financial and product knowledge and choice overload (Gustman and Steinmeier, 2001; Delpachitra and Beal, 2002; and Lusardi and Mitchell, 2007).

One of the most important, yet difficult, of these decisions is that of investment choice. In many retirement saving environments, individuals are required to choose from large menus of investment options, or else rely on a possibly inappropriate default option. In making these allocation decisions, an understanding of investment risk is paramount. We address this issue by analyzing common presentations of investment risk information and identifying those which minimize the errors individuals make when inferring the underlying distributions from the information provided.

The motivations behind this research are threefold. First, existing research has highlighted the gap between the financial competence of ordinary people and the skills needed to make sound financial decisions in retirement planning. Studies such as Delpachitra and Beal (2002) and Lusardi and Mitchell (2010) find that for an average household, choosing an investment strategy for retirement savings is a significant challenge.

Second, evidence suggests that individuals are susceptible to presentation and framing effects (Tversky and Kahneman, 1981; and Tversky and Kahneman, 1986). For example, Tversky and Kahneman (1981) demonstrate that describing a gamble in terms of the upside and then in terms of the downside caused some individuals to change their decisions to accept or reject the gamble. The way information is presented has also been shown to have strong practical implications, including buying decisions (Puto, 1987) and political campaigns (Druckman, 2001). A more recent study by Anagol and Gamble (2010) examines how investment behaviors change when investment returns are presented asset by asset or aggregated into a portfolio return, with asset by asset presentations shown to reduce risk taking, due to individuals narrowly focusing on individual asset returns rather than the aggregate return.

Third, the role and impact of alternative formats for risk information in retirement decision making has been little investigated and few studies have considered the impact of demographic factors or individual characteristics. Given the heterogeneity in risk preferences and demographic characteristics observed in studies such as Andersen, Harrison, Lau, and Rutström (2008) and Gaudecker, Soest, and Wengström (2011), the presentation effect may vary significantly across individuals.

In this context our findings will inform international regulatory efforts to develop standardized formats for presenting investment risk.[1] In Australia, for example, the industry regulator recommends the presentation of investment risk in terms of the expected number of years of negative returns in a 20 year period.[2]

Our approach is to use a discrete choice experiment (DCE) where subjects are required to choose between three investment accounts under four risk levels and nine different presentations of investment risk. The presentations are drawn from those used by pension funds in financial product disclosure documents,[3] as well as discussed in related studies such as Vlaev, Chater, and Stewart (2009). Investment decisions from the same DCE was used by Bateman, Ebling, Geweke, Louviere, Satchell, and Thorp (2011) to examine the propensity of individuals to violate implications of Expected Utility Theory. That study found overall rates of rationality violations of around 25 per cent, and substantial variation in rates across risk presentations and demographic groups. Presentations based on frequencies rather than probabilities were found to generate more violations, whilst younger individuals with low numeracy skills were found to be several times more likely to violate rationality than those with high numeracy skills.

We extend Bateman et al. (2011) by analyzing the observed investment choices using Prospect Theory utility specifications. This allows us to capture additional decision making factors such as different risk preferences in gains and losses and loss aversion. We assess the propensity of individuals to violate Prospect Theory utility under each of nine investment risk presentation formats and estimate the distribution of utility parameters in a broad heterogenous population.

[1] In US, the Department of Labor is proposing a simplified format based on historical returns (Hung, Heinberg, and Yoong, 2010). In UK, the Financial Services Authority is working to make pension disclosures easier to understand (Andrews, 2009). Cross-country co-ordination is also being initiated by multilateral organizations such as the OECD (for Economic Cooperation and Development, 2008).

[2] See 29 June 2010 Letter to Trustees, available at http://www.apra.gov.au/Super/Documents/Ltr-IRD-29-June-2010-FINAL-trustee.pdf.

[3] These presentation formats are drawn from superannuation and pension funds in Australia, Europe, and the United States.

The next section describes the survey setup and data. In Section 3 we describe the utility framework under Prospect Theory which forms the basis of our analysis and introduce the structural model. In Section 4 we present results. These include the estimated individual-specific parameters from the structural model, the error propensity under each risk presentation format and the extent to which risk presentations are understood by different sociodemographic groups. Section 5 concludes.

2 Data and Survey Setup

2.1 Overview

We use data generated from a discrete choice experiment implemented in 2010 by the Centre for Pensions and Superannuation (CPS) and the Centre for the Study of Choice (CenSoC), for the Australian Research Council (ARC) project "The paradox of choice: Unravelling complex superannuation decisions" (Bateman et al., 2011). The survey was conducted using a representative sample of 1,200 Australians aged 18-65 who held at least one superannuation (pension) account from an online panel of over 600,000 Australians maintained by PureProfile, a web panel provider.[4]

Subjects were told that the survey was part of a university project designed to inform policy makers and industry participants about ways to simplify retirement saving investment choices. Their choices in the experiment were purely hypothetical, and did not affect their flat participation fee of $3AUD.

The survey consisted of four parts, divided into background information, numeracy and financial literacy questions, the discrete choice experiment, and finally a set of questions on demographics and personal characteristics. In the first part of the survey, subjects were asked to provide a description of their retirement savings. This included the name(s) of their superannuation (pension) fund(s) and the aggregate amount in their account(s). In the second part, subjects answered standard numeracy and financial literacy questions. The numeracy questions (reported in Appendix A.1) and drawn from Gerardi, Goette, and Meier (2010), tested basic mathematical concepts such as probabilities and percentages. The financial literacy questions (reported in Appendix A.2) were drawn from Lusardi and Mitchell (2007), and were used to test subjects' knowledge of financial concepts such as inflation, compound interest, the relationship

[4]The entire survey can be accessed at http://survey.confirmit.com/wix/p1250911675.aspx.

between risk and return and diversification. Average responses to the questions are summarized in Table 1. The survey also asked about access to financial education, take-up of financial advice and stock market confidence.

In the third part of the survey, subjects were asked to complete a retirement savings investment choice task. Specific instructions can be found in Appendix A.3. This task involved a discrete choice experiment designed to elicit respondents' decisions on their allocation of retirement wealth under alterative risk presentations and risk levels. We describe this experiment in detail in the following section.

The final part of the survey asked subjects questions about their demographic characteristics, including gender, age, marital status, employment status, education attainment, income level, and composition of household. These characteristics and the relevant population statistics are summarized in Table 1.

2.2 Discrete Choice Experiment

In the discrete choice experiment the subjects were asked to nominate their "most" and "least" preferred investment option from a menu of three investment portfolios: safe ("S"), risky ("R") and mixed ("M"). The safe portfolio (S) provides a guaranteed real annual return of 2 per cent. The risky portfolio (R) provides an uncertain real return from a growth fund, which is invested in assets such as equities and property. It has an expected real annual return of 4.5 per cent. The mixed portfolio (M) is dynamically rebalanced such that 50 per cent is invested in each of the safe and risky portfolio. Thus, the portfolio return for M is the average of the safe and risky returns.

The choice sets provide information about the expected return and the investment risks of these portfolios. The risk information varies across two dimensions: the underlying risk level and the presentation (i.e., description) of the risk. There were four risk levels and nine different risk presentations making a total of 36 choice sets. Each subject was shown three of these risk presentations across each of the four risk levels, a total of 12 choice sets.

2.2.1 Risk Levels

The four risk levels were selected such that the expected returns remain the same for each portfolio, but the volatilities vary. A log-normal distribution was used to construct the values for the alternative risk presentation formats. Let r_j denote the net real return for portfolio R under risk level j, where $j = 1, 2, 3, 4$, it follows that the gross real return

Table 1: Comparison of Sample and Australian Population Demographic Characteristics

	Survey (%)	Population (%)		Survey (%)	Population (%)
Gender			***Highest Year of School Completed***		
Male	49.90	50.10	Year 12 or equivalent	70.49	46.87
Female	50.10	49.90	Year 10-11 or equivalent	26.23	36.44
Age (as % of 18-65 group)			Year 9 or below	3.20	15.72
18-34	35.80	37.40	Did not go to school	0.08	0.96
35-54	43.20	43.60	***Highest Post-School Qualification***		
55-65	21.10	18.90	Postgraduate or equivalent	13.59	6.58
Marital Status			Graduate Diploma or Certificate	8.43	3.64
Not living with long term partner	42.94	46.72	Bachelor Degree	30.77	29.33
Married or living with long term partner	57.06	53.28	Advance Diploma and Diploma	20.65	18.01
Work Status			Certificate or equivalent	26.55	42.43
Employed full-time	51.72	40.79	***Numeracy (5 questions)***		
Employed part-time	23.52	18.79	Less than 1 correct answer	1.42	-
Unemployed	3.44	3.53	2-4 correct answers	21.18	-
Not in the labor force	21.31	36.89	All correct answers	77.40	-
Annual Total Household Pre-Tax Income			***Financial Literacy***		
Less than $18,200	3.28	4.72	*Basic (Q. 1-5)*		
$18,200-$72,799	34.33	39.49	Less than 1 correct answer	6.17	-
$72,800-$129,999	31.64	28.44	2-4 correct answers	57.55	-
$130,000 or more	16.88	14.93	All correct answers	36.28	-
Prefer not to answer	13.87	12.42	*Sophisticated (Q. 6-9)*		
Net Wealth			Less than 1 correct answer	19.85	-
Under $10,000	13.93	-	2-3 correct answers	44.87	-
$10,000-$99,999	27.54	18.21	All correct answers	35.28	-
$100,000-$999,999	35.00	62.44			
$1,000,000 or more	6.80	19.35			
Prefer not to answer	16.72	-			

Source for population statistics: Australian Bureau of Statistics Census of Population and Housing & Household Wealth and Wealth Distribution, Australia 2005-2006

$1 + r_j$ has a log-normal distribution with parameters μ_j and σ_j. This return is assumed to be independent and identically distributed for each future period. Let $1 + r_f$ denote the guaranteed gross real return for portfolio S, then we can express the gross real return for portfolio M as $1 + \frac{1}{2}(r_j + r_f)$, i.e., the average of the risky and risk-free gross returns. Table 2 shows the various parameters used for the log-normal distribution under different risk levels, and the corresponding means and standard deviations of the portfolio net returns. Note that the mean net return for portfolio R is fixed at 4.5 per cent. It follows that the mean net return for portfolio M is fixed at 3.25 per cent. The idea that gross returns are log-normally distributed was not conveyed to respondents. Later we analyze the extent to which individuals make errors when inferring the risk distribution under each presentation of investment risk.

Table 2: Log-normal Parameters and Portfolio Returns

Risk Level	Parameters		Portfolio R		Portfolio M		Portfolio S	
j	μ_j	σ_j	Mean	s.d.	Mean	s.d.	Mean	s.d.
1	0.03747	0.11446	4.5%	12%	3.25%	6%	2%	0
2	0.03243	0.15222	4.5%	16%	3.25%	8%	2%	0
3	0.02603	0.18967	4.5%	20%	3.25%	10%	2%	0
4	0.00935	0.26331	4.5%	28%	3.25%	14%	2%	0

2.2.2 Risk Presentations

The risk and return information was presented to subjects under nine different presentation formats. Since the expected returns are the same for each portfolio across all four risk levels, only the presentation of investment risk actually changed. In eight presentations the investment risk is described in a textual format using a combination of words and numbers. In the ninth presentation investment risk is presented in a graphical and textual format. The wording of the presentations is shown in Table 3 and the corresponding values in Table 4. Each of these presentations represents a different aspect of investment risk. In the absence of a standard format for presenting investment risk, the presentations used in the experiment are selected from prospectuses of financial service providers in Australia, Europe, and the United States, as well as in related studies such as (Vlaev et al., 2009).

