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Does the Procedure Matter?[1]

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Abstract

When searching for which products to buy, consumers are typically bombarded with options. Some suppliers try and simplify the issue of decision-making for their potential buyers in some way. One typical procedure used to ease the decision-making process for potential customers is to present the products in sequential pages and request shoppers to select an item from each page, entering them into a wish list from which the final choice will be made. This study experimentally investigates how the final decision is affected by the number of items on each page and, hence, by the number of items in a wish list. The parameters of a stochastic model are estimated to 'explain' the data, in particular, examining the noisiness of the choices at each stage. The results show that procedure matters and that the trade-off between an increased number of options per page and an increased number of pages is indeed influential.

Keywords: Sequential Decision-Making, Online Behaviour, Choice Overload, Experiment, Stochastic Risk Aversion

JEL: C91, D91, O33, D81

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1. Introduction

In this Internet era, there is a significant choice overload issue for those searching for a new product; for example, at the time of research[2], there were 1,125 milk products available on Ocado's website and more than 300 rooms available for Christmas Eve in London on Airbnb. Some internet sites (such as Netflix) try to simplify the process for the consumer, structuring the search process in some way. One obvious way to improve the experience for consumers is to sequentially present the various options in subsets (pages) and request that they select one or more options from each page to enter into a wish list, before asking them to select one option from the wish list. This might be termed a *sequential decision-making procedure.*

To be more precise about what a sequential decision-making procedure is, it involves two decision making stages: (1) selecting a product (or products) from each page, referred to as the *Subset stage*, and (2) making a final decision from items entered into the wish list or shopping bag, referred to as the *Wish List stage*. Suppose there are a total of n options out there (1,125 in the case of milk products on Ocado or more than 300 rooms for Christmas Eve in London on Airbnb). These can be presented to the consumer in subsets, each containing m options; therefore, there would be n/m such pages. If, for each subset, the consumer was asked to put one option in a wish list, there would be a total of n/m options in the wish list. As such, the consumer would be asked n/m times to select one of m options available and to finish by choosing one of n/m options from a wish list. This might be a simpler process, and lead to better decision-making, than choosing one option out of n.

One might legitimately consider whether this kind of procedure simplifies or improves the decision-making process. To answer this question, one needs to specify what is meant by 'improving' the decision. Besedes *et al*. (2015) have researched this sequential procedure from the perspective of choice overload and produced evidence that a sequential procedure mitigates the negative effect of choice overload better than a simultaneous one when faced with a large choice set. However, inspired by their findings, the purpose of this paper is to

[2] June 29, 2020.

discover what *m* should be and whether there is an optimal value for *m*. When the total number of options is the same, there will be a trade-off between the two stages. The procedure with more options within each subset (based on a smaller number of subsets) requires consumers to spend more time processing and comparing options within each subset, but a smaller number of options need to be compared in the wish list. On the other hand, a fewer number of options within each subset (based on a larger number of subsets) enables the consumer to quickly pick the preferred option within each subset but requires making more decisions and spending more time processing and comparing options in the wish list. To illustrate this further, consider a set of six options {1, 2, 3, 4, 5, 6}. There are two possible sequential compositions – choosing from subsets {1, 2}, {3, 4} and {5, 6} and making a final decision from a three-option wish list, or choosing from subsets {1 ,2, 3} and {4, 5, 6} and making a final decision from a two-option wish list. The hypothesis arises as to whether different sequential procedures influence behaviour. Intuitively, increased subsets imply a longer period of decision-making, which may lead to decision-fatigue, whereas increased available options may overwhelm a consumer's -attention. Subsequently, the number of subsets and the number of available options within a subset may lead to different influences, suggesting that the procedure may well matter. Thus, this study reports on an experiment designed to answer or, at least, shed light on this notion. We ask: does the procedure matter? And, if so, how does procedure matter?

In designing the experiment, it first needed to be decided what the options should be. As has been made clear above, ideally, the options needed to be ones that could be objectively ranked, so that the best choice could be specified, and the best procedure determined. If the objective ranking depended on the preferences of people, their true preferences would need to be known, which would defeat the whole point of the experiment[3].

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[3] This raises an interesting point: if consumer choices depend upon the procedure, which procedure reveals their true preferences would need to be known and, to determine this, so would their true preferences. The problem is compounded if there is noise in the subject's responses; repeated observations would be necessary, and subjects would learn about the nature of the items from which they were choosing.

The experiment could have followed the lead of Besedes *et al*. (2015), who addressed a similar issue but from a different perspective[4]: their options were lotteries, cleverly chosen, so that they could be objectively ranked through *dominance*. This study also opted to use lotteries but focused on choosing ones that could be ranked by *riskiness* (details as to how risk was defined and options were chosen shall be provided further on). This selection influenced the inferences that could be made, as described below.

To do this, the inference procedure must be anticipated and, in particular, the stochastic assumptions made in the econometric analysis (Section 4). It is assumed that the decision-maker (DM) is an expected utility maximiser and has a Constant Relative Risk Aversion utility function, which is stochastically more risk averse (Wilcox, 2011); the coefficient of relative risk aversion is denoted by r. As always, in the analysis of experimental data, there is noise in the subjects' responses, and this noise must be modelled in some way. To do this, the Random Preference Model[5] (RPM) is followed and it is assumed that r is random over decisions and subjects. More specifically, it is assumed that r is normally distributed with mean μ and standard deviation σ; for each procedure, we estimate μ and σ.

The premise is that, in making any decision, the DM draws at random a value of r from the distribution and uses that value in their decision. As μ and σ are estimated for each procedure, it can be seen how noisy each procedure is (with σ) and how risk-averse they are, on average, (with μ) for each procedure. The true values of μ and σ are not known, but a comparison of the different procedures can be made.

The results show that the distribution of risk attitude differs across different procedures. Procedures with a greater number of subsets (m), which require more decisions, are noisier. Moreover, a smaller number of options within each subset (n/m) made the subjects, on

[4] The main point of their research is to investigate whether making decisions sequentially is better than making decisions simultaneously, when faced with large choice set. The purpose of this experiment is to investigate how people behave in sequential procedures and whether there is a trade-off between the two stages.

[5] We get similar results if we assume the Random Utility Model (RUM).

average, less risk averse. The crucial conclusion is that the procedure **does** indeed matter. It affects the (average) risk aversion and the noisiness of the subjects' responses.

This study is organised as follows: Section 2 describes the experimental design in detail, Section 3 contains the experimental procedures and data details, Section 4 discusses the estimation from econometric specifications, Section 5 analyses the results and insights of the data, and Section 6 draws conclusions.

2. Experimental design

The discussion of the experimental design begins with a discussion on the *type* and *number* of the options, from which the subjects are asked to choose. Regarding the type of options used, ideally (as we have already noted) they would be options for which the subjects' preferences are known. Physical goods seemed appropriate, but the subjects' true preferences would need to be known. This rules out physical goods with many dimensions, as this involves knowing at least *n-1* parameters where *n* is the number of dimensions. Moreover, as this is an experiment in which it is postulated that the procedure influences choice, the procedure eliciting participants' true preferences would also need to be known. This seems, *ex ante*, to be impossible.

Another option could have been to follow the procedure adopted in Besedes *et al*.'s (2015) experiment, which used lotteries as the options. Moreover, they used lotteries where the ranking of the subjects' preferences should have been clear, as lotteries were chosen by dominance[6] – so if subjects respected dominance, their preferences were known. However, and more crucially, the dominance was not obvious – so noise was introduced into subjects' behaviour – if a subject chose one option over another, it did not necessarily mean that the subject preferred the first option.

