DEFAULT AND 1/N HEURISTICS IN ANNUITY CHOICE*

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Abstract

Choices of retirement income stream products pose the usual challenges associated with credence goods. Moreover, high perceived (and actual) risk, irreversibility of most purchases, high expenditure, little opportunity for social learning and distant consequences make these choices even more intimidating to consumers. Nevertheless, governments worldwide have started to shift more responsibility for these choices to ordinary individuals, leading to decisions often driven by suboptimal heuristics instead of careful evaluation of alternatives.

This paper focuses on choices of life annuities by separating consumers' preferences from their use of default options and the 1/n heuristic in an online allocation task experiment. We use a finite mixture model to show the extent to which specific consumer groups follow simplified choice heuristics, and profile members of the groups. Our results have important implications for public policy and marketing related to annuities, but also more generally for understanding the impact of heuristics in choices of credence goods like financial products and health care.

Keywords: *choice heuristics, credence goods, retirement benefits, annuity demand*

INTRODUCTION

Choosing a retirement income stream is one of the most important financial decisions in a consumer's life. As with most financial decisions, this choice involves high stakes, interplay of several risks, and often irreversibility. It requires strong financial competence and expertise to manage different uncertain time horizons and interactions with regulations (Agnew et al. 2008; Bateman et al. 2014b; Brown et al. 2013b). Further, like any credence good, a high degree of information asymmetry exists between sellers and buyers, making consumers an easier target for unethical behavior by sellers (Brown and Minor 2012).

Despite these challenges and growing evidence that many people frequently make serious financial mistakes (Campbell et al. 2011), many governments, including the U.S., the UK, Australia and Germany, have shifted the responsibility for these decisions to ordinary consumers (Agnew et al. 2013; Mitchell et al. 2011). The potential welfare implications of inappropriate choices of retirement income streams are very serious given the massive scale of this market: For example, the Global Pension Assets Study by Towers Watson (2013) reports retirement assets totaled 108% of GDP (US$16.9T) in the U.S., 112% of GDP (US$2.7T) in the UK, and 101% of GDP (US$1.6 T) in Australia. What's more, these values will rise sharply over the next few decades as populations age.

Thus, not surprisingly, a large literature in finance, economics, marketing and psychology has studied the market for retirement income products. Many studies have focused on lifetime annuities, motivated by the strong theoretical support for the purchase of longevity-insured income streams (Davidoff et al. 2005; Yaari 1965), and a surprisingly low uptake of these products by consumers (Bateman et al. 2013; Bateman and Piggott 2011). Annuities also are typical credence goods (Brown and Minor 2012; Crosby and Stephens 1987), implying that consumers face substantial information deficits when making choices. Further, because of their particular characteristics, people have "poorly defined preferences" in this area (Brown

et al. 2013b). Both factors lead to high uncertainty about the exact consequences of actions in the annuity market and conflict experiences about how to make trade-offs among different products. According to Shafir et al. (1993), people resolve this conflict by seeking and constructing reasons that help justify their choices. Consequently, in addition to explanations based on standard lifecycle models, much new research offers behavioral or psychological explanations (see Benartzi et al. 2011; Brown 2008 for an overview) for choices in this product category.

The relative influence of behavioral factors remains under-researched. How much of consumers' behavior is actually due to simplifying heuristics? Existing work shows that different consumer groups vary in tendencies to use simplification strategies (Agnew et al. 2008; Hedesström et al. 2007); so accounting for consumer heterogeneity is a key to answering this question. As (Johnson 2013, p. 154) states: "even the simple goal of prediction requires the incorporation of context". Being able to determine who relies on which decision strategy and to what extent, is a necessary first step to determine the true demand for annuities, to understand how to design choice environments (Benartzi et al. 2011; Beshears et al. 2009; Swait and Adamowicz 2001), how to frame descriptions of choice options (Beshears et al. 2013; Brown et al. 2013a; Hershfield et al. 2011; Levin et al. 1998), and how to protect vulnerable consumers (see Thaler and Sunstein 2003 for a discussion on libertarian paternalism).

These solutions matter to academics, policy makers and marketing managers alike. Also, answers to these questions matter for other goods (particularly credence goods like health care or other financial products) where consumers lack well-defined preferences and rely on heuristics to make choices.

We used an online choice allocation task to investigate the extent to which, and by whom, heuristics are used to choose retirement income products. We asked a sample of consumers to allocate their wealth between a phased withdrawal product (an investment account with flexi-

ble income withdrawals and no longevity insurance) and an immediate life annuity (a guaranteed income contract until end of life, but with little flexibility) under different default settings and different risks of exhausting wealth before end of life. Consistent with existing research, allocations made by participants in the experiment depended on the default settings with a clear peak at a 50/50 allocation, supporting the notion that they used both the default and the 1/n heuristics (Hedesstrom et al. 2004; Morrin et al. 2012). We also found considerable heterogeneity in the allocations, suggesting that people differ in the extent to which they use these heuristics.

One way to quantify the impact of heuristics in general, and default options more specifically, is to view them as an additional contributor (usually an indicator variable) to the utility of a product (Agnew et al. 2008). In Marketing, the concept of state dependence (closely related to default bias) has been investigated extensively in such a framework (Erdem 1996; Keane 1997). We propose and develop a new method to capture heterogeneity in use of heuristics in our allocation experiment. We follow a similar logic to models of state dependence in simple Markov models (Morrison 1966) and their more complex extensions (Chintagunta 1998); namely we treat the decision to stick with a particular heuristic as a choice strategy that posits an alternative to other (potentially) rational choice strategies. Our model thus recognizes that reliance on heuristics ultimately is driven by a desire to simplify decision tasks (Shah and Oppenheimer 2008). More specifically, we identify and explain observed multimodality in the choices with a finite mixture model that combines a flexible beta-binomial distribution (unconstrained choice strategy) with four degenerate probability density functions that account for respondents' reliance on the default and the 1/n heuristic, as well as their tendency to allocate all their wealth entirely to either extreme in the allocation continuum. In contrast to mixture models based on continuous mixture densities (Allenby and Rossi 1998) this formulation allows us to explicitly account for these four obvious spikes in the choice data that are

not accompanied by any noticeable additional mass in their neighbourhoods. We estimate the relative importance of each of the five different choice strategies (i.e., their weight in the combined mixture of the probability density functions) and the parameters of the beta-binomial as functions of the products' attributes and respondents' characteristics. The estimates of the latter parameters indicate that other decision strategies, including conventionally rational behavior, can be attributed to the flexible beta-binomial distribution[1], while the estimated coefficients in the weights of the mixture allow us to identify who tends to rely on which choice strategy.

We found that more than 30% of choices were based on the default or the 1/n heuristics. We confirm prior results on who chooses the default heuristic, and as far as we are aware, we are the first to extensively investigate consumer characteristics that lead to stronger reliance on the 1/n heuristic. We also show that reliance on these two heuristics depends not only on respondents' characteristics, but also on the risk of running out of money (higher risk leads to less reliance on heuristics). As such, we confirm and extend Hedesström et al. (2007) on default bias. Finally, we contribute to a better understanding of the fundamental drivers of annuitization choices, by carefully accounting for the choice environments where these decisions are made.