As indicated in Table 3, presentations 1 and 2 describe the risk as a range of returns, providing the probability of returns falling outside or within on both the upper and lower

Table 3: Alternative Presentations of Investment Risk

Presentation	Presentation Format of Investment Risk
1	There is a 9 in 10 chance of a return between $x\%$ and $y\%$
2	There is a 1 in 10 chance of a return outside $x\%$ and $y\%$
3	There is a 1 in 20 chance of a return above $y\%$
4	There is a 1 in 20 chance of a return below $x\%$
5	On average, positive returns occur 20 - x years in every 20 years
6	On average, negative returns occur x years in every 20 years
7	On average, returns above the bank account occur 20 - x years in every 20 years
8	On average, returns below the bank account occur x years in every 20 years
9	See Figure 1: Graphical display of 5% to 95% quantile

Table 4: Representative Values of Investment Risk at Each Risk Levels

Presentations	1-4: (x, y)		5-6: x		7-8: x	
Risk Levels	M	R	M	R	M	R
1	(-6, 14)	(-14, 25.5)	6	7	9	9.5
2	(-9, 17.5)	(-19.5, 32.5)	7	8	9.5	10
3	(-11.5, 21)	(-25, 40)	8	9	10	10.5
4	(-16.5, 29)	(-34.5, 55.5)	9	10	11.5	11

bounds of the underlying distribution. Presentations 3 and 4 present just one side of the probability distribution: the upper tail (presentation 3) and the lower tail (presentation 4). Presentations 5 and 6 replace probabilities with frequencies of positive or negative returns in 20 years whilst presentations 7 and 8 present the returns relative to a risk-free return. Presentation 9 shows the same range information as presentations 1 to 4 in a graphical form along with the return r_f. An illustrative example of a presentation in text format and presentation 9 is provided in Appendix A.4.[5]

2.3 Experiment Results

The experiment was implemented in the following manner: subjects were randomly allocated into four groups, with each group being exposed to three of the nine risk presentations. Of the 1220 subjects recruited, 21 failed to complete their surveys so were omitted. For the remaining 1199, 300 were allocated to group A, 299 to group

[5] The presentation formats in our analysis are not all *frames* in the strictest sense (i.e., they contain different information), although some subsets are: for example, 1, 2, and 9.

B, 297 to group C, and 303 to group D. Group A saw presentations 1 and 2 (ranges); group B saw presentations 3 and 4 (probability tails); group C saw presentations 5 and 6 (frequency tails relative to zero); and group D saw presentations 7 and 8 (frequency tails relative to safe returns). All groups saw presentation 9 (graphical range). Each subject was asked to nominate their "most" and "least" preferred investment option in each of 12 choice sets: three risk presentations x four risk levels. Under this experimental setup, 12 orderings of the three portfolios, S, M and R were observed for each subject. As there were 1199 complete responses, a total of 14388 orderings were collected. A summary of the six possible orderings under each risk presentation is provided in Table 5.

Table 5: Frequency of Portfolio Orderings in Each Presentation

	Risk Presentations									
Ordering	1	2	3	4	5	6	7	8	9	Total
RMS	246	232	334	149	379	342	301	272	1625	3880
RSM	20	23	28	25	67	52	28	39	149	431
MSR	344	339	303	233	173	274	332	229	1194	3421
MRS	265	237	341	190	235	251	297	269	1066	3151
SMR	274	300	128	537	169	164	160	283	566	2581
SRM	51	69	62	62	165	105	94	120	196	924
Total	1200	1200	1196	1196	1188	1188	1212	1212	4796	14388

Source: Bateman et al. (2011) Table 6.

In related work Bateman et al. (2011) investigated the extent to which individual portfolio orderings in this DCE were consistent with the implications of expected utility theory. Under that construct, rational decision making precludes the ranking of the mixed option M as worst. Under Prospect Theory utility specifications however, the curvature of the utility function may change across gains and losses. As a result, it is possible for an individual to rank M last: doing so implies that the curvature of his utility function for gains (g) is less than the curvature for losses (l).[6] The opposite holds if he ranks M as best. Therefore, since each individual has a unique set of utility parameters, the restriction on rational choice under Prospect Theory is that an individual cannot rank portfolio M both as best and worst within a risk presentation or across risk presentations. The frequencies of this type of violation for the 1199 subjects who completed the survey are summarized in Table 6.

[6]It can be shown that an individual who ranks portfolio M last can still be rational if he does not rank M first in any of his other choices (See Appendix B.2 for the proof).

Table 6: Proportion of Inconsistencies by Groups Under Prospect Theory

Group		A	B	C	D
(f_1, f_2, f_3)		(1, 2, 9)	(3, 4, 9)	(5, 6, 9)	(7, 8, 9)
	f_1	0.100	0.054	0.125	0.109
Within	f_2	0.117	0.070	0.125	0.109
	f_3	0.103	0.087	0.064	0.102
Between		0.107	0.070	0.104	0.107
Total		0.427	0.281	0.418	0.427

Notes: The f_i correspond to the presentation formats defined in Table 3. The figures represent the proportion of violations within each risk presentation and across risk presentations for each of the four groups (A,B,C,D). The numbers for the within presentation violations are calculated by dividing the number of violations within each presentation by the number of choices made within that presentation (i.e., 1200 for presentation 1). The between presentation violations takes into account subjects that do not violate the restriction within each of their 3 presentation formats, but violate the restriction between presentations. This is calculated by dividing the number of subjects that violate this restriction by the number of subjects in each group.

When the frequencies of violation are broken down by presentation format, the results are similar to the findings under the Expected Utility framework of Bateman et al. (2011). Overall, presentations which convey investment risk using probabilities have lower error rates than presentations which use frequencies. Presentations 3 and 4 (which present investment risk using probability tails) have the lowest error rates: 5.4 per cent and 7.0 per cent of subjects respectively have ranked portfolio M both as the best and worst portfolio within the same presentation. The error rates in presentations 5 and 6 (where investment risk is presented as the frequency of positive/negative returns in 20 years) are almost double, both at 12.5 per cent. Interestingly, although subjects in group C (who see presentations 5, 6 and 9) have the highest error rate in the text-based presentations, they committed the lowest amount of errors in the graphical presentation (seen by all groups). This suggests that although subjects in group C may make relatively more rational decisions than subjects in the other three groups in the context of the graphical presentation, their abilities to correctly infer the correct distribution of investment risk may be restricted under presentations 5 and 6. This further emphasizes the shortcoming of using frequencies to convey investment risk.

Of the remaining individuals who did not violate the restriction on rational choice within any of their presentations, around 10 per cent violate the restriction between presentations. Group B, which saw the investment risk as probability tails rather than frequency tails, has the lowest error rate. This is similar to the results for the within-presentation analysis. These preliminary findings suggest that the current recommendation by Australia's superannuation industry regulator to describe investment risk in terms of "the number of negative returns in a 20 year period", may not be the best standard. On the contrary, presentations in terms of probability ranges (1, 2 and 9) and tails (3 and 4) are shown to be more effective in reducing violations of rationality under both Expected Utility Theory and Prospect Theory. These presentations may be the better formats in which to present investment risk to retirement savers.

Overall, the substantial violation rates for both Expected Utility Theory and Prospect Theory suggest that more insights can be gained by adding an error component to the modeling of these observed choices. Next we analyze the quality of the risk presentation formats used in the DCE by analyzing individuals' error propensity.

3 Theoretical Framework and Empirical Model

3.1 Utility Framework under Prospect Theory

When an individual is presented with risky choices, he makes decisions based on the possible outcomes and their respective probabilities. Each risky choice (or gamble) can be expressed in the following form:

$$\{(x_1, p_1), \ldots, (x_n, p_n)\},$$

where outcome x_i has a probability of p_i and the sum of all probabilities is equal to one. These outcomes can be positive or negative values, representing gains and losses respectively.

An individual is willing to accept a gamble (x) if and only if the expected utility value of integrating the gamble into his current wealth is greater than the utility of his current wealth. Let W_0 be the individual's initial wealth: this implies that he will assess the gamble based on the final achieved wealth, rather than the gains and losses entailed in the gamble, i.e., the individual will accept the gamble if:

$$\mathbb{E}\left[u(W_0 + x)\right] > u(W_0)$$

or equivalently,

$$\sum_{\text{all } i} [u(W_0 + x_i) \times p_i] > u(W_0). \tag{1}$$

The utility function $u(\cdot)$ typically has a positive slope, which implies that more wealth is always preferred to less wealth and the curvature of $u(\cdot)$ captures the risk preference of the individual.

There are many documented violations of the standard CRRA utility models. The main consensus is that traditional utility functions cannot fully capture the risk behaviors of individuals. Kahneman and Tversky (1979) shows evidence of individuals exhibiting different risk attitudes towards gains and losses. In general, individuals are found to have greater sensitivity to losses than gains. Köbberling and Wakker (2005) describes this as a kink in the utility function at the reference point. Therefore, we utilize a value function under Prospect Theory (Tversky and Kahneman, 1992) to allow for different risk preferences in gains and losses and loss aversion.

Under Prospect Theory, individuals assess risky choices by evaluating the potential gains and losses relative to a neutral reference point. This is in contrast to incorporating the outcomes into the initial wealth under standard utility theory. Each outcome is divided into two components, the deviation from the reference point and the associated subjective probability. Each deviation is evaluated by a value function, a special class of utility function that allows for different risk preferences in gains and losses and loss aversion. An example of a value function is illustrated in Figure 1. The function is concave for gains (risk aversion) and convex for losses (risk loving). It has a value of zero at the reference point and a steeper slope in the loss region. The steepness of this part of the curve represents the degree of loss aversion.

We begin with a standard two-part power value function given in Tversky and Kahneman (1992):

$$v(x, p_i) = \begin{cases} x^{g_i}, & \text{if } x > 0; \\ -\lambda_i(-x)^{l_i}, & \text{if } x \leq 0, \end{cases} \tag{2}$$

where $p_i = \{g_i, l_i, \lambda_i\}$ are utility parameters of individual i, and x is the deviation from the reference point.

This value function has three preference parameters, namely g_i, l_i, and λ_i to describe the risk attitude of an individual. The parameters g_i and l_i determine the curvature of

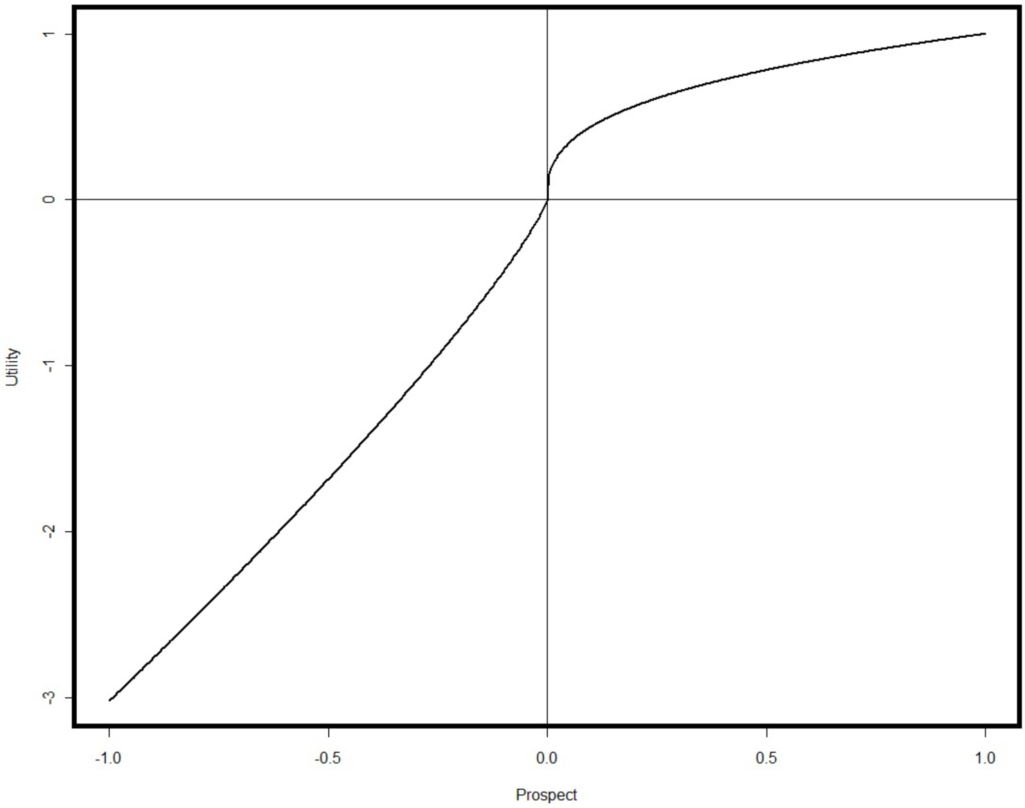

Figure 1: Value Function with Median Estimates

Notes: This curve is constructed using Equation (2), with $g = 0.36$, $l = 0.84$, and $\lambda = 3.02$. It has a convex-concave shape, consistent with Prospect Theory literature.

the value function, for gains and losses respectively. If g_i and l_i are equal to one, this represents risk neutrality across both regions of gains and losses. If both parameters are less than one, this indicates risk aversion in gains and risk loving in losses. Ceteris paribus, a higher value of the loss aversion parameter λ_i indicates higher sensitivity to losses. In general, individuals are more sensitive to losses than gains, implying λ_i is greater than one.