This experiment follows Besedes *et al*.'s (2015) in its use of lotteries, but the lotteries used in this study are described in a significantly simpler way. Moreover, instead of selecting options

[6] In other words, if the lotteries are denoted by A, B, C, and so on, they were chosen so that A (first-order stochastically dominates) B, B (first-order stochastically dominates) C, etc.

according to dominance, they were selected through ***riskiness***[7]. As riskiness, in this context, is not defined, it was operationalized by assuming individuals have a Constant Relative Risk Aversion–Stochastically More Risk Averse (CRRA-SMRA) utility function, as explained below.

Regarding the number of options, the inspiration for this research is that of the modern online shopping environment, which consistently produces a considerable number of available options. To better mimic this environment, a reasonably large number of options for this computer-based experiment were required to reflect the possible issue of choice overload. However, they also needed to be such that they could all be simultaneously displayed on the computer screen. This limited the number of options to 24.[8]

Lottery design

A 24-option choice set was created. For simplicity in portrayal and understanding, all selections were considered as two-outcome lotteries. All lotteries had one outcome x_0 in common while the other outcome x_i and the associated probability p_i varied. Let χ_i denote a lottery which gives a payoff of x_i with probability p_i and a payoff of x_0 with probability $1-p_i$, where, as we will see, $x_0 < x_1 < x_2 < \ldots < x_{24}$ and $p_0 > p_1 > p_2 > \ldots > p_{24}$.

A core concept used is that of constant relative risk aversion (CRRA) utility function which displays the property of stochastically more risk averse (SMRA)[9] (Wilcox, 2011):

$$U(x) = \frac{u(x) - u(z_1)}{u(z_2) - u(z_1)}$$

[7] In other words, if the lotteries are denoted by A, B, C, and so on, they were chosen so that A is less risky than B, B is less risky than C, etc.

[8] In talking about choice overload, one may be concerned that a total of 24 options is not large enough to induce choice overload. However, the purpose of this research is to investigate whether sequential procedure matters and to study the tradeoff between subsets and wish list, rather than how sequential procedures mitigate the choice-overload effect.

[9] The more common constant relative risk attitude function is not monotone in respect to the risk involved (Apesteguia & Ballester, 2018). SMRA solves this problem and enables us to rank lotteries by level of risk, which means that a more risk-averse individual will prefer the less risky lottery.

where the utility function $u(.)$ takes the CRRA form $u(x)=\frac{x^{1-r}}{1-r}$. When r=0, the individual is risk-neutral, when r>0, the individual is risk-averse and, when r<0, the individual is risk-loving; an increase in r represents an increase in risk aversion.

To evaluate indifference between any two lotteries i and j, a set of $r^*_{i,j}$ $(i,j=1,\ldots,24, i\neq j)$ is introduced. More specifically, for any two lotteries $\chi_{i,j}, i,j=1,\ldots,24, i\neq j$ there exists an $r^*_{i,j}$ such that $p_i u(x_i)+(1 \quad p_i)u(x_0)=p_j u(x_j)+(1 \quad p_j)u(x_0)$. In other words, at this value of r, the DM is indifferent between the two lotteries.

Formally, for indifference between lottery i and lottery j, it is required (after some manipulation) that:

$$p_i\left(\frac{u(x_i)-u(z_1)}{u(x_2)-u(z_1)}-\frac{u(x_0)-u(z_1)}{u(x_2)-u(z_1)}\right)=p_j\left(\frac{u(x_j)-u(z_1)}{u(x_2)-u(z_1)}-\frac{u(x_0)-u(z_1)}{u(x_2)-u(z_1)}\right)$$

that is $$p_i\left(\frac{x_i^{1\ r^*_{i,j}} \quad z_1^{1\ r^*_{i,j}}}{z_2^{1\ r^*_{i,j}} \quad z_1^{1\ r^*_{i,j}}} \quad \frac{x_0^{1\ r^*_{i,j}} \quad z_1^{1\ r^*_{i,j}}}{z_2^{1\ r^*_{i,j}} \quad z_1^{1\ r^*_{i,j}}}\right)=p_j\left(\frac{x_j^{1\ r^*_{i,j}} \quad z_1^{1\ r^*_{i,j}}}{z_2^{1\ r^*_{i,j}} \quad z_1^{1\ r^*_{i,j}}} \quad \frac{x_0^{1\ r^*_{i,j}} \quad z_1^{1\ r^*_{i,j}}}{z_2^{1\ r^*_{i,j}} \quad z_1^{1\ r^*_{i,j}}}\right)$$

that is $$p_i(x_i^{1\ r^*_{i,j}} \quad x_0^{1\ r^*_{i,j}})=p_j(x_j^{1\ r^*_{i,j}} \quad x_0^{1\ r^*_{i,j}})$$

or $$p_j=p_i\frac{(x_i^{1\ r^*_{i,j}} \quad x_0^{1\ r^*_{i,j}})}{(x_j^{1\ r^*_{i,j}} \quad x_0^{1\ r^*_{i,j}})} \tag{1}$$

To rank the 24 options[10] in terms of attractiveness by risk aversion, a set of $r^*_{i,j}$ and x_i is fixed and 24 lotteries, based on equation (1), are designed. We put that j=i+1, and the computation of the lotteries started from p_1=1. The experiment started with $r^*_{i,i+1}$ at 2.85 and decreased in steps of -0.2 to -1.75.[11] To keep the lotteries across the seven procedures in the same levels

[10] Lotteries in different procedures differ but are based on the same set of r^*. Details can be found in Appendix A

[11] Most experimental and empirical evidences show that people tend to be risk averse. Thus, we designed more risk-averse options than risk-loving ones.

of risk, the same $r^*_{i,i+1}$ was used in all seven procedures. The set of *x* was varied across procedures to stop subjects from simply memorising the options. For example, the highest possible payoff in Procedure 1 varies from 10 ECU[12] to 102 ECU in steps of 4, with the associated probability decreasing from 1 to 0.2; in Procedure 2, the lowest possible payoff varies from 10 ECU to 101 ECU, with the associated probability decreasing from 1 to 0.14 (details of the 24 lotteries in each procedure can be found in Appendix A). These 24 options all have one payoff in common, equal to 6 ECU and they differ in the remaining payoff and in the probabilities of achieving the two payoffs. The higher is the value of the other payoff, the lower is its probability. There is one lottery with a certain outcome, while all the others possess an element of risk.

Choice process assumed

The purpose of designing lotteries in terms of a set of fixed *r** is so that something about the risk attitude can be inferred from each decision.

In the choice process of subjects under this experimental design, a random preference framework is assumed. It is also assumed that the DMs have SMRA-CRRA preferences with risk attitude *r*, which is randomly distributed over decisions and subjects with a mean μ and variance σ^2. For a given set of options, their valuations depend upon the value of *r*. For example, suppose that a DM chooses option χ_k from an ordered[13] subset $\{\chi_i, \chi_j, \chi_k, \chi_l\}$, with a set of $r^* = \{r^*_{i,j}, r^*_{j,k}, r^*_{k,l}\}$; .We can infer from this that the risk attitude with this decision must be between $r_{j,k}{}^*$and $r_{k,l,}{}^*$. This will be discussed further in the estimation section when we discuss the econometric specification.