To summarize, this paper makes two contributions: First, we provide more insights into the use of heuristics in the context of annuity choice to help inform important public policy and managerial strategies. Second, our new modeling approach provides a useful tool to account for the impact of heuristics in many contexts and choice situations, ranging from the influence of default bias in frequently moving consumer goods markets to accepting a doctor's advice in health care.

The rest of the paper is organized as follows: The next section discusses the annuity market in more detail and prior research on choices in this market. We then outline the experi-

mental design and associated allocation task and briefly summarize the chosen allocations. We discuss the finite mixture model used to explain respondents' allocations and report the empirical estimation results. We conclude by proposing several public policy and managerial implications, and discuss the research limitations and suggest some avenues for future research.

BACKGROUND

Review of Literature on Annuity Choice

Increasingly, ordinary consumers are being held responsible for managing their own retirement savings in defined contribution (DC) plans. Whereas members of the previously prevalent defined benefit (DB) plans enjoy continuity via pre-set annuity payments, DC members face challenges in making choices that satisfy needs for liquid funds to cover unforeseen expenses or wanting to leave bequests versus expenditures for life annuities to insure against outliving their wealth (Bateman et al. 2013). Life annuities not only insure against uncertain lifetimes and volatile capital market returns, but also may help consumers overcome high cognitive complexity and self-control problems in deciding how fast to draw down their accumulated wealth (Benartzi et al. 2011). Yaari (1965) argues that in complete markets rational individuals with no bequest motive should fully annuitize because those who die early subsidize those living longer; hence, annuities offer a 'mortality premium' over normal interest rates.

Yet, the attractiveness of annuities is reduced by fees and other expenses (Mitchell et al. 1999), Social Security benefits or other defined benefit pension payment streams (Dushi 2004) or desires to leave bequests (Bernheim 1991). The risk of health shocks that simultaneously cause large uninsured expenses and shorten life expectancy (Sinclair and Smetters 2004) and the irreversibility of purchase decisions (Kingston and Thorp 2005) also reduce the

appeal of annuities. Finally, the potential of intra-family risk sharing also can reduce demand for annuities (Brown and Poterba 2000).

In contrast to these conventional economic explanations for annuity choices, more recent research has focused on psychological and behavioral factors underlying such choices (e.g. Benartzi et al. 2011; Brown 2008), such as research by Hu and Scott (2007) on mental accounting and loss aversion, Beshears et al. (2008) on limited personal experience and temporal distance and Bernheim (2002) on limited access to social learning. More importantly, Brown et al. (2013b) report that individuals have difficulty valuing annuities, while Agnew et al. (2008) and Brown et al. (2013a) show consumers are susceptible to information framing and various heuristic choice rules like default bias, diversification heuristics or 1/n heuristics (Hedesstrom et al. 2004)[2].

In summary, retirement income stream choices have attracted much past research attention that has focused on traditional lifecycle model or behavioral economics explanations. However, we are unaware of research that combines these explanations into one framework and explicitly models the contribution of the latter drivers on consumer choices.

Local Choice Context

We focus on the Australian retirement saving system, where virtually all employees are covered by a 9.25% mandatory employer contribution into an individual defined contribution (retirement) account[3](ATO 2014). At retirement or on reaching a statutory access age members can choose the mix of retirement benefits they prefer, selecting a lump sum withdrawal, a phased withdrawal product and/or an annuity. The mix chosen has implications for taxation and eligibility for a means-tested public pension (almost 80% of people over 65 years receive a full or part public pension payment (FaHCSIA 2013)). Currently around 50% of accumulations (by assets) are withdrawn as lump sums with another 50% put into phased withdrawal products with continued exposure to risky asset markets and no longevity insurance (APRA

2014). Only a very small fraction is used to purchase term annuities in a market with several million retirees (Bateman et al. 2014a).

DESIGN OF EMPIRICAL STUDY

General Purpose of the Survey

The discrete choice experiment (DCE) task was a simplified example of actual retirement income product choices made by retiring defined contribution plan members. We studied allocations of retirement wealth made by 923 near-to-retirement defined contribution plan members who were recruited from a webpanel provider in October 2012. These survey respondents chose between pairs of retirement income streams that differed with respect to liquidity and longevity insurance features: a phased withdrawal account (invested in risky assets such as stocks) and a life annuity. The DCE explicitly mirrored trade-offs consumers face between these two products, namely access to liquid balances combined with continued exposure to investment and longevity risk versus the benefits of a constant, lifetime income stream, respectively.

More specifically, the DCE asked participants to allocate their retirement wealth between a phased withdrawal product and a life annuity in two settings. In the first setting, the first product (A) was an immediate life annuity that provided a level real lifetime income stream. This annuity was fairly priced at a risk-free real interest rate of 2% and at improved mortality probabilities from the most recent population life tables (Australian Government Actuary 2009). The second product (B) was a phased withdrawal product that offered an income stream equal to the annuity via level withdrawals from an account invested in a diversified portfolio of assets yielding an uncertain return above the risk-free rate. Thus, the account balance of B was of uncertain duration but available for discretionary withdrawals and bequests.

In the second setting, the first product (C) was a life annuity with a guarantee period, a so called principal-protected life annuity. It was the same as product A but with income payments guaranteed for 15 years to the purchaser and/or beneficiaries. We used a configurator (see Figure 1) to allow respondents to compare different allocations of their wealth to products A and B in the first setting and then C and B in the second setting on a vector that increased from 0% to 100% in increments of 5 percentage points. The configurator illustrated the consequences of the different allocations by showing a) the expected annual income, b) the guaranteed part of the expected annual income, c) the share of wealth withdrawable as lump sum, and d) the risk of only receiving the guaranteed part of the income at some stage of retirement. Our configurator thus presented an "active search tool[…*that allowed participants.*…] to successively specify the products that presumptively best meet their individual preferences" (Decker and Scholz 2009, p. 44). The response outcome of each experiment for each participant was the final chosen percentage allocation to the annuity.

The purpose of the DCE was to investigate the extent to which how much consumers rely on behavioral short cuts in retirement income stream choices, so we varied two factors that should impact this reliance rather strongly: First, within subjects and as further outlined below, we varied the risk of exhausting income from the phased withdrawal product B. Under regular assumptions about concave utility over consumption (risk aversion), this should mean a decrease in allocations to product B as the risk of exhausting income increases. Second, between subjects, we varied the position of the default allocation and by showing the initial allocations to the annuity of 25%, 50%, and 75%, respectively.

We manipulated the default option because research in finance and economics has paid a lot of attention to defaults due to their impact on consumer welfare. People have a strong tendency to stick to default options (Johnson et al. 1992; Madrian and Shea 2001) that often may be suboptimal, substantially harming consumers' wellbeing (Camerer 2000; Carroll et al.

2009). More generally, default options have been shown to affect choices by a) exploiting processing limitations (Johnson et al. 1992), b) establishing an endowment and subsequent loss aversion effect (Park et al. 2000) and/or c) setting up the illusion of a marketplace meta-cognition (Brown and Krishna 2004). For the particular context of retirement income stream products, Hedesstrom et al. (2004) found more than 30% of individuals in the Swedish Premium Pension Scheme stuck to the default and Benartzi et al. (2011) provided evidence in their metastudy that when annuities are the default option, their market shares are surprisingly high.