We deviate from the traditional Prospect Theory utility function by not incorporating a subjective probability weighting. This is because we take a normative approach (i.e., what *should* individuals do) since we are interested in what would be rational choices. This is consistent with other studies (see for example, Dimmock and Kouwenberg, 2010; and Gaudecker et al., 2011).

As noted earlier, the discrete choice experiment requires individuals to rank three investment portfolios with different allocations in a risk-free asset and a risky asset. These assets have a net return of r_f and r respectively. Let α denote the proportion invested in the risky asset, then the final single period wealth achieved by investing in a portfolio can be expressed as:

$$W_1 = W_0 \left((1-\alpha)(1+r_f) + \alpha(1+r)\right),$$

where W_i is the wealth level at time i for $i = 0$ and 1. For our discrete choice experiment α takes the values of 0, 0.5, and 1, representing the safe ("S"), mixed ("M"), and risky ("R") portfolios, respectively.

We assume that the minimum expectation of each respondent is to at least achieve the risk-free return, rather then preserving his initial state, i.e., the neutral reference point is the final single period wealth accumulated at the risk-free rate: $W_0(1+r_f)$. Hence, the prospect of each portfolio is the difference between W_1 and this reference point. Let P denote this value:

$$P = W_1 - (1+r_f) \cdot W_0 = W_0 \cdot \alpha \cdot X,$$

i.e., the prospect is equal to initial wealth multiplied by the weight allocated to the risky asset and the excess gross return $X = r - r_f$.

The utility function for individual i is given by:[7]

$$u(P, p_i) = \begin{cases} (W_0\alpha)^{g_i} X^{g_i}, & \text{if } X > 0; \\ -\lambda_i (W_0\alpha)^{l_i}(-X)^{l_i}, & \text{if } X \leq 0. \end{cases}$$

Individuals are assumed to be expected utility maximizers. Therefore, we can rewrite Equation (1), and define the expected utility for our investment portfolios as:

$$\begin{aligned} \mathbb{E}[U] &= \mathbb{E}\left[u(P)\right] = \mathbb{E}[u(P) \mid P > 0] \Pr(P > 0) + \mathbb{E}[u(P) \mid X \leq 0] \Pr(P \leq 0) \\ &= {W_0}^g \alpha^g U^+ - \lambda {W_0}^l \alpha^l U^-, \end{aligned} \tag{3}$$

where $U^+ = \mathbb{E}[X^g \mid X > 0] \Pr(X > 0)$ is the conditional expected utility value given to the gains, and $U^- = \mathbb{E}[(-X)^l \mid X \leq 0] \Pr(X \leq 0)$ is the conditional expected utility value given to the losses. The reference portfolio S has a fixed utility value of zero. The conditional expected utilities U^+ and U^- depend on the uncertain gross return $1 + r$, which has a log-normal distribution $(1 + r_j) = R_j \sim LN(\mu_j, \sigma_j^2)$, for j = 1, 2, 3, and 4,

[7] For the sake of clarity, we omit the subscript i after this point.

the associated risk levels. This implies that we can rewrite Equation (3) as:

$$U^+ = \int_0^\infty x^g f_X(x)dx \qquad = \int_0^\infty x^g f_R\left(x + (1 + r_f)\right) dx;$$

$$U^- = \int_{-R_F}^0 (-x)^l f_X(x)dx = \int_{-R_F}^0 (-x)^l f_R\left(x + (1 + r_f)\right) dx,$$

where $f_X(x) = f_R\left(x + (1 + r_f)\right)$.

Lastly, we transform Equation (3) to allow for the lack of data on respondents' initial wealth. Specifically, the initial wealth factor is omitted from the utility function by:

$$\mathbb{E}[U^*] = \frac{\mathbb{E}[U]}{W_0{}^g} = \alpha^g U^+ - \lambda^* \alpha^l U^-.$$

Without loss of generality, we estimate this new scaled (individual) loss aversion parameter $\lambda^* = \lambda W_0^{l-g}$, as it is a one to one transformation from λ, given fixed values of an individual's g, l, λ, and W_0.

Thus, the final form of the expected utility function under Prospect Theory when an individual chooses portfolio R or M is:

$$\mathbb{E}[U^*] = \alpha^g \int_0^\infty x^g f_R\left(x + (1 + r_f)\right)\, dx - \lambda^* \alpha^l \int_{-R_F}^0 (-x)^{g+c} f_R\left(x + (1 + r_f)\right)\, dx. \quad (4)$$

3.2 Structural Econometric Model

From the formulation of the expected utility function described above, we have made the following assumptions to allow parameters to be estimated from observed choices using maximum likelihood method. First, we assume that individuals are expected utility maximizers. That is, given the outcomes of the portfolios and their probabilities, individuals determine their optimal choices based on maximizing their expected utilities. Second, we assume that individuals have a utility function consistent with Prospect Theory, and evaluate choices based on real world probabilities. Third, we assume that individuals make some errors when determining their expected utilities. This error is divided into an individual-specific component and a presentation effect component. Based on these assumptions, we construct a structural econometric model that allows for individual heterogeneity in preference parameters (risk preferences and loss aversion) and the propensity to make errors.

Let $CE(P, p_i, j)$ denote the certainty equivalent for individual i, with utility parameters $p_i = \{l_i, g_i, \lambda_i\}$, for portfolio $P \in \{R, M, S\}$, and at risk j. We assume that individuals calculate the certainty equivalent for each investment portfolio, but would make a calculation error, i.e.,

$$\widehat{CE}(P, p_i, j) = CE(P, p_i, j) + \epsilon_{i,f,P}, \tag{5}$$

where $\widehat{CE}(P, p_i, j)$, $P \in \{R, M, S\}$ is the certainty equivalent calculated by individual i with utility parameters p_i for portfolio P in risk j, and $\epsilon_{i,f,P}$ is the error made in portfolio P in presentation f. These errors are assumed to be independent between individuals and risk presentations. We obtain the certainty equivalent (CE) for a given portfolio choice by solving $u(CE) = \mathbb{E}[U^*]$, hence we have:

$$CE = \begin{cases} (\mathbb{E}[U^*])^{\frac{1}{g}}, & \text{if } \mathbb{E}[U^*] > 0; \\ -\left(-\frac{\mathbb{E}[U^*]}{\lambda^*}\right)^{\frac{1}{l}}, & \text{if } \mathbb{E}[U^*] \leq 0. \end{cases} \tag{6}$$

We use certainty equivalent because an individual's error propensity may be overstated in the expected utility function due to risk aversion. This represents significantly larger utility changes than a less risk averse individual over small values of excess return. Thus, for the same calculation mistakes in the excess return, the error implied would be much higher for the more risk averse individual. This dilutes the effects of individual specific characteristics and the presentation format. For example, Lusardi and Mitchell (2006) finds that an individual with low financial literacy will tend to have higher risk aversion, and make relatively more mistakes in financial calculations. Under the expected utility function, his error propensity would be a combination of the curvature effect and his financial illiteracy, which is difficult to differentiate. Since the aim here is to examine the risk presentation format that minimizes the error propensities of different individuals, we restrict the error term to individual-specific factors and presentation factors using certainty equivalence and exclude this curvature effect that arises from the expected utility function.

In the discrete choice experiment, respondents were asked to rank the investment portfolios R, M, and S, for a given risk level and presentation format. Each respondent determined the ranking based on his calculated certainty equivalent of $\widehat{CE}(R, i, p_i, f, r)$, $\widehat{CE}(M, i, p_i, f, r)$, and $\widehat{CE}(S, i, p_i, f, r)$. Let RMS denote the ordering that portfolio R

is the most preferred portfolio, and portfolio S as the least preferred, then the choices we observed from the survey imply the following:

$$C_{i,f,r} = \begin{cases} RMS, & \text{if } \widehat{CE}(R, p_i, r) > \widehat{CE}(M, p_i, r) > \widehat{CE}(S, p_i, r); \\ RSM, & \text{if } \widehat{CE}(R, p_i, r) > \widehat{CE}(S, p_i, r) > \widehat{CE}(M, p_i, r); \\ \vdots & \qquad\qquad\qquad \vdots \\ SRM, & \text{if } \widehat{CE}(S, p_i, r) > \widehat{CE}(R, p_i, r) > \widehat{CE}(M, p_i, r), \end{cases} \tag{7}$$

where $C_{i,f,r}$ denote the observed choices made by individual i under presentation f and risk r. For each respondent 12 choices were observed, i.e., for 4 risk levels at 3 different risk presentations based on the group to which he was allocated.

Gaudecker et al. (2011) shows that only a small degree of overall parameter heterogeneity can be accounted for by sociodemographic factors. Thus, a distribution is necessary to sufficiently capture the heterogenous nature of preference parameters. Furthermore, without restricting the parameter values to a reasonable set of values, some choice behaviors can be explained by extreme values that do not have any sensible meaning. Consider the extreme case if an individual actively chooses the risky portfolio regardless of the underlying risk. This choice can be explained by a unrealistic loss aversion (λ) of $-\infty$. Taking these factors into consideration, in our analysis we assume a normal distribution for the parameters.

Hence, our structural model combines (5) and (7) with:

$$\eta_i = g_\eta(\mu_p + \Sigma_p \xi_i), \qquad \eta_i \in \{g_i, l_i, \lambda_i, \sigma_i\}, \tag{8}$$

where η_i denote the four individual specific parameters, μ_p is the mean vector, Σ_p is the covariance matrix for the parameters, and ξ_i are the unobserved heterogeneity components of the parameters. The function $g_\eta(\cdot)$ allows for other theoretical distributions to be used for future studies.

We further assume that the error terms $\epsilon_{i,f,R}$, $\epsilon_{i,f,M}$, and $\epsilon_{i,f,S}$ can be divided into an individual-specific component and a presentation effect component. We express these components in the variance of the error term:

$$Var(\epsilon_{i,f,p}) = c_P \cdot (\sigma_i + \sigma_f), \tag{9}$$

where c_P is a constant for portfolio P, σ_i represents the variability of the propensity to

make errors due to individual-specific characteristics such as financial literacy, gender, and age, and σ_f represents the variability of the propensity to make errors due to the effects of different presentations of investment risk.
In other words, since we observe 12 choices for each individual, across 4 risk levels and 3 presentations, this allows us to distinguish individual-specific and presentation effects.
We assume that individual errors follow a joint normal distribution with zero means, and covariance matrix Ω:

$$\epsilon_{i,f} = \begin{bmatrix} \epsilon^R_{i,f} \\ \epsilon^M_{i,f} \\ \epsilon^S_{i,f} \end{bmatrix} \sim N(0, \Omega), \qquad \Omega = \begin{bmatrix} \sigma^{(i,f)}_{RR} & \sigma^{(i,f)}_{RM} & \sigma^{(i,f)}_{RS} \\ \sigma^{(i,f)}_{MR} & \sigma^{(i,f)}_{MM} & \sigma^{(i,f)}_{MS} \\ \sigma^{(i,f)}_{SR} & \sigma^{(i,f)}_{SM} & \sigma^{(i,f)}_{SS} \end{bmatrix}.$$