3. Experimental implementation and data

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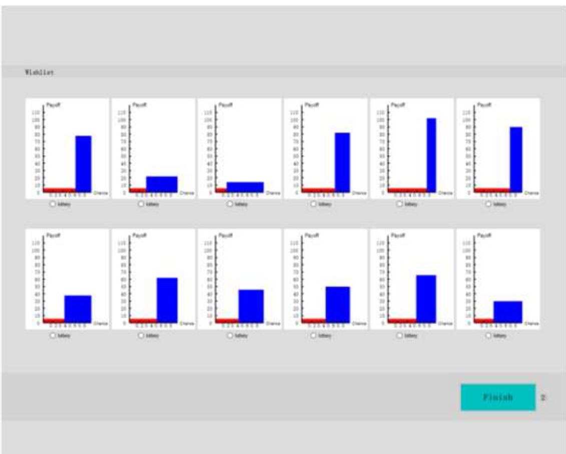
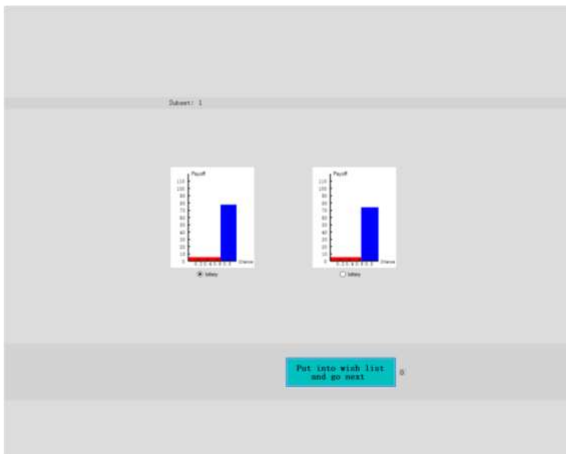
[12] All the payoffs mentioned in this experiment are in Experimental Currency Units (ECUs). The exchange rate between ECUs and pounds is given as 1 ECU = £0.47

[13] Ordered by *r**.

The purpose of this research is to investigate how different procedures influence behaviour; this is achieved through the distribution of r used in each procedure. The structure of the experiment is relatively close to that of Besedes *et al.* (2015), though the basic story has been extended into seven different procedures. In Procedure 1, 24 lotteries were displayed on one screen, and subjects were asked to choose their most preferred lottery out of the 24 options. For procedures 2 to 7, 24 lotteries were divided into a number m (12, 8, 6, 4, 3, or 2), creating subsets each containing $24/m$ (respectively 2, 3, 4, 6, 8, and 12) lotteries. The number of m varies from procedure to procedure. The m subsets were shown on the screen sequentially and each subject was provided with all seven different procedures. With each of these procedures, subjects were asked to choose their most preferred lottery in each subset, from the *24/m* lotteries in the subset, and place it in their wish list. At the end of all m subsets, participants had *24/m* options in their wish list; they were then asked to choose their most preferred lottery from those in their wish list. This was their final decision in that procedure. For each decision, subjects had to wait a minimum of 5 seconds before confirming their choice, in an attempt to prevent random selection. The procedures were displayed on the screen in random order. The lotteries within each subset were displayed randomly and the experimental software was designed by mimicking the online shopping environment. Figure 1 is a screenshot of one example of the Subset stage and one example of the Wish List stage. This experiment was run using purpose-written software, written in Visual Studio.



Screenshot of Subset stage in Procedure 2



Screenshot of Wish List stage in Procedure 2

Figure 1. Experimental screenshot

Each lottery was portrayed in a two-dimensional figure where the y-axis represents the possible outcomes and the x-axis represents the probabilities of the outcomes. As has already been mentioned, each lottery had just two possible outcomes – for this discussion, they shall be called x_0 and y – with respective probabilities $1-p$ and p. This lottery was portrayed by two columns, one blue and one red (as shown in Figure 2 below). The height of the red column shows the outcome x_0 and its width shows the probability $1-p$. The height of the blue column shows the outcome y and its width shows the probability p. One particular advantage of this method of portrayal is that the total area of the two columns shows the expected outcome of the lottery.

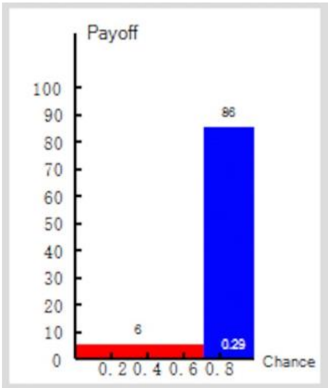


Figure 2. Lottery portrayal

This experiment was incentivised in the following way: at the end of the experiment, after a subject had responded to all seven procedures, each subject drew a disc out of a bag containing discs numbered 1 to 7. The number on the disc determined on which procedure of the experiment the subject's payment would be determined. The software recalled their lottery choice with that procedure, the subjects then played out that lottery. As mentioned earlier, the lotteries were all two-outcome lotteries with differing payoffs and probabilities. Thus, the lottery that determined their payment was a lottery leading to a payoff of x_i with a probability p_i and a payoff of 6 with a probability ($1-p_i$). The possible highest payoff x_i and the probability p_i depended on the subject's final decision. To play out the lottery, a spinning device was used. Each subject's final decision could be represented by a disc. This disc had a proportion of p_i coloured blue and a proportion of (1-p_i) coloured red, where p_i *is* the chance of winning the larger amount. Each subject spun the disc and where it came to rest determined their payment.

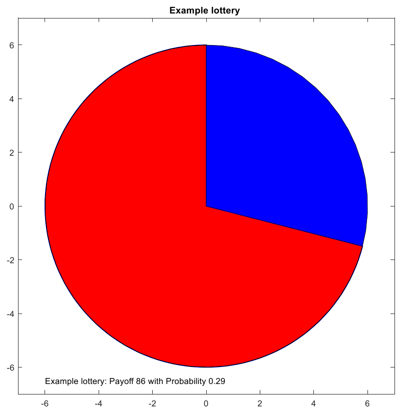


Figure 3. Payment disc portrayal[14]

Through *hroot*, 155 subjects from the University of York (mainly students) were invited to participate in this study. The average payment per subject was £18.30. Subjects took, on average, less than one hour to complete all seven procedures. In procedure 1, 155 observations were received (one decision for each subject), 2,015 observations were received for Procedure 2 (thirteen decisions for each subject), 1,240 observations for Procedure 3 (nine decisions for each subject), 930 observations for Procedure 4 (seven decisions for each subject), 775 observations for Procedure 5 (six decisions for each subject), 620 observations for Procedure 6 (four decisions for each subject), and 465 observations were received for Procedure 7 (three decisions for each subject). In general, most participants chose options 11 to 14 as their final decisions: in procedures 1, 5, and 6, most subjects chose option 11 as their final decisions, with a frequency of 25.2%, 20%, and 25.2% respectively; most subjects chose option 14 as their final decision in procedures 2 (20%) and 3 (18.1%); option 13 was chosen

[14] The lottery presented in Figure 3 is the same as that of Figure 2.

most frequently in procedures 4 (14.8%) and 7 (17.3%). Figure 4 shows the frequency distribution of the chosen option in each procedure.