Survey Design

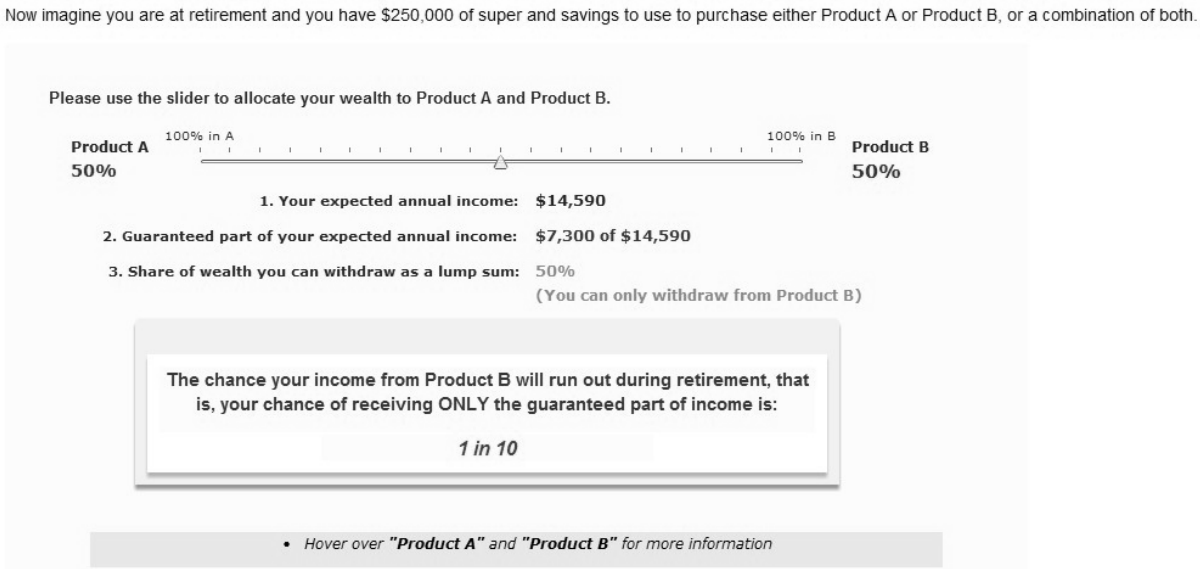
The DCE survey task asked middle-aged, non-retired respondents to make choices about the retirement income stream they would receive in the next phase of their life cycle. We reduced discrepancies between task and future real choices by controlling for moderating factors that could affect influence respondents' retirement wealth, their eligibility for public pension payment or fair pricing of their annuity. Based on their income (less than $50,000, between $50,000 and $200,000, between $200,000 and $600,000, and higher than $600,000), the planned date of retirement (retirement before or after 65) and their gender, we separated respondents into 16 treatment groups, and each treatment group received the most realistic scenario (i.e. value of products A, B, and C) for their particular circumstances.

The overall survey was designed as follows: The first part collected demographics (age, marital status, work status, occupation, industry/business, education, income) including information needed to filter and assign respondents to the 16 treatment groups. The second part was the DCE task (including product descriptions, configurator explanation and choice scenarios) that depended on the allocation to the respective treatment group. In the first four choice sets, respondents had to allocate their retirement wealth between product A (immediate

life annuity) and product B (phased withdrawal); in choice sets five to eight they allocated their retirement wealth between product C (life annuity with a guarantee period) and product B (see Figure 1). We increased the risk of exhausting income from product B in each of the four choice sets, which as noted earlier, under optimal allocation and constant risk aversion should decrease allocations to product B. The risk of exhausting income from product B before the end of life was set at 10%, 25%, 50%, and 75%, respectively and it depended on the risk and return of the underlying investment of the assets, the rate at which income is drawn from the account each period and the probability of survival. The latter two factors were constant, depending only on the participant's treatment group. We varied the risk of running out of money in product B by changing the rate of return on the underlying investment.

Figure 1

EXAMPLE OF ALLOCATION TASK



After the allocation experiment we asked two sets of questions (parts 3 and 4 of the survey) about respondent characteristics to allow us to identify which individuals were more likely to follow behavioral shortcuts in their retirement income stream choices.

The third part asked respondents to answer 18 true/false questions to test recall of the five key features of products A, B and C in the DCE product descriptions (i.e., the product quiz).

We used these answers to construct a covariate that represents the proportion of correct answers. Products A, B and C were not labeled with names of existing commercial income stream products, so participants could not answer the quiz correctly from their *ex ante* 'real world' product knowledge without reading the descriptions. Thus, our recall quiz measured their understanding of the products independent of pre-existing experiences with them. This covariate captured both survey attentiveness and cognitive processing limitations. The latter have been shown to explain use of default heuristics (Johnson et al. 1992), and it can be argued the former is strongly linked to decision involvement, which moderates the tendency to stick with the default (Hedesström et al. 2007). After the recall quiz, respondents answered questions on bequest intentions and mortality expectations plus other questions. The former variables have been shown to impact life annuity utility within standard lifecycle models and so can be expected to influence respondents' proneness to choose based on heuristics.

The final part of the survey asked questions to measure numeracy, financial literacy and self-assessed knowledge of finance that are proxies for processing limitations and financial confidence, respectively; and questions about awareness and knowledge of existing retirement income products that are proxies for choice domain knowledge. Default options give the illusion of a marketplace metacognition (Brown and Krishna 2004), so, participants with little choice domain knowledge should be more susceptible to them.

Questions about numeracy and financial literacy (see Appendix B) were based on Lipkus et al. (2001) and Lusardi and Mitchell (2009). Numeracy questions asked about proportions, percentages and simple probability; two basic financial literacy questions tested interest and inflation and two sophisticated financial literacy questions tested diversification knowledge. Awareness and knowledge of existing retirement income product was measured by the proportion of correct answers in a set of questions on real world retirement income products including the most common commercial versions of the generic products underlying the choice

sets: an allocated pension (phased withdrawal product), and lifetime and guaranteed life annuity (see Appendix C).

Finally, we also included two Instructional Manipulation Checks (IMC) similar to Oppenheimer et al. (2009) to explicitly measure respondents' survey attentiveness. The two IMCs were placed before the DCE. The first IMC can be interpreted as a reliable indicator of task involvement, as it was positioned early enough in the survey to make possible survey fatigue negligible[4].

Respondents received points (equivalent to cash) worth $A3 by the webpanel provider for fully completing the survey. We further incentivized survey attention and truthful reporting as follows: for each correct answer in the product recall questions and the financial literacy questions, respondents were entered into a lottery offering prizes worth the equivalent of $50. Three prizes were awarded.