We set the variance of the error term in portfolio R equal to $\sigma_i + \sigma_f$, and without loss of generality, we define the variables m^2 and s^2 as the constant for the variance of the error term in portfolio M and S respectively. This leads to the following expressions:

$$\begin{aligned} \sigma^{(i,f)}_{RR} &= (\sigma_i + \sigma_f); & \sigma^{(i,f)}_{MM} &= m^2 \cdot (\sigma_i + \sigma_f); & \sigma^{(i,f)}_{SS} &= s^2 \cdot (\sigma_i + \sigma_f); \\ \sigma^{(i,f)}_{RM} &= \rho_1 \cdot (\sigma_i + \sigma_f); & \sigma^{(i,f)}_{RS} &= \rho_2 \cdot s \cdot (\sigma_i + \sigma_f); & \sigma^{(i,f)}_{MS} &= \rho_3 \cdot s \cdot m \cdot (\sigma_i + \sigma_f), \end{aligned}$$

where ρ_i, $i = 1, 2, 3$ are correlation coefficients.
As outlined earlier, an objective of this research is to identify how sociodemographic characteristics influence individuals' retirement investment choices and their error propensity in each risk presentation format. The survey collected a range of sociodemographic data including age, gender, financial literacy, and numeracy skills. We first substitute the variability due to individual-specific characteristics (σ_i) with sociodemographic covariates and estimate the coefficients via maximum likelihood method. We then repeat this process for the variability due to the presentation effect (σ_f).
Specifically, we have regression 1, where:

$$\begin{cases} \sigma_i &= \mathbf{X}\beta + \zeta_i, \quad \text{for } i = 1, \ldots 1199; \\ \sigma_f &= \alpha_f, \qquad\quad\ \ \text{for } f = 1, \ldots 9, \end{cases} \tag{10}$$

where $\mathbf{X}$ is the vector of sociodemographic covariates, β is the coefficient vector, α_f is a constant for presentation f, and $\{\zeta_i, \zeta_f\}$ are the residuals. Note that for σ_i in Equation (10), we do not include a constant as an explanatory variable. This is because in our definition of the variance of the error term (see Equation (9)), the effects from

individual-specific and presentation specific factors are additive. Hence, excluding the constant as an explanatory variable makes the parameters uniquely identifiable.
In addition, we extend our analysis by investigating which presentation formats are best understood by different sociodemographic groups. Specifically, we expect that individuals with higher levels of financial literacy and numeracy skills should benefit from presentations that provide more complex investment risk information, such as those that use probabilities (i.e., presentations 1 to 4). Hence, we have regression 2, where:

$$\begin{cases} \sigma_f = \mathbf{X}\beta_f + \zeta_f, & \text{for } f = 1, \dots 8; \\ \sigma_i = \alpha_i, & \text{for } i = 1, \dots 1199. \end{cases} \tag{11}$$

In Equation (11), we only consider the text-based presentations (i.e., we exclude the graphic presentation 9). This is again due to the limited extent to which we can distinguish the individual-specific and presentation effects from the additive function in Equation (9), as the parameters are interchangeable if we have the same explanatory factors for both effects. By eliminating the coefficient vector for presentation 9 (i.e., the risk presentation format seen by all subjects), the parameters are uniquely identified. Hence, we can compare the effectiveness of each presentation format for different sociodemographic groups relative to presentation 9.

3.3 Parameter Estimation

The estimation of the parameters is based on the likelihood contribution of each individual, using the specifications of our model described in the previous section. The likelihood contribution of subject i is defined as the product of the conditional choice probabilities over the four risk levels, and his set of risk presentations $f \in F_i$ depending on the group, as well as the probability of the heterogeneous parameters:

$$L_i\left(\{\eta_i\}_{i=1}^{1199}, \{\sigma_f\}_{f=1}^{9}, \rho_1, \rho_2, \rho_3, m, s\right) = \left[\prod_{f \in F_i} \prod_{r=1}^{4} \widetilde{\Pr}^{GHK}\left(C_{i,f,r} | \eta_i\right)\right] f(\eta_i),$$

where $\widetilde{\Pr}^{GHK}\left(C_{i,f,r} | \eta_i\right)$ denote the Geweke-Hajivassiliou-Keane (Geweke, 1989; Hajivassiliou and McFadden, 1998; and Keane, 1994) estimate of the conditional choice probability at risk i and presentation f for subject i, and $f(\cdot)$ denote the joint normal probability density function with mean and standard deviation as defined in Equation

(8). We provide detailed steps for deriving the conditional probability of each observed choice, given a set of individual-specific parameters, in Appendix C.1.

The log-likelihood of all observed choices is the sum of the logarithms of $L_i(\cdot)$ over all respondents in the survey:

$$l\left(\{\eta_i\}_{i=1}^{1199}, \{\sigma_f\}_{f\in F_i}, \rho_1, \rho_2, \rho_3, m, s\right) = \sum_{i=1}^{1199} \log\left(L_i\left(\{\eta_i\}_{i=1}^{1199}, \{\sigma_f\}_{f\in F_i}, \rho_1, \rho_2, \rho_3, m, s\right)\right),$$

which can be maximized by standard methods to obtained the maximum likelihood estimates for the parameters. We utilize the Broyden-Fletcher-Goldfarb-Shanno (BFGS) (Broyden, 1970; Fletcher, 1970; Goldfarb, 1970; and Shanno, 1970) algorithm with the following gradient function to maximize the log-likelihood function:[8]

$$\begin{aligned}\frac{\partial \log L_i}{\partial \theta} &= \frac{\frac{\partial L_i}{\partial \theta}}{L_i}\\ &= \frac{\sum\limits_{f\in F_i}\sum\limits_{r=1}^{4}\left(\frac{1}{S}\sum\limits_{s=1}^{S}\left[\Phi\left(a\right)-1\right]\cdot\phi\left(b\right)\cdot\frac{\partial b}{\partial \theta}+\left[\Phi\left(b\right)-1\right]\cdot\phi\left(a\right)\cdot\frac{\partial a}{\partial \theta}\right)+f'(\eta_i)}{L_i},\end{aligned}$$

where $\theta \in \{\{\eta_i\}_{i=1}^{1199}, \{\sigma_f\}_{f\in F_i}, \rho_1, \rho_2, \rho_3, m, s\}$, $a = \frac{CE(\cdot)-CE(*)}{\omega_{11}}$, and $b = \frac{CE(\diamond)-CE(\cdot)-\omega_{21}z_1}{\omega_{22}}$ as defined in Equation (17), depending on the individual choice.

In summary, we have developed a structural model that allows individual-specific (i.e., $\{\eta_i\}_{i=1}^{1199}$) and population (i.e., $\{\{\sigma_f\}_{f\in F_i}, \rho_1, \rho_2, \rho_3, m, s\}$) parameters to be estimated using the maximum likelihood method. In the following section, we present the estimated parameter values and investigate their relationships with sociodemographic characteristics.

4 Results

We present our results in three parts. Firstly, in Section 4.1 we describe the estimated individual-specific parameters from the structural model outlined in Section 3. Secondly, we present the error propensity under each risk presentation format at a population level in Section 4.2. Lastly, in Section 4.2 we also investigate which presentations are best understood by different sociodemographic groups.

[8] For the sake of clarity, we omit the parameters in the notation.

4.1 Estimated Individual-Specific Parameters

In this section, we present the estimated individual-specific parameters for risk preferences in gains and losses, loss aversion, and error propensity. We begin by describing the median estimates of the parameters across the four groups in the experiment, which saw different presentations of investment risk. Recall that group A saw presentations 1 and 2 (investment risk described in terms of probability ranges) and presentation 9 (graphical range); group B saw presentations 3 and 4 (probability tails) and presentation 9; group C saw presentations 5 and 6 (frequency tails relative to zero) and presentation 9 and group D saw presentations 7 and 8 (frequency tails relative to the safe return) and presentation 9. We then present the estimated population distributions of the parameters and provide a comparison with theoretical normal distributions. Lastly, we investigate the significant sociodemographic characteristics influencing our parameters.

Table 7: Median of Estimated Parameters by Group

Group	g_i	l_i	λ_i	σ_i
A	0.4073	0.8654	3.0257	0.0025
B	0.3947	0.8346	3.0177	0.0037
C	0.2948	0.8341	3.0173	0.0053
D	0.3375	0.8479	3.0171	0.0051
Total	0.3553	0.8436	3.0195	0.0048

Table 7 presents the median of the estimated individual-specific parameters $\eta_i \in \{g_i, l_i, \lambda_i, \sigma_i\}$, where g_i is the curvature parameter for gains, l_i is the curvature parameter for losses, λ_i is the loss aversion parameter, and σ_i is the variability of the propensity to make errors due to individual-specific characteristics. The medians for each parameter are similar across the four groups (A, B, C, and D), especially for the loss aversion parameter. The population median estimate for g is 0.36, which represents a concave utility function. This implies that individuals are risk averse in gains. Alternatively, the population median estimate for l is 0.84, which represents a convex utility function (risk loving) in losses. Recall that Figure 1 displays the utility function for gains and losses based on the population medians.

Using the non-parametric Wilcoxon signed-rank test (Wilcoxon, 1945) we reject the null hypothesis that the risk preference parameters are the same in gains and losses even at a level of significance of 1%. Furthermore, we find that all individual estimates for the loss aversion parameter are above 1. This implies that all subjects are loss averse. These results support the utility specifications of our model under Prospect Theory.

We employ the Arrow-Pratt coefficient of absolute risk aversion (Arrow, 1971; and Pratt, 1964) to compare the curvature parameters across the four groups (A, B, C and D). This is given by $A(\cdot) = -\frac{u''(\cdot)}{u'(\cdot)}$, where $u(\cdot)$ is the utility function defined in Equation (2). For gains, a lower curvature value indicates a higher absolute risk aversion. From the first column of Table 7, subjects in group C (who saw investment risk presented as frequency tails) have a noticeably higher absolute risk aversion than subjects in groups A and B (who saw investment risk presented as probabilities). Subjects in group D (who saw investment risk presented as frequencies relative to safe returns) are the most inline with population median level. Similarly, a lower curvature value in losses indicates a higher preference for taking risk. Again, as shown in the second column of Table 7, subjects in group C have the highest degree of risk loving attitude, although the difference is less prominent. The seemingly different risk preferences for subjects in group C compared with the other groups may play a role in their decision making and propensity to make errors.

The median estimates for loss aversion are depicted in the third column of Table 7. The values are almost identical across the four groups (A, B, C, and D), with a population median of 3.02. Note that the loss aversion parameter in our study is different to previous estimates, due to a lack of data on subjects' initial wealth (see Section 3.1. for details). Nonetheless, all estimated values are greater than 1, indicating that all subjects exhibit loss aversion. The small difference between individuals may be due to the hypothetical nature of the survey, where subjects' choices were not incentivized. This small difference differs to the findings in Gaudecker et al. (2011), which reports a significant difference in loss aversion across hypothetical and incentivized groups as a result of subjects incorporating the monetary incentive into the choice experiment.

The last column of Table 7 depicts the variability of error propensity due to individual-specific characteristics (the other component being the presentation effect). Subjects in groups C and D have a median estimate of above 0.5 per cent, which indicates that they are more likely to make errors in calculating the certainty equivalent of the investment portfolios than subjects in groups A and B. As there are no significant differences in the characteristics of subjects between groups, the poorer performance of group C and D may be a result of the presentation formats assigned to them in the experiment. As outlined in Section 2, groups A and B saw presentations that describe investment risk using probabilities, rather than frequencies. These presentations may mitigate the propensity to make errors due to individual-specific characteristics.

Given the dispersion observed in our estimated parameters, an important question to ask is whether sociodemographic characteristics contribute to this heterogeneity. The online survey collected a range of data on subjects' personal characteristics including gender, age, amount of superannuation savings, post-school qualification, marital status, financial literacy, and numeracy skills. These particular covariates were chosen as they are found to influence decision making in retirement planning. In particular, given the increasing concern about levels of financial literacy among working age individuals, we are interested in whether a higher level of financial literacy and numeracy skills will improve decision making in retirement planning. We used questions drawn from Lusardi and Mitchell (2007), which assess financial literacy in two parts: a basic component that tests concepts such inflation, compounding and time value of money, and a sophisticated component that includes concepts relevant to the investment decisions in retirement savings (such as asset classes and diversification). We assessed numeracy skills using questions drawn from Gerardi et al. (2010), which are closely linked to cognitive ability (Banks, 2010). Individuals' competence in these areas are measured by the percentage of correct answers in the respective category. By including all three categories, we can identify which skill sets are important for investment decisions in retirement planning. We summarize the coefficients of the covariates and their significance in Table 8.