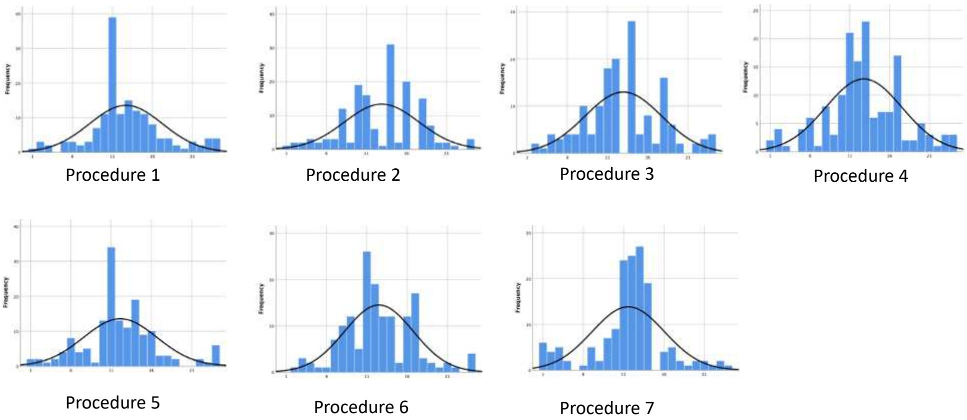


Figure 4. Detailed frequency distributions of final decisions

4. Econometric specification

The econometrics of this study focuses on risk attitude. From the choice process described in Section 3, the likelihood of contributions for subjects' choices in each observation was obtained. It was assumed that *r* has a normal distribution with two parameters: the mean μ and the standard deviation σ. Maximum likelihood estimation was applied to estimate the parameters of μ and σ and the choice process was modelled as described. The selected lottery was denoted by χ_i . The contribution to the likelihood depends upon the choice set (which varies by procedure and through each procedure). Suppose the choice set is $\{\chi_1, \chi_2, \chi_3, \ldots \chi_N\}$. A crucial indicator in our design is the *r** which determines the indifference point between two adjacent lotteries (by adjacent, we mean in the context of that particular choice). It is supposed in what follows that the choice set $\{\chi_1, \chi_2, \chi_3, \ldots \chi_N\}$ is *ordered* in terms of riskiness, from the safest χ_1 to the riskiest χ_N .

Next, the contribution to the likelihood of each decision is specified. Each decision depends upon the risk attitude in the context of that specific choice. There are three conditions leading to different probability expressions:

If the decision χ_i is the riskiest option χ_N in the choice set (that is *i=N*), the probability that it is chosen is the probability that *r* is less than $r^*_{N-1,N}$, and hence the contribution to the likelihood is

$$P(r \le r^*_{N-1,N}) = F(r^*_{N-1,N}, \mu, \sigma)$$

where *F(.,μ,σ)* denotes the cumulative distribution of a normal with mean μ and standard deviation σ and $r^*_{N-1,N}$ denotes the indifference point between lottery *N-1* and lottery *N*.

If the decision χ_i is the *least* risky option in the choice set (that is, *i=1*), the probability that it is chosen is the probability that *r* is greater than $r^*_{1,2}$, and hence the contribution to the likelihood is

$$P(r > r^*_{1,2}) = 1 - F(r^*_{1,2}, \mu, \sigma)$$

If it is neither the least risky nor the most risky (that is, *i* is between 1 and *N*), the probability that it is chosen is the probability that *r* is between $r^*_{i,j+1}$ *and* $r^*_{i-1,j}$ and hence the contribution to the likelihood is：

$$P(r^*_{i,j+1} r \le r^*_{i-1,j}) = F(r^*_{i-1,j}, \mu, \sigma) - F(^*_{i,j+1}, \mu, \sigma)$$

As discussed, each procedure consists of two stages: the Subset stage and the Wish List stage. It is worth noting that, in a given procedure, the number of options in each subset and in the wish list is different. Decisions in different stages may be not equally weighed mentally in terms of the stage type and the size of each choice set. The greater the number of options in each subset, the fewer the number of options in the Wish list. Intuitively, the decision from larger choice sets may be more important, because it requires the processing of more options. The simplest way to explain this intuition is that each option represents an opportunity and choosing from larger choice sets involves a higher opportunity cost. From another perspective, the decision for the wish list may play a more important role, because it is the last chance to decide, although it is unclear whether this is true or not. To some extent, the length of decision time can reflect how much attention is paid to option evaluation. Table 1, which shows the average time taken to make decisions, could provide some clues:

Table 1. Average time taken to make decision

	Number of options in wish list	Number of options in each subset	Average decision time in each subset(s)	Average decision time in wish list	Total(s)
Procedure 1	-	-	-	-	75.13
Procedure 2	12	2	10.16	51.68	173.60
Procedure 3	8	3	13.24	31.97	137.89
Procedure 4	6	4	16.91	28.58	130.04
Procedure 5	4	6	24.41	19.65	117.29
Procedure 6	3	8	28.78	20.38	106.72
Procedure 7	2	12	36.65	15.62	88.92

When the number of available options in each subset and wish list increases, the length of time taken to make decisions becomes longer. On the other hand, with the same number of options, the average staying time at the Wish List stage is always longer than that of the Subset stage[15]. For example, the Wish List stage in Procedure 2 has the same number of options as the Subset stage of Procedure 7. Moreover, the average staying time (51.68 seconds) in the Wish List stage of Procedure 2 is longer than in the Subset stage of Procedure 7 (36.65 seconds).

[15] The decision time on all subjects are significantly longer at the level of 5% in the Wish List stage when comparing the Subset stage of Procedure 2 and the Wish List stage of Procedure 7； when comparing the Subset stage of Procedure 3 and the Wish List stage of Procedure 6； when comparing the Subset stage of Procedure 6 and the Wish List stage of Procedure 3； and when comparing the Subset stage of Procedure 7 and the Wish List stage of Procedure 2. The results are not significant for a comparison of the Subset stage of Procedure 4 and the Wish List stage of Procedure 5; nor when comparing the Subset stage of Procedure 5 and the Wish List stage of Procedure 6. Even though they are not all statistical significance, this is not the main results we want to discuss. The purpose of mentioning the decision time is to find relevant clues for our assumed weighting criteria.

Taking these two assumptions into consideration, two weighted versions[16] are proposed, providing different weights to decisions in both the Subset and Wish List stages, depending on the size of the respective consideration set (CSW) or stage type (STW):

1. **Version 1 (CSW): decisions made from larger choice sets are more important.**

The number of options in each subset is *24/m* and the number of options in the wish list is *m*. Thus, the weight of each decision in the Subset stage is *24/m*1/(24+m),* while the weight of the decision in the Wish List stage is *m/(24+m).*

2. **Version 2 (STW): the decision made in the Wish List stage is more important.[17]**

This assumes that the final decision is the last chance and, therefore, more attention is paid to it. Subsequently, the decision in the Wish List stage should be more important and, therefore, given a *1/2* weighting. For a given procedure, the weight of each decision in each subset is *1/(2*m)*.

5. Estimation and Discussion

Estimation of the parameters μ and σ^2 across all subjects in the RPM specification[18] was carried out by maximum likelihood[19]. The estimation results of the unweighted version and

[16] Even though evidence of the decision time in the different stages shows that subjects seem to consider decisions in the wish list more carefully, we cannot exclude the influence of the number of options and their possible interactive influences. We cannot know which is true. Our purpose is to propose two weighted stories to capture different patterns.

[17] If this is true, to what degree the decision in the wish list more important is hard to measure. The purpose of this research is to investigate how procedure matters, not the effect of the wish list; however, this could be a question to consider for future research.

[18] To test the robustness of our results, estimation based on the random utility model (RUM) was also run; it produced similar results to those of RPM. Details can be found in Appendix C.

[19] The maximum likelihood estimations were programmed in Matlab.

two weighted versions are reported in Table 2. Estimations on the Subset stage and the Wish List stage were also performed to compare the differences between the two stages; these results are reported in Table 3.

It should be noted that a comparison of the estimation results for Procedure 1 and the results for the other Procedures is not really meaningful, as Procedure 1 was simultaneous, while all the others were sequential. The initial purpose of including Procedure 1 was to capture any potential insights in terms of the difference between simultaneous and sequential procedures. However, this was not the focus of this research.