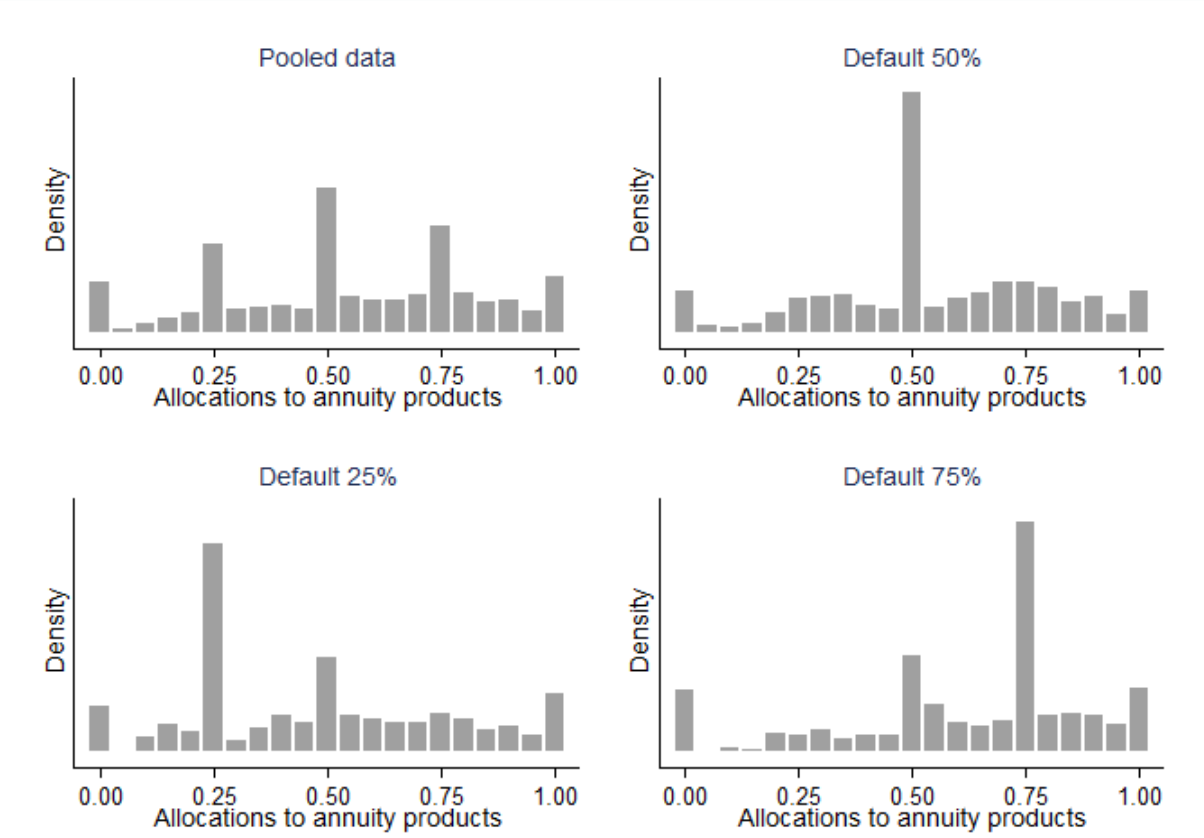
Initial Results

Figure 2 shows the allocations of respondents' wealth aggregated over the four risk levels and the two annuity products A and C, but differentiated by default configurator version: The figure at the left, middle and right show participant allocations for a 25%, 50%, an 75% allocation to annuity default, respectively. Three things stand out: 1) the position of the default clearly influences participant choices (i.e., a default heuristic), 2) participants show a tendency to allocate their wealth equally between the two products (i.e., a 1/n heuristic), and 3) a tendency to seek extremes and allocate all wealth to one product exclusively, which contrasts to Hedesstrom et al. (2004) who found extremeness aversion in fund choices in the Swedish Premium Pension Scheme. These extreme allocations may be simply a sign that participants are certain about their preferences for the product attributes (Simonson 1989). Indeed, we cannot separately identify whether boundary choices were made because those who were

conventionally rational find the 0-100% constraint binding (that is, we allow no borrowing against one product to support a greater-than-100% allocation to the other), or because they used an ‘extremeness seeking’ heuristic.

Figure 2

OBSERVED ALLOCATION POOLED ACROSS RISK LEVELS AND PRODUCTS A AND C



In any case, the pattern of allocations provides strong *prima facie* evidence that different heuristics influence participant choices, indicating that a model that explains these allocations must account for the evident multimodality.

FINITE MIXTURE MODEL WITH DEGENERATE COMPONENTS

Mixture of Degenerate Probability Density Functions and Beta-Binomial Distribution

As discussed above, our observed allocation data clearly requires a mixture of several dis-

tributions to explain its multimodal features. However, classical mixture models usually assume continuous mixture densities (Allenby and Rossi 1998), restricting their applicability and contraindicating using them for our discretized allocation task. We are aware of only one Marketing application of a mixture of discrete distributions, namely Brijs et al. (2004) that used a mixture of Poissons to model clusters of shoppers by their category-specific purchase frequencies. Unfortunately, however, these mixture densities do not match a) the obvious spikes in our choice data at the extremes, the default locations, and the 1/n location, and/or b) the lack of noticeable additional mass in their neighbourhoods. One way to model such a pattern is to use a mixture that includes degenerate distributions that can capture spikes in the data. An additional non-degenerate component in the mixture, represented by a beta-binomial distribution, captures the choice process underlying allocations independent of the spikes. This mixture of probability density functions follows a logic similar to traditional models used to describe a spike at a particular location (e.g., the zero-inflated Poisson model), but is much more general because it allows these spikes to occur more than once in any location the researcher specifies. The global climate model of (Cao and Yao 2012) has one spike, and is a limited special case of our approach.

The mixture model has the following components:

1) 1/n heuristic: when using this rule, respondents choose the 50%/50% allocation with certainty
2) Default heuristic: when using this rule, respondents choose the allocation that was presented to them in the beginning of the task (i.e. default allocation of 25%, 50% or 75% allocation to life annuity) with certainty.
3) Phased withdrawal boundary: respondents choose 100% allocation to the phased withdrawal product with certainty.
4) Annuity boundary: respondents choose 100% allocation to the life annuity with cer-

tainty.

5) Unconstrained allocation: respondents choose their allocation (to the annuity product) according to a beta-binomial distribution[5].

Thus the mixture probability density function is defined by four weight parameters, and two parameters to capture the shape of the beta-binomial distribution. The main modelling objective is to a) determine the size of the weights to provide an estimate of the magnitude of heuristic influences in retirement annuity choices, b) relate the weights to participant characteristics to profile susceptible people, and c) relate the shape of the beta-binomial component of the mixture to characteristics of the products in the choice sets.

With no loss of generality, we parameterize the mixture weights of the components representing the four heuristics and adjust the fifth weight to ensure they are non-negative and sum to 1. More specifically, let w^{**}, g^{**}, f^{**}, and h^{**} be the weights associated with the 1/n, default, 100% phased withdrawal boundary, and 100% annuity boundary, respectively. We further parameterize the weights as follows to ensure that they lie within the unity intervals

$$w^{**}=\exp(w^{*})/(1+\exp(w^{*})+\exp(g^{*})+\exp(f^{*})+\exp(h^{*})),$$

$$g^{**}=\exp(g^{*})/(1+\exp(w^{*})+\exp(g^{*})+\exp(f^{*})+\exp(h^{*})),$$

$$f^{**}=\exp(f^{*})/(1+\exp(w^{*})+\exp(g^{*})+\exp(f^{*})+\exp(h^{*})),$$

$$h^{**}=\exp(h^{*})/(1+\exp(w^{*})+\exp(g^{*})+\exp(f^{*})+\exp(h^{*})),$$

where w^{*} and g^{*} are parameters dependent on observed sociodemographic characteristics of participants and product attributes X. We assume $w^{*}=Xw$, $g^{*}=Xg$, and $f^{*}=f$, $h^{*}=h$ to facilitate identification. Parameter vectors w, g, f and h are estimated with maximum likelihood as described below.