As described above, the curvature parameter for gains is inversely related to risk aversion. From the first column of Table 8, our maximum likelihood estimates show a positive relationship between the amount of retirement savings and risk aversion. This finding is consistent with existing literature (see, for example, Paravisini, Rappoport, and Ravina, 2011). The positive relationship with employment contrasts the findings in Dulebohn and Murray (2007). A possible explanation is that individuals who are employed are more likely to have a higher level of retirement savings, which would lead to higher risk aversion. The associations with gender, education, and marital status are not significant. Interestingly, knowledge on sophisticated financial concepts and numeracy skills have opposite effects on risk aversion. Prior studies such as Benjamin, Brown, and Shapiro (2006) and Gaudecker et al. (2011) observed a negative association between risk aversion and cognitive ability. However, our findings suggest that individuals who are less knowledgeable in sophisticated financial concepts may take on too much risk. This reduces their estimated degrees of risk aversion.

The results for risk preference in losses are similar. A higher value of l represents a lower preference for taking risk. Again, we observed a significant negative relationship

Table 8: Estimated Parameters and Sociodemographic Characteristics

Covariate	g	l	λ	σ_i
Constant	0.3336***	0.7976***	3.0140***	-
Female	0.0166	-0.0016	0.0035	-0.0004**
Age 35-54	0.0077	0.0000	0.0032	-0.0003
Age 55+	0.0136	0.0054	0.0136***	-0.0002
Retirement savings $20k-79k	-0.0449***	0.0075*	-0.0088**	-0.0001
Retirement savings $80k-499k	-0.0449***	0.0153***	-0.0060	0.0000
Retirement savings $500k+	-0.0876***	0.0236**	-0.0068	0.0002
Post-school qualification	0.0111	-0.0047	0.0003	0.0002
Living with long term partner	0.0155	-0.0023	0.0001	0.0001
Employment	-0.0254**	-0.0017	0.0000	0.0003
Fin. literacy (Basic)	-0.0331	0.0354***	-0.0072	-0.0011**
Fin. literacy (Sophisticated)	-0.1024***	0.0206***	-0.0112**	0.0004
Numeracy	0.0326***	0.0008	0.0039	-0.0003**

Significance code: *** 0.01 ** 0.05 * 0.10

Notes: We substitute individual-specific parameters in our model with sociodemographic covariates. The coefficient vector β is estimated using maximum likelihood method, with 1,199 observations. The regression for σ_i do not include a constant, which allows the individual-specific and presentation effects to be uniquely identifiable. The sociodemographic characteristics that are left out as a result of setting dummy variables for categorical data are: male, age 18-34, retirement savings below $20,000, primary and secondary education, do not live with long term partner, and unemployed. Variables measuring financial literacy and numeracy are calculated as the percentage of correct answers.

between retirement savings and risk taking attitude. We further find that subjects who are less knowledgeable about basic and sophisticated financial literacy concepts have a higher degree of risk loving attitude. This could be a result of not understanding the underlying risks of the investment portfolios.

The third column of Table 8 shows the coefficients for the loss aversion parameters. We find that as individuals approach the last decade of their working life, they become more loss averse. This is consistent with Gächter, Johnson, and Herrmann (2010) and Gerrans, Clark-Murphy, and Speelman (2010), which observed a positive relationship between age and loss aversion. However, we observe a negative relationship for loss aversion at low levels of retirement savings. There are three plausible explanations. Firstly, subjects may not incorporate their retirement savings into their wealth, especially when the amount is small. Secondly, Australia's means-tested public age pension provides an offset to insufficient retirement savings, which limits the actual losses a superannuation member may incurred. Given that our survey explicitly framed the discrete choice experiment in the context of retirement planning, subjects may have taken this offset into account when making their choices. Hence, this may indicate why we do not observe the same positive relationship between wealth and loss aversion as suggested in the literature. Lastly, loss aversion also declines with the level of sophisticated financial literacy. This is similar to Gächter et al. (2010), which finds that loss aversion decreases with education level. Assuming that financial literacy and education levels are proxies for cognitive and memory abilities, Johnson and Häubl (2007) provides a possible explanation that loss aversion is negatively related to the ability to retrieve features of the risky choice from memory. Hence, individuals who have poorer memory skills, such as the elderly or the less financially educated, may have a higher degree of loss aversion.

As expected, results for the variability of individual-specific error propensity (shown in column four of Table 8) show a significant negative relationship between financial and numeracy skills and the propensity to make errors in investment decisions. This is in line with Lusardi and Mitchell (2010), which finds that individuals with higher levels of financial literacy are more likely to succeed in their retirement planning. This highlights the importance of financial education. We also find that women have a lower propensity to make errors than men. This suggests that although women are less confident in making financial decisions, they do not necessarily make poorer decisions than men, possibly because men may be over confident in their abilities and therefore make more mistakes.

In summary, our parameter estimates showed the suitability of using Prospect Theory utility specifications in analyzing observed choices, due to the observed difference in risk preference for gains and losses, and loss aversion. We also found significant differences in risk preferences and error propensity across sociodemographic groups. The important characteristics that influence utility parameters are financial literacy and the amount of retirement savings, with the former also significantly reducing the propensity to make errors.

4.2 Presentation and Demographical Effects

In the model described in Section 3, we assumed that the propensity to make errors due to the presentation effect (i.e., the format for the presentation of investment risk) is the same for all subjects under each presentation format. The difference in error propensities across subjects is solely a result of individual-specific characteristics, as described in the previous section. Hence, we obtain nine estimates in total, one for each presentation format. Figure 2 presents our results.

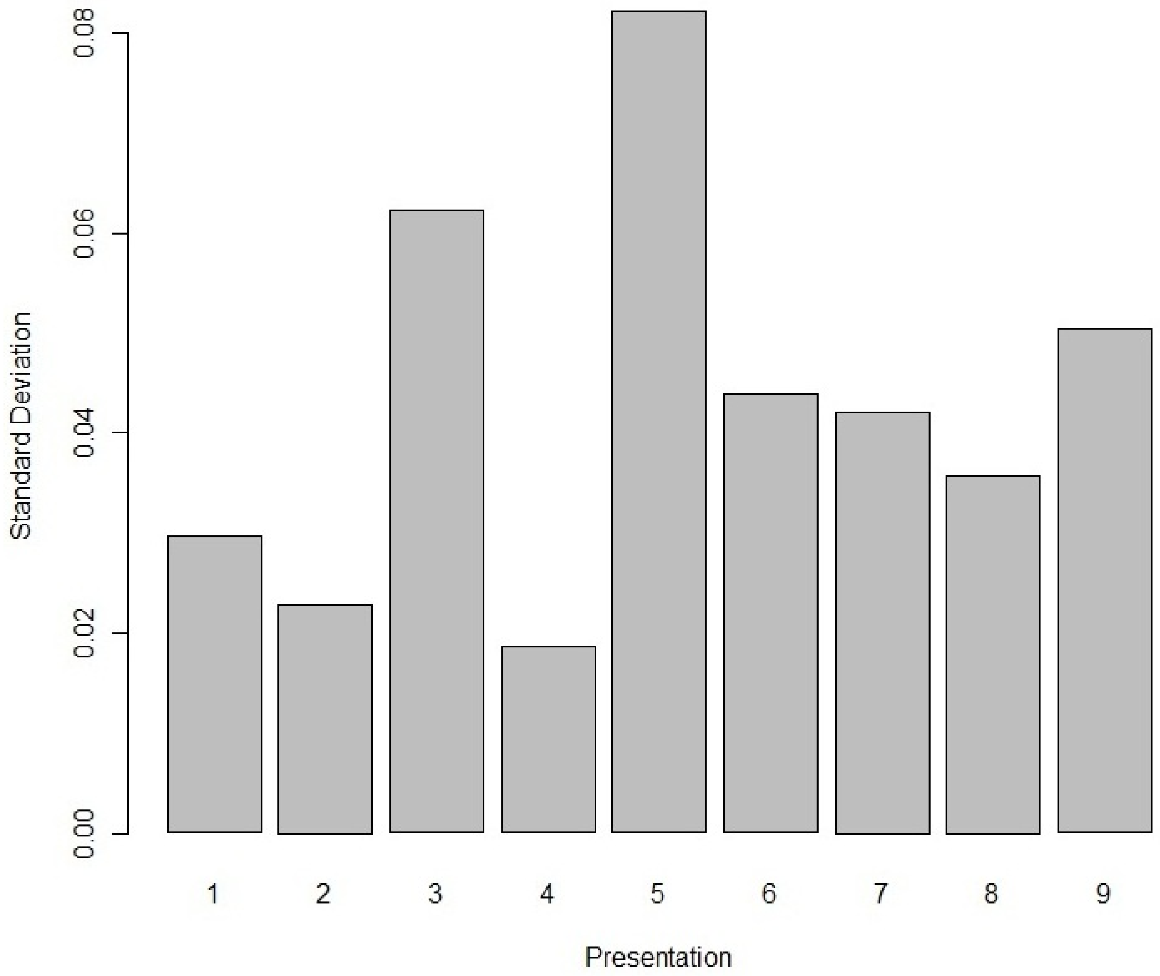

Figure 2: Standard Deviations of the Error Term by Risk Presentation Format
Notes: These values measure the effect of each presentation format on individual's propensity to make error when calculating the certainty equivalent of the investment portfolios. It is separated from individual-specific characteristics according to Equation (9).

The standard deviations of the error term due to the presentation effect are substantially larger than the individual-specific component. Their values range from 0.0186 to 0.0438. Presentations that have the highest error propensity are presentation 3, 5, and 9. Presentation 3 describes only the upside of investment risk as a 1 in 20 chance of achieving a return above a threshold. Over 80 per cent of subjects selected a risky portfolio (either R or M) as their most preferred investment strategy. However, the error estimate suggests that presentation 3 may induce over optimism and therefore lead individuals to overstate the gains, or underestimate the losses in a risky investment portfolio, and therefore increase the chance of making poor decisions. Similarly, presentation 5 describes the upside of investment risk as the frequency of positive returns in a 20 year period. Compared with presentation 3, the higher standard deviation in presentation 5 provides evidence that using frequencies rather than probabilities to describe investment risk makes subjects more susceptible to the presentation effect, i.e., the over optimistic perception of the risky portfolios. Presentation 9 is the only presentation that describes the investment risk in a graphical format, and is the presentation seen by all subjects. The high standard deviation of the error term associate with this risk presentation suggests that showing the 90 percentile range of yearly returns may not be as effective as text-based presentation formats, even though it provides the same information as presentation 1 and 2. A possible explanation is that presentation 9 shows only the range and not the distribution of annual returns, which may lead subjects to assume a uniform distribution (or other probability distributions) when making choices, which may increase the propensity to make errors. Note that the presentations in our experiment are based on yearly returns, rather than the aggregate returns over a number of years. Therefore, our findings are different to Benartzi and Thaler (1999), which shows that graphical presentation of return distributions can address individuals' inability to statistically aggregate investment returns (i.e., narrow framing).

In general, with the exception of presentation 3, presentation formats that describe investment risk using probabilities (i.e., presentation 1, 2, and 4) have lower standard deviations in the error term than presentations that use frequencies (i.e., presentation 5 to 8). These results are consistent with the analysis in section 2, which examines violations of Expected Utility Theory and Prospect Theory utility specifications under each presentation. Bateman et al. (2011) shows that presentation 5 and 6 yield the highest rate of violating Expected Utility restrictions. This is closely followed by presentation 7 and 8. Our analysis show similar results under Prospect Theory specifications. Furthermore, as described in the previous section, subjects who saw presentation 5 to 8 also have the highest individual error propensity. This suggests that presentations using probabilities to describe investment risk may actually reduce error propensity due to individual-specific characteristics. Hence, our findings support the notion that presentations that describe investment risk using probabilities are more effective than presentations using frequencies.

Lastly, it is interesting to note that in groups B, C, and D, subjects have a lower error propensity in presentations that portray the downside of investment risk (i.e., presentations 4, 6, and 8). These lower error propensities may be a result of subjects' aversion to making losses when presented with the downside of investment risk. Similar results were found in Gaudecker et al. (2011). A plausible explanation for this is that the fear of incurring a loss increases subjects' cognitive effort when they make risky choices. Given the observed loss aversion in the population, our findings further show that presentations showing the downside of investment risk outperform those that emphasize the upside.