Table 2. Estimation based on different versions

			STW weighted version		CSW weighted version		Unweighted version	
	Number of subsets	Number of options in each subset	μ	σ2	μ	σ2	μ	σ2
Procedure 1	-	-	0.6	0.93	0.6	0.93	0.60	0.93
Procedure 2	12	2	0.27	1.19	-0.58	2.1	0.08	1.37
Procedure 3	8	3	0.44	1.15	0.29	1.44	0.36	1.31
Procedure 4	6	4	0.61	1.11	0.63	1.29	0.63	1.25
Procedure 5	4	6	0.69	1.07	0.62	1.15	0.61	1.17
Procedure 6	3	8	0.67	1.02	0.62	1.11	0.61	1.15
Procedure 7	2	12	0.81	1.01	0.76	1.01	0.71	1.01

Crucially for this paper, Table 2 shows that the distributions of the risk parameter for different procedures are different, regardless of whether the weighted or the unweighted version is used. How procedure matters is shown more clearly in Figures 5, 6, and 7, where the implied distributions are graphed. More importantly, a clear pattern can be found in terms of the numbers of subsets and the number of options within each subset: from Procedure 2 to Procedure 7, the standard deviation becomes smaller with the increasing number of options within the subset (decreasing number of subsets), indicating that decision making in procedures 2 to 7 become less noisy. Moreover, the mean becomes larger from procedure 2 to 7, showing that subjects tend to become more risk averse as the number of options within each subset increases.

The results clearly show that procedure matters in terms of risk attitude. In particular, subjects seem to become more risk averse as they progress from procedures 2 to 7 and the size of subset increases. Results confirming that procedure matters are not surprising – one can easily find similar evidence from context-dependent preference research. In this field, two main results stem from the research: the reference-dependent preference effect and the choice set effect. The latter supports the main hypothesis of this study: why procedure matters. Evidence from neurobiology and neuroeconomics shows that humans encode information in choice sets, depending not only on the value of the stimuli but also on the context (Carandini, 2004). In particular, they evaluate options based on their normalised value, which neural response associates with a particular value, depending on its relative position in the distribution of values, under a given context (Louie *et al.*, 2011). We do not know how a human brain encodes this normalisation process when the distribution of available options varies, but we could get some inspiration from a normalisation algorithm applied in machine learning and neural network models, such as Min-Max scaling. In machine learning, the purpose of data normalisation is to convert different sources of data sets with varying scales and units into the same standard, even within a range of [0, 1]. Human brains, like supercomputers, may do something similar to rescale values when evaluating options under different contexts and scales. Simply put, each procedure with a different composition of options in the Subset stage changes the choice set which changes the context and scale of choice. From procedures 2 to 7, the Subset stage has features spanning varying degrees of magnitude and range; to illustrate this further, consider one possible subset in procedure 3 {A: 10,1; B: 17, 0.72; C: 24,0.65}, with corresponding $r_{i,j}^*$ ={-0.2, 0}, and another possible subset in procedure 4 {D: 10,1 ; E: 16, 0.73; F: 22, 0.66; G: 28, 0.63}, with corresponding $r_{i,j}^*$={-0.2, 0, 0.2}. The scale of risk between the riskiest option and the safest option in the two subsets is different. In this example, the largest corresponding $r_{i,j}^*$ from both subsets could be rescaled as 1, based on the Max-Min scaling formula[20], and they would become the same. Thus, the level of risk in option C and G become the same because they have the same position given their context. However, whether or not the range of $r_{i,j}^{*}$ in each subset of different procedures guides subjects in a specific decision-making direction still cannot explicitly be answered and may present an interesting topic for future research. A potential research question, as to whether decreasing the Min–Max scale of each choice set will influence people to perceive less risk, also arises.

Regarding the variations of standard deviation, the results clearly show that participants' preference becomes more inconsistent as the number of subsets increases, requiring subjects to make more decisions – it is a trade-off between making more decisions and making decisions from more available options. Research on decision-fatigue in decision-making and psychology provides support for these results, as they refer to the deteriorating quality of decisions made by an individual after a long session of decision-making. From procedures 7 to 2, the greater the number of subsets within a procedure, the greater the frequency of evaluation and decision-making, which deplete energy and lead to decision-fatigue.

[20] The formula for normalization is :r'=（r-rmin)/(rmax-rmin).