In addition, let $d^{*}>0$ and $e^{*}>0$ denote parameters of the beta-binomial distribution that represent the flexible component of the mixture distribution. We assume $d^{*}=Xd$ and keep $e^{*}=e$

constant to facilitate identification. Higher values of d^* are associated with higher allocation to the annuity products, thus higher estimates of the elements of *d* should be interpreted in the same way. The parameter vector *d and the parameter e* are estimated jointly with the other parameters[6].

The log-likelihood function for the model is then given by

$$L(w,g,f,h,d,e,X,Y)$$

$$= \sum_{i=1}^{K}\sum_{j=1}^{N} y(i,j) * \ log[w^{**}pdf_w(j) + g^{**}pdf_g(j) + f^{**}pdf_f(j) + h^{**}pdf_h(j)$$

$$+ (1 - w^{**} - g^{**} - f^{**} - h^{**})pdf_{bb}(d^*, e^*, j)],$$

where *K* is the number of observed data points, *N=21* is the number of discrete points on the allocation task (described above), the weights are given by the expressions above, and *Y={y(i,j)}* denotes the observed allocations, i.e. *y(i,j)=1* if respondent's *i* choice is given by point *j* on the discretized allocation scale, and *y(i,j)= 0* otherwise. The unrestricted beta-binomial probability density function $pdf_{bb}(d,e,j)$ is given by

$$pdf_{bb}(d^*, e^*, j) = \frac{\binom{N}{j} B(j + d^*, N - j + e^*)}{B(d^*, e^*)} \quad j = 1, \dots, N,$$

where *B* is the beta function. The degenerate pdfs are defined with the indicator function *I{condition}=1* if the particular condition is satisfied and *0* otherwise. We have

$pdf_w(j)=I\{j=floor(N/2+1)\}=I\{j=11\}$ (1/n heuristic),

$pdf_g(j)=I\{j \text{ is default allocation}\}$ (default heuristic),

$pdf_f(j)=I\{j=N\}$ (boundary, phased withdrawal),

$pdf_h(j)=I\{j=1\}$ (boundary, annuity).

The model is estimated on 6,884 of the 7,384 observations by maximizing *L(w,g,f,h,d,e,X,Y)* with respect to *(w,g,f,h,d,e)* given the observed data on personal and product characteristics *X*

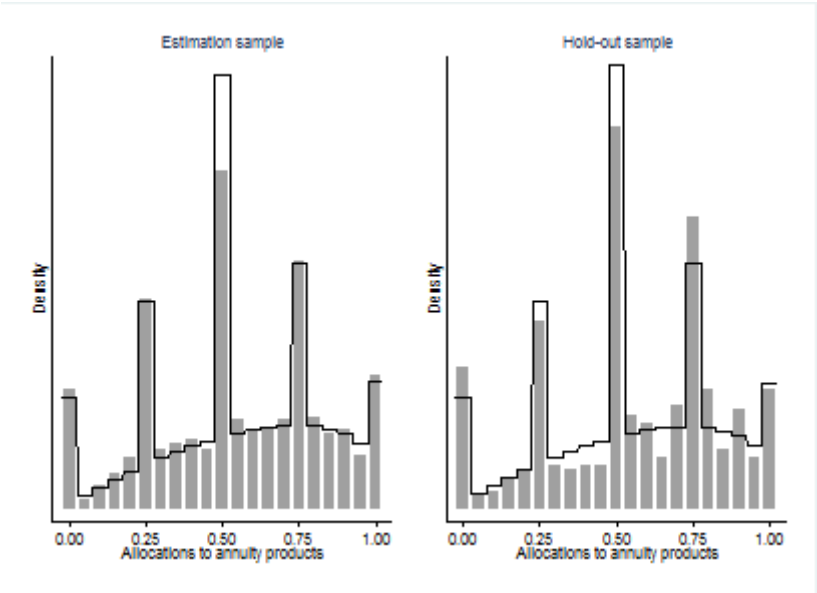
and choice data *Y*. The remaining (randomly selected) 500 observations are used for hold-out sample performance assessment.

Model Estimates

Model fit. Figure 3 graphically illustrates the proposed mixture model's fit to the pooled allocation data for the estimation and the hold-out sample. Figure 4 shows model predictions versus actual allocations by version for both estimation and hold-out sample.

Figure 3

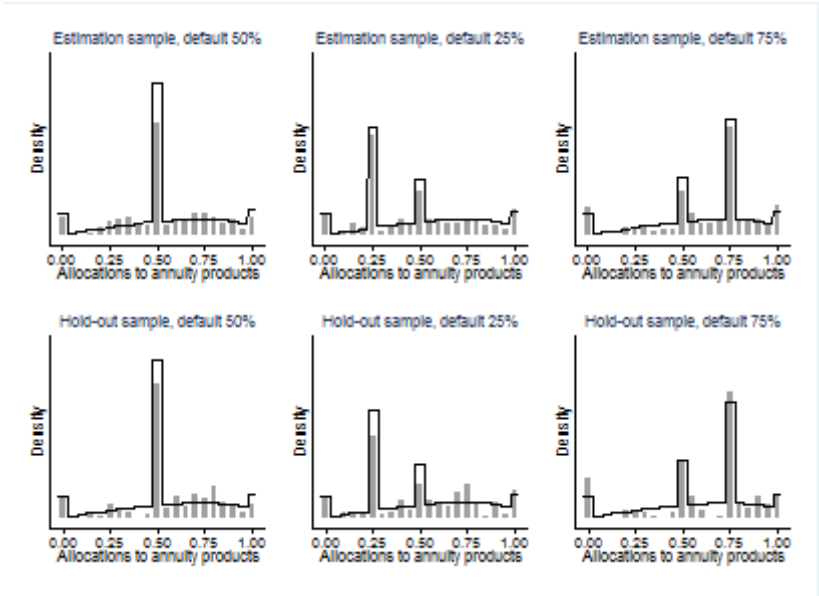
OBSERVED ALLOCATIONS AND FITTED MIXTURE DISTRIBUTION FOR POOLED DATA



The bars correspond to the actual allocations whereas the black lines represent predicted choice probabilities. The figures show the model fits the data quite well, for both estimation and hold-out samples. The model is particularly successful in capturing the extremes as well as the default heuristic, and only slightly overpredicts the use of the 1/n heuristic. The larger prediction error at the 0.50 point (50%/50% allocation) is possibly due to compounding of prediction errors of the two heuristics that apply there. Other spikes are modeled by only one heuristic.

Figure 4

OBSERVED ALLOCATIONS AND FITTED MIXTURE DISTRIBUTION BY DEFAULT VERSION



The good fit for the hold-out sample also indicates that the model does not overfit the data, which is further supported by the root likelihood of the two samples. The root likelihood is a transformation of the likelihood value and can be used to compare the fit of the model to the main and hold out samples. Here, the confidence interval for the hold-out root likelihood equals .072 (95% confidence interval: [.066, .079]), and encompasses the in-sample root likelihood of .068 (95% confidence interval: [.066, .069]. The fact that here the statistic is statistically similar in size for both in-sample and hold-out sample supports the appropriateness of the model (e.g. Frischknecht et al. 2013).

Parameter estimates.