In summary, we assessed the quality of nine alternative and feasible risk presentation formats by the extent to which they minimize error propensity. Using this measure, presentation 4 (which presents investment risk as the probability of returns below a threshold is most effective at a population level). By comparison, presentations that show the probability of returns above a threshold, or describe investment risk using frequencies, or as graphical ranges are less effective. This has strong implications for policy makers or regulators who are considering prescribing investment risk presentations for the mass market.

So far, we have examined the extent to which each presentation format minimizes the variability of error propensity at a population level. As reviewed in Section 1, retirement planning behaviors can vary significantly across different sociodemographic groups. Therefore, we now extend our analysis by identifying which risk presentations are best understood by different sociodemographic groups. Specifically, we are interested in whether individuals with a higher level of financial literacy and numeracy skills will benefit from presentations that provide more complex investment information.

Hence, we substitute the variability of error propensity due to the presentation effect (i.e., σ_f) with individual sociodemographic variables, as outlined in Equation (11). We exclude the coefficients for presentation 9 to enable the coefficients in other presentations to be uniquely identifiable, so the results are relative to presentation 9. This means that if a covariate has a negative coefficient in presentation f, then the corresponding sociodemographic group would have a lower error propensity in presentation f than in presentation 9. The results are summarized in Table 9.

Table 9 reveals a relationship between levels of financial literacy and numeracy skills with the presentation of investment risk. Individuals who are more knowledgeable in basic financial concepts such as time value of money and inflation do not benefit from the information provided in text-based presentations (i.e., presentations 1 to 8). The positive coefficient in all text-based presentations indicates that the graphical presentation is more effective in minimizing the variability in error propensity. This is because individuals with only basic financial literacy may find the information provided in pre-

Table 9: Presentation Error Propensity and Sociodemographic Characteristics

Covariate	1	2	3	4	5	6	7	8
Female	0.439***	0.353***	-0.058	0.216	-1.036***	-0.198	-0.098	-0.408***
Age 35-54	-0.287*	0.256	-0.117	-0.686***	0.964***	0.195	-0.126	0.145
Age 54+	0.207	0.253	0.437	-0.929***	0.567	0.177	-0.230	0.084
Retirement Savings $20k-79k	-0.112	-0.293	-0.004	0.510***	0.971***	0.709***	0.953***	0.611**
Retirement Savings $79k-499k	0.419*	-0.170	0.193	0.335*	0.735	0.209	0.092	0.309
Retirement Savings $500k+	1.037	1.185	-0.317	0.871	0.260	0.097	0.000	0.294
Non-school qualification	0.541***	0.105	-0.252	0.716***	0.368*	-0.201	-0.054	-0.007
Living with long term partner	0.123	-0.051	-0.005	0.512***	-0.606***	-0.303*	-0.098	-0.449***
Employment	0.687***	0.544***	0.517***	0.417***	-0.092	-0.372***	-0.115	0.479***
Financial literacy (Basic)	-0.875***	-0.255***	0.858***	-0.068	-0.313	-0.400***	-0.235*	0.314***
Financial literacy (Sophisticated)	-0.036	0.119	-0.193	0.069	0.993***	0.392**	0.998***	0.193
Numeracy	-0.322***	-0.346***	-0.266***	-0.389***	-0.321***	-0.319	-0.362***	-0.389***

Significance code: *** 0.01 ** 0.05 * 0.10

Notes: We substitute σ_f in our model with sociodemographic covariates using Equation (11). Coefficients are obtained from maximum likelihood method, with observations equal to the number of subjects within each group (for example, 300 in group A). Results are relative to presentation 9, i.e., a significant positive coefficient at presentation f means the sociodemographic group would make low error propensity due to the presentation effect in f than presentation 9. The sociodemographic characteristics that are left out as a result of setting dummy variables for categorical data are: male, age 18-34, retirement savings below $20,000, primary and secondary education, do not live with long term partner, and unemployed. Variables measuring financial literacy and numeracy are calculated as the percentage of correct answers.

sentations 1 to 8 more difficult to understand than the simple illustration of investment risk in presentation 9. On the contrary, individuals who are knowledgable in both basic and sophisticated financial concepts such as diversification and the difference between the risk characteristics of shares and bonds are able to use the additional information provided in text-based presentations to reduce error propensity in investment choices. In presentations 4 and 6, in which the downside of investment risk is described, the negative coefficient for sophisticated financial literacy is larger than the positive coefficient in basic financial literacy. This offsets the relative ineffectiveness of text-based presentations compared to presentation 9 under basic financial literacy, for individuals who are also knowledgeable on sophisticated financial concepts.

Results for numeracy skills, and non-school qualification reveal similar findings. With the exception of presentations 1 and 5, individuals who have higher levels of numeracy skills have lower variability in error propensity in text-based presentations than in presentation 9. This is because they are able to interpret the information on investment risk that is being presented using either frequencies or probabilities. The positive relationship between the effectiveness of text-based presentations and cognitive ability is also evident in the non-school qualification covariates. The overall negative coefficients for non-school qualification across text-based presentations show that individuals who completed education above the secondary level better understand the additional information given in text-based presentations. Hence, our results show that individuals with a higher level of cognitive ability, have a lower propensity to make non-optimal investment choices in text-based presentations, than in presentation 9.

In terms of other sociodemographic characteristics, women, who have higher risk of accumulating insufficient retirement savings due to their higher life expectancy and lower income compared to men, have lower error propensity in the graphical presentation. In other words, text-based presentations are only effective in reducing variability in error propensity for men. This suggests a bias towards men in the current recommended format for describing investment risk in Australia (i.e., based on presentation 6).

Interestingly, individuals who are employed have lower variability in error propensity in the graphical presentation than in text-based presentations. This is unexpected, given that people who are employed generally have a higher level cognitive ability than those who are unemployed, and should benefit from text-based information. A plausible explanation is that in our sample over three quarters of subjects are employed and implies that the level of financial literacy and numeracy skills may vary significantly across subjects who are employed. Hence, employment status may not be a significant characteristic for determining the appropriate risk presentation for different individuals. Lastly, the effectiveness of text-based presentations in reducing the variability in error propensity relative to the graphical presentation is very specific for sociodemographic groups characterized by age and amount of retirement savings. Coefficient estimates for these characteristics show a peak for the effectiveness of text-based presentations, at age 35-54 and retirement savings amount in the range of $80,000 to $499,999. However, this effectiveness generally decreases as individuals approach the last decade of their working years or accumulate a very high amount of retirement savings. The similarity between these two covariates is unsurprising, given that among the 29 subjects that have retirement savings greater than half a million dollars, 22 are aged above 55. Again, these findings show the importance of defining different standards for presenting investment risk to target specific sociodemographic groups.

In summary, we extended our analysis by showing that the effectiveness of the risk presentation depends on sociodemographic factors. We show that text-based and graphical presentations are better understood by different segments of the population. We find that proxies for cognitive ability (i.e., financial literacy and numeracy skills) are important determinants in selecting the appropriate risk presentation for different individuals. Individuals with a low cognitive ability are relatively better in the graphical presentation. In general, text-based presentations are more effective than graphical presentations for individuals who are males, aged 35-54, knowledgable in both sophisticated and basic financial concepts, have good numeracy skills, possess non-school qualification, and have a moderate amount of retirement savings. Alternatively, the graphical presentation is more appropriate for sociodemographic groups which are more at risk of accumulating insufficient retirement savings, such as women and those with low levels of retirement savings. These findings suggest that regulators should consider setting different standards for presenting investment risk to different sociodemographic groups. Furthermore, pension and superannuation fund managers should have accurate and up to date information about the sociodemographic characteristics of their members.

5 Conclusion

This paper analyzes common presentations of investment risk information found in retirement investment choice menus funds in developed countries such as Australia and

US. Our analysis is motivated by international efforts in developing a simplified and effective standard for disclosing investment risk to ordinary people. Regulators around the world, including the Department of Labor in the US (Hung et al., 2010), the Financial Services Authority in the UK (Andrews, 2009), and the Australian Prudential Regulation Authority in Australia (APRA, 2010), are investigating suitable descriptions of investment risk to assist ordinary people in their retirement planning decisions. Using Prospect Theory utility specifications we contribute to this investigation by identifying the risk presentation format that minimizes the variability of individual's propensity to make non-optimal investment choices in their retirement planning, both at a population level and by sociodemographic characteristics.

We describe the design and implementation of a discrete choice experiment designed to elicit investment choices under nine alternative investment risk presentations and four levels of risk. We analyzed the data using Prospect Theory utility specifications, and estimated individual-specific parameters for risk preferences in gains and losses, loss aversion, and error propensity variability using maximum likelihood method. Our estimates of risk preference parameters are consistent with Prospect Theory with a clear S-shaped utility function at the median level. An innovation of our model is that we distinguished the variability in the propensity of individuals to make errors in investment decisions into an individual-specific component and a presentation effect component. This allowed us to identify the extent to which each risk presentation format minimized an individual's error propensity and therefore enabled them to make rational investment choices.

Our main finding is that at a population level, presentations that describe investment risk using the probability of returns below or above thresholds, have lower variability in error propensity than presentations based on frequency of returns below or above thresholds. We also showed that the variability of error propensities are lower in presentations that describe the downside of investment risk, possibly as a result of increased cognitive effort due to loss aversion. The risk presentation that minimizes this variability is presentation 4, which shows investment risk as a 1 in 20 chance of a return above a threshold. Importantly, our findings show that the risk presentation format recommended by Australia's financial regulator (i.e., presentation 6) may not be as effective as some other presentation formats.

At an individual level, we find that risk preferences and error propensity vary significantly across sociodemographic groups and that financial literacy is key: those sociodemographic groups who are more at risk of accumulating insufficient retirement savings better understand graphical presentation of investment risk, whilst the more financially sophisticated would benefit from the additional information provided in presentation 4 (investment risk presented as a 1 in 20 chance of a return below a threshold).

Our contributions to the academic literature, to policy makers and the financial services interest are threefold. First, we have demonstrated an approach to evaluate the quality of risk presentation formats from observed choices in a broad population using a structural model with Prospect Theory specifications. In addition, this model is non-restrictive in the utility specifications and can be generalized to other utility functions by incorporating additional parameters. Second, developed the literature by examining the effects of common risk presentation formats on individual's propensity to make errors in retirement investment decisions. This complements Bateman et al. (2011), and establishes a starting point for the development of a standardized framework of presenting investment risk to retirement savers. Finally, we showed that different sociodemographic groups may benefit from different risk presentation formats, in particular graphical presentations may better suit individuals with low basic financial literacy and numeracy skills (i.e., proxies for cognitive ability). Presentation formats that describe investment risk using probabilities are more advantages for individuals with a high level of sophisticated financial knowledge.

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A Survey Details

A.1 Numeracy Questions

1. In a sale, a shop is selling all items at half price. Before the sale, a sofa costs \$300. How much will it cost in the sale? (Answers: \$150; \$300; \$600; Do not know; Refuse to answer.)

2. If the chance of getting a disease is 10 per cent, how many people out of 1,000 would be expected to get the disease? (Answers: 10; 100; 1000; Do not know; Refuse to answer.)

3. A second hand car dealer is selling a car for \$6,000. This is two-thirds of what it cost new. How much did the car cost new? (Answers: \$4,000; \$6,600; \$9,000; Do not know; Refuse to answer.)

4. If 5 independent, unrelated people all have the winning numbers in the lottery and the prize is \$2 million, how much will each of them get? (Answers: \$40,000; \$400,000; \$500,000; Do not know; Refuse to answer.)

5. If there is a 1 in 10 chance of getting a disease, how many people out of 1,000 would be expected to get the disease? (Answers: 10; 100; 1000; Do not know; Refuse to answer.)

A.2 Financial Literacy Questions

Basic (Inflation, Simple and Compound Interest, Time Value of Money)

1. Suppose that in the year 2020, your income has doubled and prices of all goods have doubled too. In 2020, how much will you be able to buy with your income? (More than today, Exactly the same, Less than today, Do not know, Refuse to answer)

2. Suppose you had \$100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?

3. Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the

money in this account?