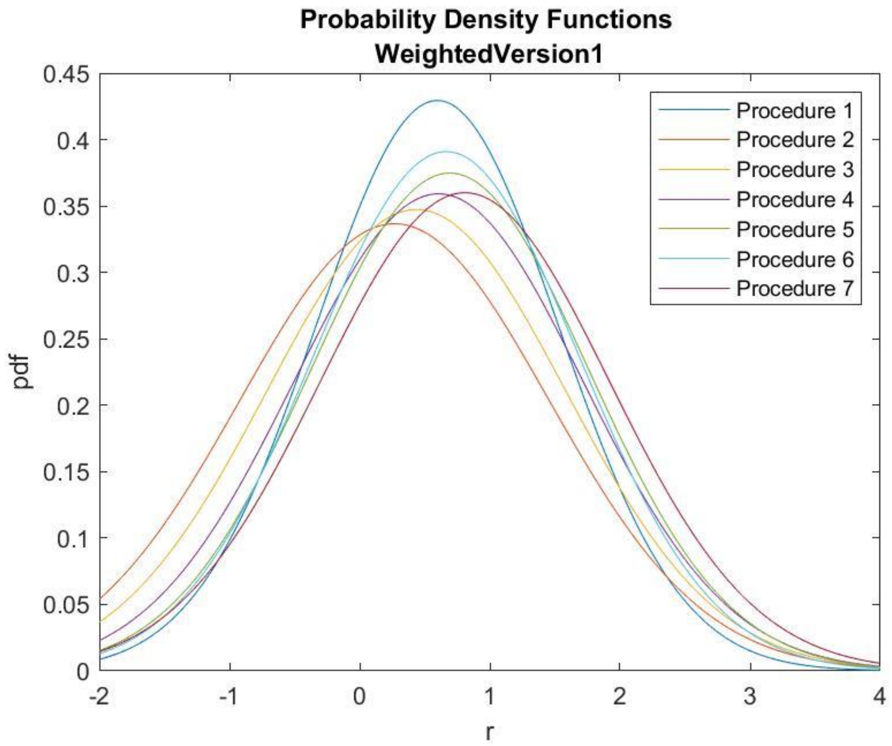


Figure 5. Estimated distribution based on STW weighted version

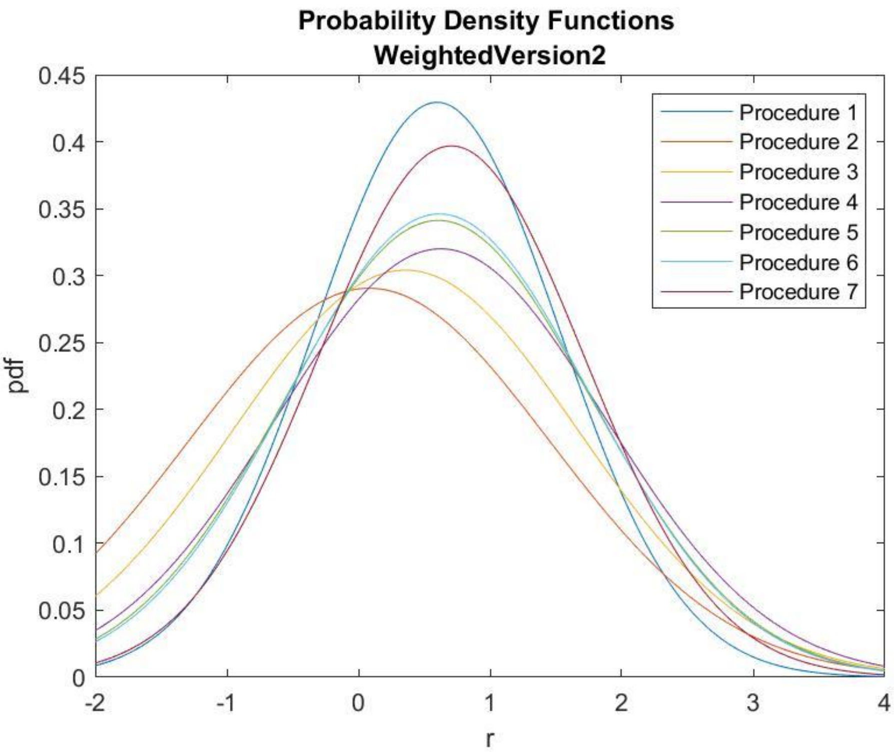


Figure 6. Estimated distribution based on CSW weighted version

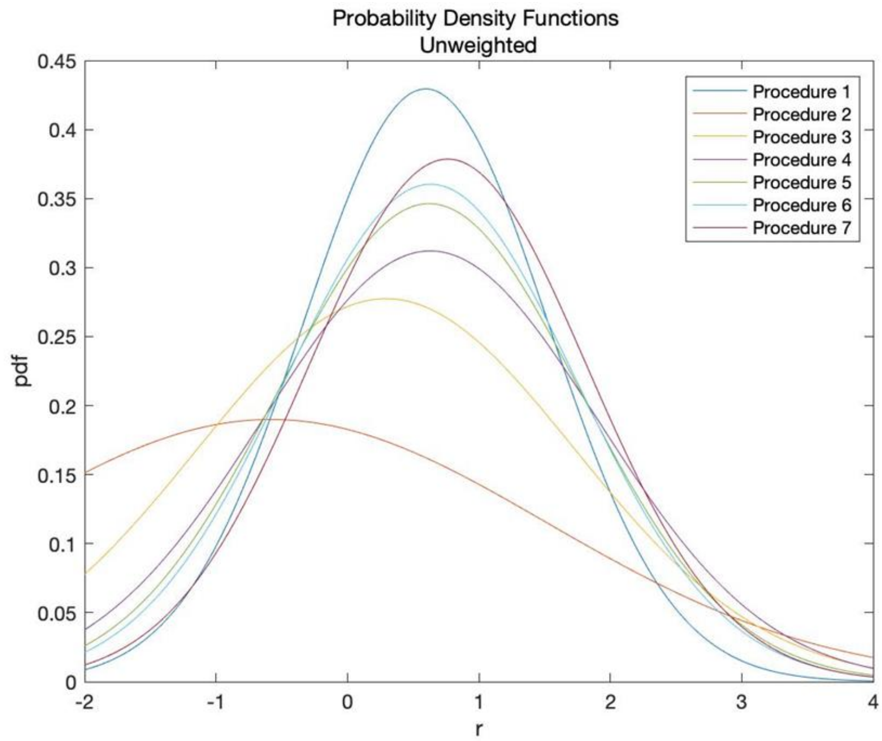


Figure 7. Estimated distribution based on unweighted version

Table 3. Separate estimations on the Subset stage and Wish List stage

			Subset		Wish list	
	Number of subsets	Number of options in each subset	μ	σ2	μ	σ2
Procedure 2	12	2	-1.24	2.97	0.53	0.91
Procedure 3	8	3	0.22	1.57	0.52	0.94
Procedure 4	6	4	0.64	1.37	0.58	0.95
Procedure 5	4	6	0.57	1.21	0.78	0.92
Procedure 6	3	8	0.60	1.19	0.72	0.81
Procedure 7	2	12	0.69	1.00	0.70	0.80

As hypothesised, the Wish List stage and the Subset stage seem to carry different mental weighting. If the parameters of the Subset stage and the Wish List stage are estimated separately, they clearly show that decisions in the Subset stage are noisier than in the Wish List stage. Even though the standard deviation is decreasing, with respect to the decreasing number of subsets from procedures 2 to 7, the standard deviation of the wish list is always smaller than the subset and shows a slightly decreasing trend within a limited range. As predicted, subjects seemed to pay more attention to the final decision, perhaps because this is the last chance to make a decision. One question that arises here is whether subjects apply different strategies in the Subset stage to the Wish List stage. The choice process could be to select something satisfactory from each subset and then carefully trade-off in the wish list.

In this case, the choice overload does not exist. As mentioned earlier, Besedes *et al.* (2015) investigated a similar procedure from a choice overload perspective. Choice overload in larger choice sets leads to negative influences on the decision-making process, due to overwhelming the information processing capacity of humans. Following this line of reasoning, the results of Procedure 1, which displayed 24 options at the same time, should be noisier than any of the sequential procedures. However, the results are in direct contrast to this, when compared with the sequential procedures. In this study, the number of options in the Subset stage increases as it progresses from Procedure 2 through to Procedure 7, while the number of options in the Wish List stage decreases. In looking at the results in the Subset stage and the Wish List stage separately, we should find noisier results in the Subset stage and less noisy results in the Wishlist stage from Procedure 2 to 7. However, this is not the case. To date, most choice overload research [21] uses consumer goods experiments, which consist of different decision-making standards and heuristics. A further potential research question arises, as to the existence of choice overload in the risk aversion context. Intuitively, risk aversion may trigger more attention to the decision-making process.

[21] A comprehensive literature review in experiments on choice overload is found in Chernev *et al*. (2005). Few of them are concerned with decision-making under risk.

6. Conclusions

Past research and theories have attempted to model different decision-making sequential procedures from different perspectives. Apesteguia and Ballester (2012) proposed three decision-making strategies, with the notion of a sequential behaviour guided by routes, namely: status-quo bias, rationalisability by game trees, and sequential rationalisability. They argued that decision-making is route-dependent. Similar to their sequential rationalisability, Manzini and Mariotti (2007) proposed a Rational Shortlist Method: they describe a two-stage rational behaviour based on 'fast and frugal' heuristics. Tyson (2011) also modelled a shortlisting behaviour, in which two attention filters and sequential criteria are applied in two-stage decision-making procedures. Even though these studies focused on investigating preference reversal and bounded rationality, they all operated under a similar presumption – that procedure matters. One point that should be noted is that the procedures used in these studies are all endogenous with roots in behaviour, whereas the context of this current study is exogenous, focusing on changing the information present in procedures with the absence of decision-making patterns. This logic is similar to the framing effect, the anchor effect, and nudging, all of which influence behaviour using an external force. Although the latent variable behind these behaviours in the results of this current study cannot be explicitly identified, some explanation for them can be found in behavioural economics and psychology.

In contrast, this study extends the general binary comparison into an extensive context – it does not assume people will make decisions following any specific strategies or route, although they may apply some decision-making strategies, such as pairwise comparisons (Manzini & Mariotti, 2007) or elimination procedures (Gigerenzer & Todd, 1999) in this context. The multi-choice environment can better reflect the real environment in which people now make choices; however, the decision-making trajectories and strategies become more untraceable. Considering the openness of the environment, this stochastic model with simple parameters can capture the dynamic behavioural changes, something that is not possible with the standard model.

The original motivation in designing this experiment was to understand online decision-making behaviours. It can be seen that the notion of sequential procedures suggests some behaviour patterns useful for online companies or website designers; however, the results also suggest a new line for future research. The number of options within each stage influence the level of risk attitude, while the number of pages influences the average consistency of decision-making. Furthermore, the Wish List stage appeared to attract greater attention, a result that could potentially be an opportunity for marketing strategy investigation.