Table 1 reports parameter estimates for the mixture model. The average weights of the mixture pdfs at the bottom of the table reveal that 22.4% of choices are based on the default heuristic and 9.7% of choices are based on the 1/n heuristic. More than 8% of choices are at the boundaries and almost 60% of choices are made without relying on any of these behaviors.

Table 1

PARAMETER ESTIMATES MIXTURE MODEL

	Uncon-strained allocation, beta binomial (d)	*Uncon-strained allocation, beta bino-mial (e)*	*1/n weight (w)*	*default weight (g)*	*100% phased withdrawal weight (f)*	*100% annuity weight (h)*
Gender = female	-.013		-.092	.082		
Marital status = married	.080*		.038	.075		
Understanding of DCE products	.570**		-.323	-2.567***		
Higher Education	.158***		.072	-.161***		
Numeracy	-.436*		-.012	.183		
Basic financial literacy	-.223		-.678*	-.206		
Sophisticated financial literacy	-.072		.042	-.080		
Self-assessed financial literacy	-.191***		-.100	-.088		
Wealth (in $100K)	-.017		-.285	-.033**		
Wealth squared (in $1T)	.045		.030	.101***		
IMC1 correct	.137***		.012	-.217***		
Knowledge of products currently on the market	-.143		-1.040***	-.193		
Deviation of subjective life expectancy	-.007		.008	.007		
Intention to leave be-quest	-.097**		.162***	.023		
Intention to retire early	-.021		-.144**	-.064		
Risk	1.568***		-.436*	-.415**		
prodAB (1=product A, -1=product C)	.060		.095*	.012		
prodAB*with intention to leave bequest	.002		.025	.025		
Risk*numeracy	2.418***		-.144	-.422		
Risk*basic financial literacy	.495		-.075	-.010		
Risk*sophisticated fi-nancial literacy	.262		.136	-.010		
Risk*self-assessed fi-nancial literacy	-.021		.208	-.011		
Risk*wealth (in $100k)	.015		.021	-.009		
Risk*female	-.010		.081	-.001		
Risk*deviation of sub-jective life expectancy	-.005		.010	.012		
Constant	2.350***	1.379***	-.125	1.494***	-2.495***	-2.799***
Average mixture weight	*.593*		*. 097*	*. 224*	*.049*	*.036*

LR=919.4; p>χ^2(75)=.000

*=p< .1; **=p< .05; ***=p<.01

In what follows we discuss the impact of the selected sociodemographics and product characteristics on the weights associated with different heuristics and the shape of the beta-binomial distribution that reflects allocations to the annuity.

Impact of covariates on allocation to annuity.

Our results indicate that gender does not impact allocations of wealth to the annuity, which contrasts with Benartzi et al. (2011), who found that women were more likely to choose annuities, and Bütler and Teppa (2007), who showed that men were more likely to choose annuities. We found married participants generally were more likely to allocate more wealth to the annuity ($p<.1$). This is inconsistent with intra-family risk sharing and also to the results of Brown and Poterba (2000), but this may be due to the lower per person public pension given to couples (under the Australian arrangements) that encourages private annuity purchase.

Participants who performed better in the DCE product quiz (i.e., they were likely to have been more attentive to the survey and have less processing limitations) allocated more of their wealth to the annuity ($p<.05$). Attentiveness to product features may have helped form more definite preferences favoring one or another product, confirming Brown et al. (2013b) findings of complexity as a barrier to annuitization. Consistent with existing studies (Inkmann et al. 2011) we found that better educated respondents were more likely to allocate more wealth to the annuity ($p<.01$). Surprisingly, higher numeracy skills lead to lower annuitization ($p<.1$), though this finding was partly mitigated by the interaction of numeracy skills with risk of exhausting income discussed below. We found no impact for the other two measures of financial literacy (i.e., basic and sophisticated financial literacy) on the allocations. Consistent with conclusions drawn in Agnew et al. (2008) that financial over-confidence leads to more risky behavior, we found that respondents who judged their own financial literacy as high (which did not necessarily correlate with their true literacy), allocated less wealth to the insurance

product ($p<.01$). This result is also in line with findings by Zhu et al. (2012) who show that online community members with strong ties are more likely to engage in risky behavior because they assume that they will receive help and support from other members should difficulties arise. It is also conceivable, that our result reflects the fact that consumers with high self-assessed financial literacy have a higher competitive desire to outsmart the market with a resulting stronger urge to exploit unintended value (Sela et al. 2013).

In contrast to Benartzi et al. (2011) participant wealth did not impact their allocations to annuities. Higher survey attention, as measured by our Instructional Manipulation Check, was associated with higher allocations to the annuity product ($p<.01$). If one assumes that higher survey attention represents higher task involvement with retirement income stream choice in general, one would conclude that more involved consumers were more likely to (at least partly) annuitize their wealth, as theory would typically recommend. Further, higher domain knowledge (reflected by knowledge of products currently on the market) did not impact annuitization choices. These two findings and the result that better performance in the DCE product quiz led to higher annuitization suggests that product-specific instead of generic market knowledge and interest drive more annuitization.

Deviation of subjective expected life duration from the population tables did not impact annuity choices. So, we cannot confirm the adverse selection in annuity choices reported by Inkmann et al. (2011), Finkelstein and Poterba (2002) and Finkelstein and Poterba (2004). However, consistent with standard lifecycle models (Bernheim 1991), we can confirm that participants who want to leave a bequest are significantly less likely to allocate their wealth to annuities ($p<.05$).

Regarding product characteristics varied in the DCE choice sets, we showed that higher risk of exhausting income leads to more annuitization ($p<.01$). This result is consistent with rational reactions of risk averse consumers (Bateman et al. 2013). In contrast to Brown et al.

(2008) we found no additional demand for annuities when we offered a 15 years guarantee period on annuity payments (i.e., product C versus product A), irrespective of participant bequest intentions. Finally, when interacting product risk levels with sociodemograhics, we found that particularly numerate respondents reacted strongly to higher risk and consequently allocated more wealth to the annuity ($p<.01$).

Impact of covariates on weight of 1/n heuristic.

There is little research on covariates that could impact use of the 1/n heuristic (we are only aware of Hedesström et al. 2007 who discuss disengagement as a possible determinant of the use of the 1/n heuristic). So, our results represent a preliminary basis for better understanding these covariates. Consistent with the general notion that reduced cognitive resources lead to increased use of heuristics (De Neys 2006; Shah and Oppenheimer 2008), we found lower domain knowledge (reflected in lower basic financial literacy – knowledge of interest rates and inflation - and lower knowledge of products currently on the market) led to higher likelihood of using the 1/n heuristic ($p<.1$ and $p<.01$, respectively).

Intentions to leave a bequest increase ($p<.01$), whereas intentions to retire early decrease the likelihood ($p<.05$) of sticking to the 1/n heuristic. We also found higher risk of exhausting income associated with phased withdrawal made participants less likely to follow the 1/n heuristic ($p<.1$), while offering them the annuity that excluded the guarantee period made them more likely to follow it ($p<.1$). All four results may reflect the fact that as the stakes get higher, consumers are more careful with their allocation decisions and less likely to choose based on heuristics than when stakes are lower, consistent with a similar result by (Hedesstrom et al. 2004) for the use of the default heuristic. (Early retirement means no access to the public pension until later in retirement, effectively raising the stakes of the experimental choice in terms of personal wealth.) Individuals who want to leave bequests and view them as luxury options (payments that are made contingent on not outliving one’s wealth) also tend to prefer risky

portfolio allocations (Ding et al. 2014), which may explain why they tend not to use this heuristic.