4. Assume a friend inherits $10,000 today and his sibling inherits $10,000 three years from now. In three years, who is richer because of the inheritance?

5. Suppose you had $100 in a savings account and the interest rate is 20% per year and you never withdraw money or interest payments. After 5 years, how much would you have on this account in total?

Sophisticated (Stocks, Bonds, and Diversification)

6. Is the following statement true or false? Shares are normally riskier than bonds.

7. Considering a long time period (for example 10 or 20 years), which asset normally gives the highest return? (Bonds, Savings accounts, Shares, Do not know, Refuse to answer)

8. Normally, which asset displays the highest fluctuations over time? (Bonds, Savings accounts, Shares, Do not know, Refuse to answer)

9. When an investor spreads his money among different assets, does the risk of losing money? (Increase, Decrease, Stay the same, Do not know, Refuse to answer)

A.3 Discrete Choice Experiment Instructions

The Australian Government is concerned about the complexity of superannuation arrangements and is looking for ways to simplify superannuation investment choices. One possibility is to offer only three investment options for all superannuation accounts. Each investment option has a different average annual rate of return (the average rate at which your investment will grow each year), and a different amount of investment risk (year to year UPSIDE AND DOWNSIDE variation in the return on your investment). The options are:

- Option A: All (100%) of your superannuation account is invested in a guaranteed bank deposit with a fixed rate of interest paid each year.
- Option B: Your superannuation account will be divided half and half (50%-50%) between the bank account and growth assets. You can anticipate that savings in

this option will grow faster than the bank deposit (Option A) but will grow more slowly and be less risky than only choosing growth assets (Option C).

- Option C: All (100%) of your superannuation account is invested in assets like shares and property. On average, you can anticipate that savings in this option will grow at a faster rate than for the bank deposit (Option A) but without a guarantee. There is some risk that your account value will grow faster or slower than average if you choose this option.

We are going to show you 12 sets of these options for investing your superannuation. Each set includes 3 investment options like the ones described above. Each investment option has a average rate of return and investment risk. The average rates of return stay the same in each of the twelve sets; only the risk will change. Remember that more risk of high returns also means more risk of low returns.

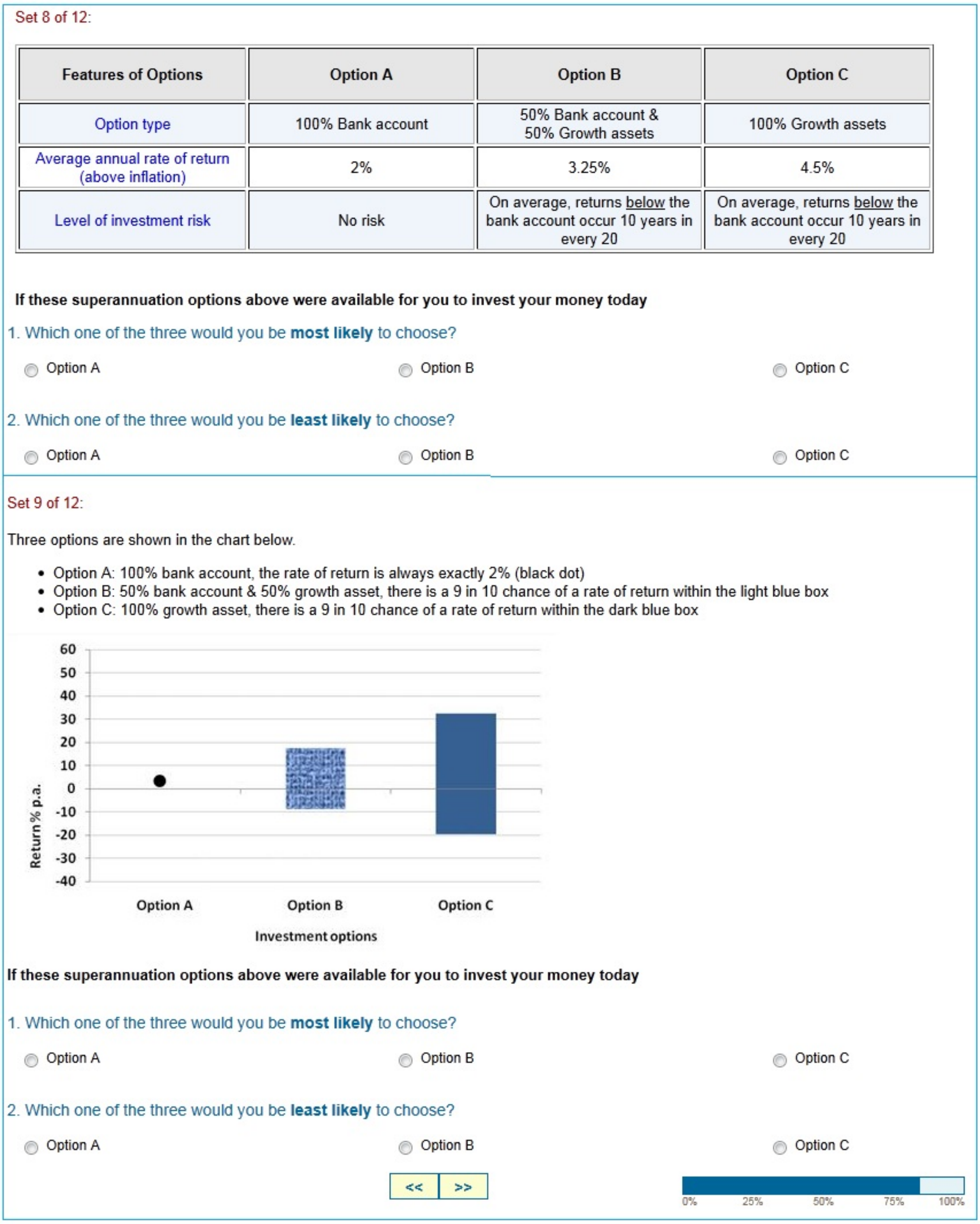
What we want you to do is simple. There are two questions to answer about each set of options:

- If these superannuation options were available for you to invest your money today, which one of the three would you be most likely to choose?

- If these superannuation options were available for you to invest your money today, which one of the three would you be least likely to choose?

Your choices will inform government and industry about better ways to simplify superannuation information and options.

A.4 Illustrative Discrete Choice Experiment



Set 8 of 12:

Features of Options	Option A	Option B	Option C
Option type	100% Bank account	50% Bank account & 50% Growth assets	100% Growth assets
Average annual rate of return (above inflation)	2%	3.25%	4.5%
Level of investment risk	No risk	On average, returns below the bank account occur 10 years in every 20	On average, returns below the bank account occur 10 years in every 20

If these superannuation options above were available for you to invest your money today

1. Which one of the three would you be **most likely** to choose?

Option A Option B Option C

2. Which one of the three would you be **least likely** to choose?

Option A Option B Option C

Set 9 of 12:

Three options are shown in the chart below.

- Option A: 100% bank account, the rate of return is always exactly 2% (black dot)
- Option B: 50% bank account & 50% growth asset, there is a 9 in 10 chance of a rate of return within the light blue box
- Option C: 100% growth asset, there is a 9 in 10 chance of a rate of return within the dark blue box

If these superannuation options above were available for you to invest your money today

1. Which one of the three would you be **most likely** to choose?

Option A Option B Option C

2. Which one of the three would you be **least likely** to choose?

Option A Option B Option C

<< >>

0% 25% 50% 75% 100%

Figure 3: Text-Based Presentation Format and Presentation 9

B Proof of choice inconsistencies under utility framework

B.1 CRRA Utility Framework

The return for portfolio M (r_M) is the average of the risky return r and risk free return r_f. Assuming a concave utility function, this implies the following:

$$\begin{aligned}
r_M &= r + r_f \\
U(r_M) &= U\left(\frac{r + r_f}{2}\right) \\
&> \frac{U(r) + U(r_f)}{2} \\
\therefore \mathbb{E}[U(r_m)] &> \frac{\mathbb{E}[U(r)] + U(r_f)}{2}
\end{aligned}$$

Hence, either $\mathbb{E}[U(r_m)] > \mathbb{E}[U(r)]$, or $\mathbb{E}[U(r_m)] > U(r_f)$, or both. Therefore, under the standard expected utility theory assumption of a concave utility function, individuals should never rank portfolio M as the worst portfolio.

B.2 Prospect Theory Framework

The expected utility values for portfolio M and R are defined as:

$$\begin{aligned}
U(M) &= 0.5^g U^+ - \lambda 0.5^{g+c} U^-; \\
U(R) &= U^+ - \lambda U^-,
\end{aligned}$$

with $g + c = l$. g And l are the curvature parameters of the utility function for gains and losses respectively. λ Is the loss aversion parameter.

Consider the two cases where portfolio M is ranked last:

RSM :

$$\begin{aligned}
U(R) &> 0 & U(M) &< 0 \\
U^+ - \lambda U^- &> 0 & 0.5^g U^+ - \lambda 0.5^{g+c} U^- &< 0 \\
\frac{U^+}{U^- \lambda} &> 1 & \frac{U^+}{U^- \lambda} &< 0.5^c.
\end{aligned}$$

$$\therefore 1 < \frac{U^+}{U^-\lambda} < 0.5^c. \tag{12}$$

SRM:

$$\begin{aligned}
U(R) &< 0 & U(M) &< U(R) \\
\frac{U^+}{U^-} &< \lambda & 0.5^g U^+ - \lambda 0.5^{g+c} U^- &< U^+ - \lambda U^- \\
\frac{U^+}{U^-\lambda} &< 1 & \frac{1-0.5^{g+c}}{1-0.5^g} &< \frac{U^+}{U^-\lambda},
\end{aligned}$$

$$\begin{aligned}
&\therefore 1 > \frac{1-0.5^{g+c}}{1-0.5^g} \\
&0.5^c > 1.
\end{aligned} \tag{13}$$

Both (12) and (13) hold when c is negative, i.e., $g > l$.

For the alternate cases where portfolio M is ranked first (i.e., MSR and MRS), it can be shown by switching the inequality signs that when portfolio M is ranked first, the value of c is positive. i.e., $g < l$.

Hence, given that each individual has a unique set of utility parameter values, the value of g must either be greater or less than l, but not both. Therefore, if within the same presentation format or across different presentation formats an individual ranks the portfolio M both as his most preferred and least preferred portfolio, his choice behavior is considered inconsistent.

C Choice Probabilities

C.1 Derivation of Probability for Choice RMS

In this appendix we provide detailed steps for determining the conditional probability of choice RMS. This can be generalized into other observed choices using a similar process. Let $\Pr(C_{i,f,r}|\eta_i)$ denote the conditional probability of the observed choice for individual i in presentation f and risk r, given a set of parameters η_i, then:[9]

$$
\begin{aligned}
&\Pr\left(C_{i,f,r}|\eta_i = RMS\right) \\
&\quad = \Pr\left(\widehat{CE}(R) > \widehat{CE}(M), \widehat{CE}(M) > \widehat{CE}(S)\right) \\
&\quad = \Pr\left(\epsilon_{i,f}^{R} - \epsilon_{i,f}^{M} > CE(M) - CE(R), \epsilon_{i,f}^{M} - \epsilon_{i,f}^{S} > CE(S) - CE(R)\right) \\
&\quad = \Pr\left(\epsilon_{i,f,1}^{RMS} > CE(M) - CE(R), \epsilon_{i,f,2}^{RMS} > CE(S) - CE(R)\right) \\
&\quad = \Pr\left(\epsilon_{i,f,1}^{RMS} > CE(M) - CE(R)\right) \\
&\qquad\qquad \times \Pr\left(\epsilon_{i,f,2}^{RMS} > CE(S) - CE(R) | \epsilon_{i,f,1}^{RMS} > CE(M) - CE(R)\right)
\end{aligned} \tag{14}
$$

From Equation (14), the probability of an individual making the choice RMS can be express in terms of the joint normal distribution of the error terms. Specifically:

$$
\begin{bmatrix} \epsilon_{i,f,1}^{RMS} \\ \epsilon_{i,f,2}^{RMS} \end{bmatrix} = \begin{bmatrix} \epsilon_{i,f}^{R} - \epsilon_{i,f}^{M} \\ \epsilon_{i,f}^{M} - \epsilon_{i,f}^{S} \end{bmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \Sigma_{RMS}\right) \tag{15}
$$

where

$$
\begin{aligned}
\Sigma_{RMS} = &\begin{bmatrix} \sigma_{RR}^{(i,f)} + \sigma_{MM}^{(i,f)} - 2\sigma_{RM}^{(i,f)} & \sigma_{RM}^{(i,f)} - \sigma_{RS}^{(i,f)} - \sigma_{MM}^{(i,f)} + \sigma_{MS}^{(i,f)} \\ \sigma_{RM}^{(i,f)} - \sigma_{RS}^{(i,f)} - \sigma_{MM}^{(i,f)} + \sigma_{MS}^{(i,f)} & \sigma_{MM}^{(i,f)} + \sigma_{SS}^{(i,f)} - 2\sigma_{MS}^{(i,f)} \end{bmatrix} \\
= &(\sigma_i^2 + \sigma_f^2) \begin{bmatrix} 1 + m^2 - 2\rho_1 m & \rho_1 m - \rho_2 s - m + \rho_3 sm \\ \rho_1 m - \rho_2 s - m + \rho_3 sm & m^2 + s^2 - 2\rho_3 sm \end{bmatrix}.
\end{aligned}
$$

The analytical solution to the conditional probability is difficult to derive. We utilize the Geweke-Hajivassiliou-Keane (GHK) recursive conditioning method to provide an approximation to this probability.