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Appendix A: **lottery details**

procedure 1			procedure 2				procedure 3				procedure 4				procedure 5				procedure 6				procedure 7		
10	1.00	6	0.00	10	1.00	6	0.00	10	1.00	6	0.00	10	1.00	6	0.00	10	1.00	6	0.00	10	1.00	6	0.00	10	1.00
14	0.77	6	0.23	13	0.80	6	0.20	15	0.75	6	0.25	14	0.77	6	0.23	16	0.73	6	0.27	17	0.72	6	0.28	17	0.72
18	0.70	6	0.30	16	0.72	6	0.28	20	0.68	6	0.32	18	0.70	6	0.30	22	0.66	6	0.34	24	0.65	6	0.35	24	0.65
22	0.65	6	0.35	19	0.68	6	0.32	25	0.64	6	0.36	22	0.65	6	0.35	28	0.63	6	0.37	31	0.62	6	0.38	31	0.62
26	0.62	6	0.38	22	0.64	6	0.36	30	0.61	6	0.39	26	0.62	6	0.38	34	0.61	6	0.39	38	0.60	6	0.40	38	0.60
30	0.60	6	0.40	25	0.62	6	0.38	35	0.59	6	0.41	30	0.60	6	0.40	40	0.59	6	0.41	45	0.59	6	0.41	45	0.59
34	0.58	6	0.42	28	0.59	6	0.41	40	0.58	6	0.42	34	0.58	6	0.42	46	0.57	6	0.43	52	0.57	6	0.43	52	0.57
38	0.56	6	0.44	31	0.57	6	0.43	45	0.56	6	0.44	38	0.56	6	0.44	52	0.56	6	0.44	59	0.56	6	0.44	59	0.56
42	0.54	6	0.46	34	0.55	6	0.45	50	0.54	6	0.46	42	0.54	6	0.46	58	0.54	6	0.46	66	0.54	6	0.46	66	0.54
46	0.53	6	0.47	37	0.53	6	0.47	55	0.52	6	0.48	46	0.53	6	0.47	64	0.53	6	0.47	73	0.53	6	0.47	73	0.53
50	0.51	6	0.49	40	0.51	6	0.49	60	0.51	6	0.49	50	0.51	6	0.49	70	0.51	6	0.49	80	0.51	6	0.49	80	0.51
54	0.48	6	0.52	43	0.49	6	0.51	65	0.49	6	0.51	54	0.48	6	0.52	76	0.49	6	0.51	87	0.49	6	0.51	87	0.49
58	0.46	6	0.54	46	0.47	6	0.53	70	0.46	6	0.54	58	0.46	6	0.54	82	0.47	6	0.53	94	0.47	6	0.53	94	0.47
62	0.44	6	0.56	51	0.43	6	0.57	73	0.45	6	0.55	61	0.45	6	0.55	84	0.46	6	0.54	95	0.47	6	0.53	95	0.47
66	0.42	6	0.58	56	0.39	6	0.61	76	0.43	6	0.57	64	0.43	6	0.57	86	0.45	6	0.55	96	0.46	6	0.54	96	0.46
70	0.39	6	0.61	61	0.36	6	0.64	79	0.42	6	0.58	67	0.41	6	0.59	88	0.44	6	0.56	97	0.46	6	0.54	97	0.46
74	0.37	6	0.63	66	0.33	6	0.67	82	0.40	6	0.60	70	0.38	6	0.62	90	0.43	6	0.57	98	0.45	6	0.55	98	0.45
78	0.34	6	0.66	71	0.29	6	0.71	85	0.38	6	0.62	73	0.36	6	0.64	92	0.41	6	0.59	99	0.45	6	0.55	99	0.45
82	0.31	6	0.69	76	0.26	6	0.74	88	0.36	6	0.64	76	0.34	6	0.66	94	0.40	6	0.60	100	0.44	6	0.56	100	0.44
86	0.29	6	0.71	81	0.24	6	0.76	91	0.34	6	0.66	79	0.32	6	0.68	96	0.39	6	0.61	101	0.43	6	0.57	101	0.43
90	0.26	6	0.74	86	0.21	6	0.79	94	0.32	6	0.68	82	0.30	6	0.70	98	0.37	6	0.63	102	0.42	6	0.58	102	0.42
94	0.24	6	0.76	91	0.19	6	0.81	97	0.30	6	0.70	85	0.27	6	0.73	100	0.35	6	0.65	103	0.41	6	0.59	103	0.41
98	0.22	6	0.78	96	0.16	6	0.84	100	0.28	6	0.72	88	0.25	6	0.75	102	0.34	6	0.66	104	0.40	6	0.60	104	0.40
102	0.20	6	0.80	101	0.14	6	0.86	103	0.26	6	0.74	91	0.23	6	0.77	104	0.32	6	0.68	105	0.39	6	0.61	105	0.39

Appendix B **: instructions and software screenshot**

Instructions

Preamble

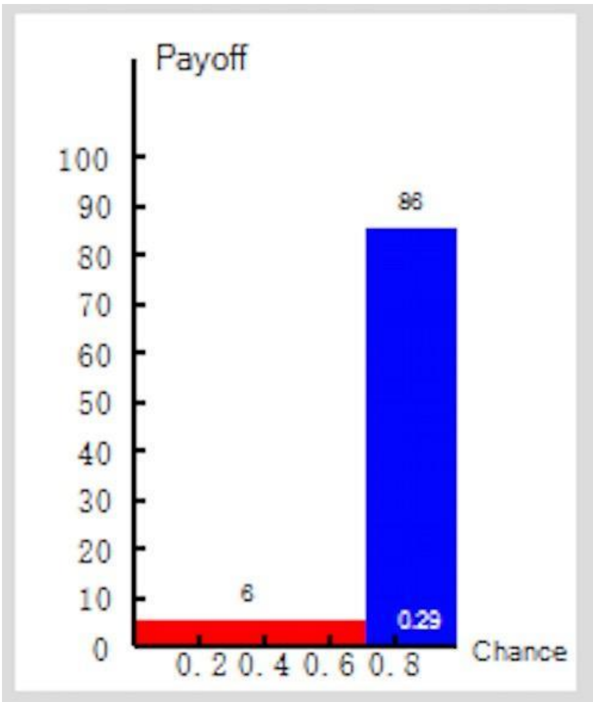
Welcome to this experiment. These instructions are to help you to understand what you are being asked to do during the experiment and how you will be paid. The experiment is simple and gives you the chance to earn a considerable amount of money, which will be paid to you in cash after you have completed the experiment. The payment described below is *in addition* to a participation fee of £2.50 that you will be paid independently of your answers. All the payoffs mentioned in this experiment are in Experimental Currency Units (ECUs). The exchange rate between ECUs and pounds is given by 1 ECU= £0.47. Please do not talk to others during the experiment and please turn off your mobile phone.

The Experiment

The experiment is interested in how you make choices with different choice *procedures*. There are no right or wrong answers. There are 7 different procedures. With each of these procedures you will be asked to choose your most preferred *lottery*. At the end of all seven procedures, one of the seven procedures will be randomly selected; the software will recall your lottery choice with that procedure, and then you will play out that lottery. The outcome of playing out this lottery will lead to a *payoff* to you, and we shall pay this to you in cash, plus the participation fee of £2.50, immediately after you have completed the experiment. How all this will be done will be explained below. We start by describing a generic lottery. Then we describe the seven procedures; you will not necessarily get them in the order that they are described; they will be presented in a random order in the experiment.