Impact of covariates on weight of default heuristic.

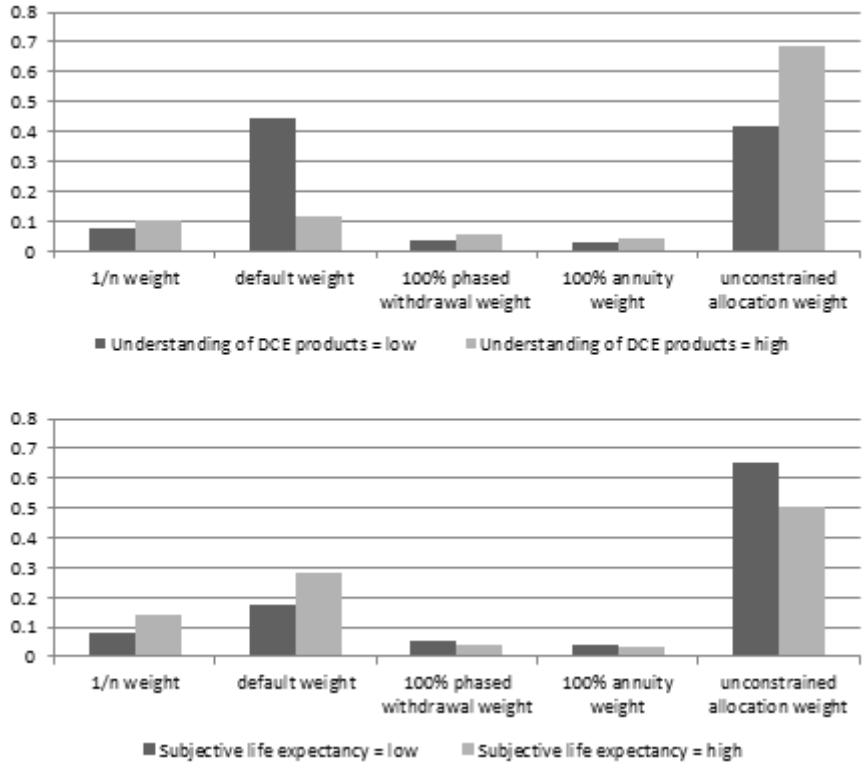
Results for the use of the default heuristic also confirm and extend prior findings. To wit, lower scores in the DCE product quiz and lower education (both signs of processing limitations) increase the likelihood of choosing the default option ($p<.01$), again consistent with general findings on using heuristics discussed earlier.

We found a U-shaped response for wealth, such that very poor and very rich people were more likely to choose the default heuristic. This result may be due to the fact that these two groups do not care much about the particular investment of their retirement savings because it's either too small an amount to care about, or is only a small fraction of their overall wealth. Thus, this result may reflect lack of involvement by very rich or very poor respondents. Lack of involvement being associated with using the default heuristic is also supported by finding that participants who showed little survey attention in the Instructional Manipulation Check also were more likely to rely on the default allocation ($p<.01$). Thus, we can confirm the results of Hedesström et al. (2007), who showed disengaged consumers were more likely to stick with the default fund.

Finally, as with the 1/n heuristic, we found increased risk led to a lower likelihood ($p<.05$) of sticking with the default (see also Hedesstrom et al. 2004).

Figure 5

MIXTURE WEIGHTS FOR DIFFERENT RESPONDENT GROUPS



Reliance of different groups on different heuristics was more obvious when we graphed the mixture weights of these groups against each other. Figure 5 shows such a comparison for two representative participants whose characteristics (except those named) are fixed at sample means. The top panel of Figure 5 presents the effect of understanding of the DCE products as a measure or survey attentiveness and processing limitations; the bottom panel of Figure 5 presents the effect of subjective life expectancy. These again show that if limited learning about DCE products occurred, participants largely relied on the default heuristic, whereas those expecting to live shorter lives seemed to more carefully engage in how to invest their retirement income.

CONCLUSIONS & DISCUSSION

This paper discussed a method to capture heuristics in credence good choices. In particular, we used a finite mixture model with degenerate components to investigate the use of the default and the 1/n heuristics for annuity purchases, a category previously studied from the standpoint of conventional economic theory and psychology and behavioral economics. We used an online discrete choice experiment that asked consumers to allocate their retirement wealth between a life annuity and a phased withdrawal product. We varied the level of risk of exhausting income from the phased withdrawal products before the end of life within-subjects, and varied the initial (i.e. default) allocation between-subjects. Both factors impacted the extent of annuitization, as discussed extensively in the two streams of literature mentioned above.

Allocations in the DCE clearly indicated great heterogeneity in participant preferences, revealing the importance of heuristics in these choices. We formulated a finite mixture model with degenerate components for different heuristics and boundary allocations, and a flexible beta-binomial distribution for the remaining allocations. The model estimation results showed that 30% of choices were consistent with default or 1/n heuristic use. The model also allowed us to associate use of these two heuristic rules with consumer characteristics. Our results are largely consistent with prior findings; for example, they confirm that processing limitations are a key driver of heuristic use (Johnson et al. 2002), or that risks associated with phased withdrawal products or intentions to leave bequests influence annuitization choices (Bateman et al. 2013; Bernheim 1991). More specifically, we extend the sparse literature on determinants of using the 1/n heuristic by showing that Hedesstrom et al. (2004)‘s result that (fortunately) when stakes are high consumers seem to care more and are rely less on heuristics applies to both the default heuristic and the 1/n heuristic. Our results also extend recent research by Benartzi et al. (2011), who questioned the existence of the so-called “annuity puzzle” (i.e.,

the discrepancy between a strong theoretical support for, but low empirical uptake of annuities). Indeed, annuity uptake in our DCE was rather high; so it seems that offering an annuity and explaining it in plain English may be sufficient to increase uptake. Finally, we confirmed the usual characteristics of vulnerable consumers, such as processing limitations, but we think policy makers and managers should pay attention to people who assess themselves as highly financial literate. Our results suggest that this confidence does not necessarily reflect true literacy, but instead seems to be associated with a possibly dangerous over-confidence in their ability to make financial decisions. Thus, it may be worthwhile asking these consumers to take knowledge tests and give them feedback on their financial skills before they make important choices.

We see two key contributions of our research: 1) we advance understanding of annuitization choices and the impact of preferences and heuristics on them, and 2) our finite mixture model represents a more general and flexible way to study choices of credence goods, where psychological and behavioral reasons can be as important as rational utility maximization in explaining consumer behavior. Moreover, our mixture model is not limited to the particular allocation task we studied. Instead, we think that combining traditional choice models like conditional logit models with degenerate pdfs that capture heuristics, may provide a fruitful avenue for future research and a flexible approach to understanding consumer behavior in a variety of contexts.