The idea behind the GHK method is to first simulate multiple independent draws from a truncated distribution, and then approximate the conditional probability of the draws via a Monte Carlo approach. Following Equation (14) and (15), we can express the truncated distribution of the error terms as:

$$
\boldsymbol{\epsilon_{i,f}^{RMS}} = \begin{bmatrix} \epsilon_{i,f,1}^{RMS} \\ \epsilon_{i,f,2}^{RMS} \end{bmatrix} \sim N\left(\boldsymbol{\mu}, \Sigma_{RMS}, \mathbf{L}, \mathbf{U}\right), \tag{16}
$$

where $\boldsymbol{\mu}$ is the zero mean vector, $\mathbf{L}$ is the lower truncation vector $\begin{pmatrix} U_{i,r}(M) - U_{i,r}(R) \\ U_{i,r}(S) - U_{i,r}(M) \end{pmatrix}$,

[9]For formatting reason, we omit the parameters from certainty equivalent $CE(\cdot)$.

and $\mathbf{U}$ is the upper truncation vector $\begin{pmatrix} \infty \\ \infty \end{pmatrix}$.

Let z_1 and z_2 be independent multivariate standard normal random variables, and Ω be the lower-triangular Cholesky decomposition of Σ_{RMS}, with elements:

$$\begin{bmatrix} \omega_{11} & 0 \\ \omega_{21} & \omega_{22} \end{bmatrix}.$$

then we can express (16) as:

$$\boldsymbol{\epsilon_{i,f}^{RMS}} = \boldsymbol{\mu} + \Omega \boldsymbol{z} \sim N\left(\boldsymbol{\mu}, \Sigma_{RMS}\right),$$

such that

$$\begin{pmatrix} \frac{L_1-\mu_1}{\omega_{11}} \\ \frac{L_2-\mu_2-\omega_{21}z_1}{\omega_{22}} \end{pmatrix} < \begin{pmatrix} z_1 \\ z_2 \end{pmatrix} < \begin{pmatrix} \infty \\ \infty \end{pmatrix}.$$

Hence, we can rewrite Equation (14) as:

$$\begin{aligned}
&\Pr\left(C_{i,f,r}|\eta_i = RMS\right) \\
&\quad = \Pr\left(\epsilon_{i,f,1}^{RMS} > CE(M) - CE(R)\right) \\
&\qquad\qquad \times \Pr\left(\epsilon_{i,f,2}^{RMS} > CE(S) - CE(R)|\epsilon_{i,f,1}^{RMS} > CE(M) - CE(R)\right) \\
&\quad = \Pr\left(z_1 > \frac{CE(M) - CE(R)}{\omega_{11}}\right) \\
&\qquad\qquad \times \Pr\left(z_2 > \frac{CE(S) - CE(R) - \omega_{21}z_1}{\omega_{22}}|z_1 > \frac{CE(M) - CE(R)}{\omega_{11}}\right) \\
&\quad = \Pr\left(z_1 > \frac{CE(M) - CE(R)}{\omega_{11}}\right) \cdot \Pr\left(z_2 > \frac{CE(S) - CE(R) - \omega_{21}z_1}{\omega_{22}}\right) \\
&\quad = \left[1 - \Phi\left(\frac{CE(M) - CE(R)}{\omega_{11}}\right)\right] \cdot \left[1 - \Phi\left(\frac{CE(S) - CE(R) - \omega_{21}z_1}{\omega_{22}}\right)\right],
\end{aligned}$$

since z_1 and z_2 are independent.

Because we do not observe z_1, we simulate z_1^s from a truncated standard normal density with lower truncation point $\frac{CE(M)-CE(R)}{\omega_{11}}$ and upper truncation point ∞. This is achieved by first drawing an uniform random variable u from [0,1]. Then transform this variable into another uniform random variable $\widetilde{u}$, which is bounded by the above truncation points using:

$$\widetilde{u} = \Phi\left(\frac{CE(M) - CE(R)}{\omega_{11}}\right) + \left(\Phi(\infty) - \Phi(\frac{CE(M) - CE(R)}{\omega_{11}})\right)\widehat{u}.$$

The random variable z_1^s is obtained using the standard normal quantile function, i.e., $z_1^s = \Phi^{-1}(\widetilde{u})$. This provides one realization for the choice probability. Thus, by a recursive process of length 1000, we approximate the choice probability using Monte Carlo techniques:

$$\begin{aligned}\widetilde{\Pr}^{GHK}&(C_{i,f,r}|\eta_i = RMS)\\ &= \frac{1}{1000}\sum_{s=1}^{1000}\left[1 - \Phi\underbrace{\left(\frac{CE(M) - CE(R)}{\omega_{11}}\right)}_{a}\right]\cdot\left[1 - \Phi\underbrace{\left(\frac{CE(S) - CE(R) - \omega_{21}z_1}{\omega_{22}}\right)}_{b}\right]\end{aligned} \tag{17}$$

We define the probability of the remaining five patterns of portfolio ordering using similar methods, by changing the order of the certainty equivalents in a and b according to (7). The covariance matrix of the error terms and the resulting probability for each portfolio ordering are summarized in Appendix C.2.

C.2 Summary of Choice Probabilities and Covariance Matrices

In this appendix we provide a summary of the conditional choice probabilities and covariance matrices for the six possible pattern of choice orderings in our experiment.

RMS

$$
\begin{aligned}
\widetilde{\Pr}^{GHK} & (C_{i,f,r} = RMS) \\
&= \frac{1}{S}\sum_{s=1}^{S}\left[1-\Phi\left(\frac{CE(M)-CE(R)}{\omega_{11}}\right)\right]\cdot\left[1-\Phi\left(\frac{CE(S)-CE(M)-\omega_{21}z_1^s}{\omega_{22}}\right)\right] \\
\Sigma_{RMS} &= (\sigma_i^2+\sigma_f^2)\begin{bmatrix} 1+m-2\rho_1\sqrt{m} & \rho_1\sqrt{m}-\rho_2\sqrt{s}-m+\rho_3\sqrt{sm} \\ \rho_1\sqrt{m}-\rho_2\sqrt{s}-m+\rho_3\sqrt{sm} & m+s-2\rho_3\sqrt{sm} \end{bmatrix}
\end{aligned}
$$

RSM

$$
\begin{aligned}
\widetilde{\Pr}^{GHK} & (C_{i,f,r} = RSM) \\
&= \frac{1}{S}\sum_{s=1}^{S}\left[1-\Phi\left(\frac{CE(S)-CE(R)}{\omega_{11}}\right)\right]\cdot\left[1-\Phi\left(\frac{CE(M)-CE(S)-\omega_{21}z_1^s}{\omega_{22}}\right)\right] \\
\Sigma_{RSM} &= (\sigma_i^2+\sigma_f^2)\begin{bmatrix} 1+s-2\rho_2\sqrt{s} & \rho_2\sqrt{s}-\rho_1\sqrt{m}-s+\rho_3\sqrt{sm} \\ \rho_2\sqrt{s}-\rho_1\sqrt{m}-s+\rho_3\sqrt{sm} & m+s-2\rho_3\sqrt{sm} \end{bmatrix}
\end{aligned}
$$

MSR

$$
\begin{aligned}
\widetilde{\Pr}^{GHK} & (C_{i,f,r} = MSR) \\
&= \frac{1}{S}\sum_{s=1}^{S}\left[1-\Phi\left(\frac{CE(S)-CE(M)}{\omega_{11}}\right)\right]\cdot\left[1-\Phi\left(\frac{CE(R)-CE(S)-\omega_{21}z_1^s}{\omega_{22}}\right)\right] \\
\Sigma_{MSR} &= (\sigma_i^2+\sigma_f^2)\begin{bmatrix} m+s-2\rho_3\sqrt{sm} & \rho_3\sqrt{sm}-\rho_1\sqrt{m}-s+\rho_2\sqrt{s} \\ \rho_3\sqrt{sm}-\rho_1\sqrt{m}-s+\rho_2\sqrt{s} & s+1-2\rho_2\sqrt{s} \end{bmatrix}
\end{aligned}
$$

MRS

$$\begin{aligned}
&\widetilde{\Pr}^{GHK}(C_{i,f,r} = MRS) \\
&\quad = \frac{1}{S}\sum_{s=1}^{S}\left[1-\Phi\left(\frac{CE(R)-CE(M)}{\omega_{11}}\right)\right]\cdot\left[1-\Phi\left(\frac{CE(S)-CE(R)-\omega_{21}z_1^s}{\omega_{22}}\right)\right] \\
\Sigma_{MRS} &= (\sigma_i^2+\sigma_f^2)\begin{bmatrix} m+1-2\rho_1\sqrt{m} & \rho_1\sqrt{m}-\rho_3\sqrt{sm}-1+\rho_2\sqrt{s} \\ \rho_1\sqrt{m}-\rho_3\sqrt{sm}-1+\rho_2\sqrt{s} & 1+s-2\rho_2\sqrt{s} \end{bmatrix}
\end{aligned}$$

SRM

$$\begin{aligned}
&\widetilde{\Pr}^{GHK}(C_{i,f,r} = SRM) \\
&\quad = \frac{1}{S}\sum_{s=1}^{S}\left[1-\Phi\left(\frac{CE(R)-CE(S)}{\omega_{11}}\right)\right]\cdot\left[1-\Phi\left(\frac{CE(M)-CE(R)-\omega_{21}z_1^s}{\omega_{22}}\right)\right] \\
\Sigma_{SRM} &= (\sigma_i^2+\sigma_f^2)\begin{bmatrix} s+1-2\rho_2\sqrt{s} & \rho_2\sqrt{s}-\rho_3\sqrt{sm}-1+\rho_1\sqrt{m} \\ \rho_2\sqrt{s}-\rho_3\sqrt{sm}-1+\rho_1\sqrt{m} & 1+m-2\rho_1\sqrt{m} \end{bmatrix}
\end{aligned}$$

SMR

$$\begin{aligned}
&\widetilde{\Pr}^{GHK}(C_{i,f,r} = SMR) \\
&\quad = \frac{1}{S}\sum_{s=1}^{S}\left[1-\Phi\left(\frac{CE(M)-CE(S)}{\omega_{11}}\right)\right]\cdot\left[1-\Phi\left(\frac{CE(R)-CE(M)-\omega_{21}z_1^s}{\omega_{22}}\right)\right] \\
\Sigma_{SMR} &= (\sigma_i^2+\sigma_f^2)\begin{bmatrix} s+m-2\rho_3\sqrt{sm} & \rho_3\sqrt{sm}-\rho_2\sqrt{s}-m+\rho_1\sqrt{m} \\ \rho_3\sqrt{sm}-\rho_2\sqrt{s}-m+\rho_1\sqrt{m} & 1+m-2\rho_1\sqrt{m} \end{bmatrix}
\end{aligned}$$