A Generic Lottery

We describe now what we mean by a 'Generic Lottery'. We represent each lottery visually. We do this in two different ways. The first is that which is used throughout the experiment; the second is that which is used in the payoff. The first portrayal is the following:



It is simplest to explain this in terms of the implications for your payment if this is selected to be played out at the end of the experiment. There are two rectangles coloured differently; these represent the two possible outcomes of the lottery. The x-axis represents your chance of getting a specific payoff; the y-axis represents the payoff you would get. So the horizontal length of one rectangle specifies the probability of getting a specific payoff, this latter being indicated by the vertical height of this rectangle. In the example above, the horizontal length of the red rectangle is 0.71, and the vertical height is 6; for the blue rectangle, the horizontal length is 0.29 and the vertical height is 86. So this means that you have a 0.71 chance to get a payoff of 6 ECU (£2.82) and 0.29 chance to get a payoff of 86 ECU (£40.42) if this lottery is played out at the end of the experiment.

These 24 options all have one payoff in common (represented by the height of the red rectangle) equal to 6 ECU. They differ in the other payoff (represented by the height of the blue rectangle) and the probabilities of getting the two payoffs. You will see that the higher is the value of the other payoff, the lower is its probability. Visually, the higher the blue rectangle is, the narrower it is. There is one lottery with a certain outcome, while all the others are risky. You should note that the higher the value of the other (blue) payoff, the riskier is the lottery. So, as the value of the other (blue) payoff increases, so does the riskiness of the lottery.

The different procedures

We now describe the seven different procedures in this experiment. Remember that you might not get them in the order presented here. With all procedures, lotteries will be presented as described above.

Procedure 1

In this Procedure, you will see 24 lotteries displayed on one screen and you will be asked to choose your most preferred lottery out of the 24. You will not be allowed to express your decision until at least five seconds have elapsed, but you can take as long as you like.

Procedures 2 to 7

With these procedures 24 lotteries are divided into a number *m (*which will be *2, 3, 4, 6, 8* or *12)* subsets each containing *24/m* (respectively 12, 8, 6, 4, 3 or 2) lotteries. The number *m* will vary from Procedure to Procedure, as specified below. With each of these procedures, you will be asked to choose, for each of the *m* subsets, your most preferred lottery from the *24/m* (namely 12, 8, 6, 4, 3, or 2) lotteries shown in the subset, and put it into your *Wish List*. At the end of all *m* subsets, you will have *24/m* options in your Wish List; you will then be asked to choose your most preferred lottery from those in your Wish List. This will be your final decision on that procedure. You cannot put more than one option into your Wish List from each subset; and you will not be able to go back to change what you have put into Wish List once you press the 'next' button. You will not be allowed to express your decision until at least five seconds have elapsed, but you can take as long as you like. These 7 procedures will be played randomly. For example, *your* procedure 2 is not necessary the Procedure 2 listed below.

Procedure 2

Here *m* is 12, so there will be 12 subsets each containing 2 lotteries and your Wish List will contain 12 lotteries.

Procedure 3

Here *m* is 8, so there will be 8 subsets each containing 3 lotteries and your Wish List will contain 8 lotteries.

Procedure 4

Here *m* is 6, so there will be 6 subsets each containing 4 lotteries and your Wish List will contain 6 lotteries.

Procedure 5

Here *m* is 4, so there will be 4 subsets each containing 6 lotteries and your Wish List will contain 4 lotteries.

Procedure 6

Here *m* is 3, so there will be 3 subsets each containing 8 lotteries and your Wish List will contain 3 lotteries.

Procedure 7

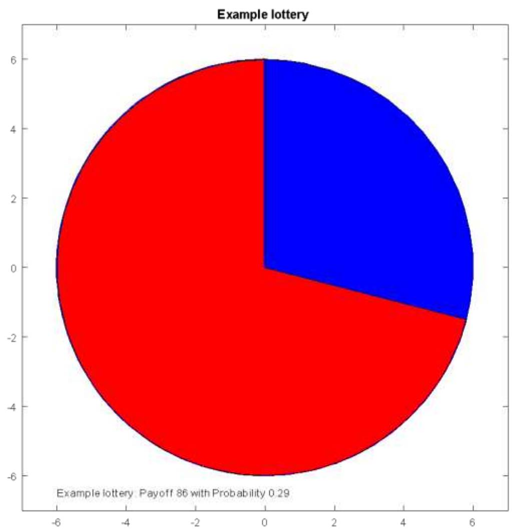
Here *m* is 2, so there will be 2 subsets each containing 12 lotteries and your Wish List will contain 2 lotteries.

The Payment Procedure

When you have completed the experiment, one of the experimenters will come to you. You will then be asked to go into an adjoining room for payment. There will be another experimenter, who has on their computer all the decisions that you took. Then the following procedure will be followed.

1. First you will draw – without looking – a disk out of a bag containing disks numbered from 1 to 7. The number on the disk will determine on which Procedure of the experiment your payment will be determined, where the Procedures are numbered as in these Instructions (and not in the order that they were presented to you).
2. The experimenter will recall your final decision with that Procedure. This will be a lottery leading to a payoff of *x* with probability *p* and to a payoff of 6 with probability *(1-p)*, where *x* and *p* depend on your final decision.

3. The experimenter will then show you a disk representing your final decision; this is the second way of portraying a lottery. This disk will have a proportion *p* coloured blue and a proportion *(1-p)* coloured red, where *p* is the chance of winning the larger amount. Below there is an example, for the same lottery as that shown above, in which there is a 0.29 chance of getting 86 ECU and a 0.71 chance of getting 6 ECU. (Blue represents 86 ECU and Red 6 ECU).



There will be a 'spinning device' in the payment room; the experimenter will put this on top of the disk; and you will spin it. Where it comes to rest determines your payment. This will all be explained in the payment room.

The show-up fee of £2.50 will be added to the payment as described above. You will be paid in cash, be asked to sign a receipt and then you are free to go.

If you have any questions, please ask one of the experimenters.

Appendix C: **estimation based on the Random Utility Model**

The Random Utility Model is another way to model randomness in behaviour. The choice process under RUM is different from that with the RPM as it assumes a deterministic risk attitude *r*, with noise entering through the DM's calculation of the expected utility of each option. Suppose that the true expected utility of some option is U_i* (based on the true value or *r*) , then, under the RUM, DM's take decisions on the basis of the *calculated* expected utility $U_i = U_i* + \varepsilon_i$ where ε_i is N(0,σ^2) , U_i* is the true utility, and it is assumed that the ε_i are independent across decisions. It follows that $U_i - U_j$ is normal with mean $U_i* - U_j*$ and variance $2\sigma^2$. Thus the probability that $U_i > U_j$ is equal to the probability that $U_i* - U_j* > 0$. This is the probability that $U_i - U_j$ is positive given that it comes from a normal distribution with mean $U_i* - U_j*$ and variance $2\sigma^2$.

We apply the Maximum Likelihood Estimation method to estimate the parameters *r* and $\sigma^{2.}$ The estimated results are similar to those from the RPM. From procedure 2 to procedure 7, subjects tend to be more risk averse. Procedures with more subsets are noisier.

Table C1. Estimation on RUM

	number of subsets	number of options	r	σ^2
procedure 1	0	24	0.50	0.50
procedure 2	12	2	0.41	0.05
procedure 3	8	3	0.66	0.05
procedure 4	6	4	0.68	0.04
procedure 5	4	6	0.90	0.03
procedure 6	3	8	1.04	0.02
procedure 7	2	12	1.72	0.01