A key limitation of our work, of course, is that we used a hypothetical experiment. In turn, this also applies to the incentives provided to participants. The median duration of the DCE (18 minutes) suggests that participants took the task seriously, but of course one can question whether the choices truly reflect those made when lifetime savings are at stake. Similarly, we communicated our products in a consumption frame, which may have increased the annuities' appeal (Brown et al. 2013a; Brown et al. 2008). Although the generalizability of our results

may be subject to further study, we think that the use of the mixture model to investigate the use of heuristics is a promising avenue for future research on credence goods and/or in other areas where psychological and behavioral reasons can play an important role in purchase decisions.

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ENDNOTES

[1] It is worth noting that the flexible beta-binomial distribution may include other than rational behavioral strategies.

[2] Some authors view the 1/n heuristic as a special case of the diversification heuristic Benartzi, Shlomo and Richard H Thaler (2001), "Naive diversification strategies in defined contribution saving plans," American economic review, 91 (1), 79-98..

[3] Note that before 1 July 2013, i.e. including the time of data collection, the minimum employer contribution was 9%.

[4] The assumption that IMC1 is much less susceptible to survey fatigue and a much better indicator for involvement is also supported by the cross tabulation of correct answers in IMC1 versus IMC2. This cross tabulation shows that while ca 45% of respondents who passed IMC1 did not click correctly in IMC2, only 6% of respondents who did not pass IMC1 clicked correctly in IMC2.

[5] The beta-binomial distribution was chosen as it allows for the discrete nature of our allocation task, i.e. the 21 vector increments of 5% from 0% to 100%

[6] We apply constrained likelihood approach to ensure that the constraints on d and e are satisfied. The maximum of the likelihood function is attained at the inner point, indicating that the constraints were not affecting the estimates.

APPENDIX A

Numeracy:

- Imagine that we rolled a fair, six-sided die 1,000 times. Out of 1,000 rolls, how many times do you think the die would come up with even numbers?
- In a lottery, the chance of winning a $10 prize is 1%. What is your best guess about how many people would win a $10 price if 1,000 people each buy a single ticket to the lottery.
- In a raffle, the chance of winning a car is 1 in 1,000. What percent of tickets in the raffle win a car?

Basic Financial Literacy:

- 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?
- 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?

Sophisticated Financial Literacy

- When an investor spreads his money among different assets, does the risk of losing money increase, decrease, or stay the same?
- Please tell me whether this statement is true or false. ‘Buying a single company's shares usually provides a safer return than a share managed fund.’

APPENDIX B

Experiment instructions

”In the next few questions we will ask you to complete **4** sets of choice tasks about **2** financial products.

On leaving the workforce, most people need to use money from their superannuation and other savings to cover their spending. Industry and Government are looking for simple financial products to help Australians manage their superannuation and savings during retirement.

The retirement income products we are going to show you are designed by large financial firms, like insurance companies and superannuation funds, to cover spending and manage financial risks in retirement.

Product A: Get a guaranteed income.

- Who provides this product?
  - It is supplied by large life insurance firms. These firms have to meet strict government regulations to be allowed to sell this product.
- How much income will I receive?
  - You will receive a fixed regular income.
- How long do payments last?
  - You will receive the regular income for as long as you live, regardless of how long or short that is.
- What happens if I die?
  - If you die, payments stop.
- Can I withdraw a lump sum for unforeseen events or changes of plans?
  - No. To purchase this product, you pay a lump sum to the insurance firm in exchange for the income stream and you cannot get it back. Your beneficiaries do not get the lump sum back if you die.

Product B: Withdraw a regular income.

- Who provides this product?
  - It is supplied by superannuation funds. Your money is held in an account and invested in financial assets like shares and bonds.
- How much income will I receive?
  - You can decide how much of your balance to withdraw each year. Your account balance will fluctuate each year with financial markets. You will pay fees each year to the fund that manages your account.
- How long do payments last?
  - There is no guarantee you will have a lifetime income. How long payments last depends on investment returns, fees and your withdrawals.
- What happens if I die?
  - If you die, remaining money in your account goes to your dependents or your estate.
- Can I withdraw a lump sum for unforeseen events or changes of plans?
  - Yes. You can take all or a part of any remaining money out, but if you do it will not be available to pay you income in the future.”

Respondents were then shown several examples of the product configurator and completed four choices. After that they saw another screen:

"`Thank you for completing the last 4 tasks. Now we want you to compare Product B with a different type of guaranteed income product in another 4 similar tasks.

Product C: Get a guaranteed income with a fixed term payment period.

- Who provides this product?
    - It is supplied by large life insurance firms. These firms have to meet strict government regulations to be allowed to sell this product.
- How much income will I receive?
    - You or your beneficiaries will receive a fixed regular income.
- How long do payments last?
    - You personally will receive the regular income for as long as you live, regardless of how long or short that is. If you die within the fixed term period, the regular income continues to be paid to your beneficiaries or estate up to the end of the 15h year.
- What happens if I die?
    - Payments are guaranteed to you or your beneficiaries for the first 15 years, even if you die within that period. Payments are guaranteed only to you after that time.
- Can I withdraw a lump sum for unforeseen events or changes of plans?
    - No. To purchase this product, you pay a lump sum to the insurance firm in exchange for the income stream and you cannot get it back. Your beneficiaries do not get the lump sum back if you pass away."

APPENDIX C

Commercial product knowledge

"Below is a list of features for products. For each product listed in column(s), please select all product features that you think apply to each product.

Please select all that apply for each product in column(s) that you have heard of."

	Allocated (or account-based) pension	Lifetime annuity	Superannuation pension	Fixed term annuity	Reversionary annuity	Indexed annuity	Variable annuity	Transition to retirement pension
To purchase this product, I pay a lump sum of my capital and do not get it back.	☐	☐	☐	☐	☐	☐	☐	☐
My capital is tied up for a fixed term.	☐	☐	☐	☐	☐	☐	☐	☐
My account balance will go up and down with the financial markets.	☐	☐	☐	☐	☐	☐	☐	☐
I can choose the amount of income I withdraw, as long as I withdraw the minimum required by the government.	☐	☐	☐	☐	☐	☐	☐	☐
I can withdraw my capital/ balance at any time or leave it to someone in	☐	☐	☐	☐	☐	☐	☐	☐

	Allocated (or account-based) pension	Lifetime annuity	Superannuation pension	Fixed term annuity	Reversionary annuity	Indexed annuity	Variable annuity	Transition to retirement pension
my will.								
The dollar amount of my capital is guaranteed not to go down.	☐	☐	☐	☐	☐	☐	☐	☐
I can choose where my money is invested.	☐	☐	☐	☐	☐	☐	☐	☐
The dollar amount of my income is guaranteed not to go down.	☐	☐	☐	☐	☐	☐	☐	☐
My income is guaranteed to increase with inflation.	☐	☐	☐	☐	☐	☐	☐	☐
The value of my capital is guaranteed to increase with inflation.	☐	☐	☐	☐	☐	☐	☐	☐
Income from this product lasts my whole life regardless of how long I live.	☐	☐	☐	☐	☐	☐	☐	☐
If I die, my partner can receive the income from this product.	☐	☐	☐	☐	☐	☐	☐	☐

	Allocated (or account-based) pension	Lifetime annuity	Superannuation pension	Fixed term annuity	Reversionary annuity	Indexed annuity	Variable annuity	Transition to retirement pension
If I die, my partner or beneficiaries can receive the capital/balance from this product.	☐	☐	☐	☐	☐	☐	☐	☐