Studies of Decision Making Under Risk and Uncertainty

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Abstract

This dissertation experimentally examines how the decision-making under risk of individuals' is influenced by choice procedures, decision context, frames and exogenous information. The first study investigates a sequential procedure (to ease the choice overload problem) by presenting the products in sequential pages and requesting the decision-maker 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. The second study proposes an *Asymmetric Risk Averse Quantal Response Equilibrium (QRE)* extension of a cheap-talk model in lemon market. This extension better explains the observed deviations in Siegenthaler (2017)'s experiment from theoretical predictions. The third study experimentally investigates how the composition of choices and menus influences the decision-making in a two-stage context - one in which the decision-maker must first choose a menu from a set of menus, and secondly must choose an item from the chosen menu. Several choices of menu theories have been applied to identify how different types of decision-makers are influenced by different menu frames. The fourth study experimentally examine how social information, personal experience and professional suggestions interactively influence subjects' decisions under risk. This study found an important factor: *information congruence* between information sources significantly affects the evolution of the decisions in a group.

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Finally to my grandfather, in my loving memory.

Declaration

Some of the work addressed in this thesis has previously been published and presented in conference. They are listed as follows:

Lin, L. (2022). Does Risk-Aversion Explain Behaviour in a Lemon Market? , published by Bulletin of Economic Research

Lin, L. (2020). Does the procedure matter?, published by Journal Of Behavioral and Experimental Economics, 90, 101618. doi: 10.1016/j.socec.2020.101618l.

Lin, L and Hey John (2022)Can the frame of menu influence how people make the decision?, paper presented to Foundations of Utility and Risk Conference (FUR).

All the work contained within this thesis represents the original contribution of the author, except where otherwise indicated.

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Chapter 1 Introduction

Numerous studies have studied the deviation between classical economic theories and actual behaviour in the real world: humans have biased beliefs, have limited rationality, and do not always have well-defined preferences; these contradict the assumptions of neoclassical economics (Thaler, 2018). Indeed, classical economic theories build essential blocks for any kind of economic analysis. Incorporating behavioural factors into economic analysis enables us to characterize better and predict actual behaviour in the real world. Tversky and Kahneman's early work (1982) concludes that people make predictable errors driven by different patterns of heuristics and bias, which will lead the observed behaviour departure from rational decision-making theoretical predictions. After that, abundant research explores a variety of behaviour factors and applies them to improve the explanatory power of economic models.

Following this vein, four studies in this dissertation analyse economic behaviour under risk based on behavioural factors and effects and examine how decision-making changes in various circumstances. These studies are mainly inspired by two of most well-known lines of behavioural economics, *nudging theory* (Thaler & Sunstein,2021) and p*rospect theory* (Kahneman & Tversky, 1979). The concept "*nudges*" is first proposed by Thaler and Sunstein's research (2021) on how decisions on health, wealth and happiness can be positively affected by choice architecture (i.e., the choice environment). For example, the most classical example on the default effect on increasing the tendency of choosing a particular pension plan. For traditional economic theories, a default clicked option will not influence decisions. This has been applied by governments' policy making. *Prospect theory* is a descriptive model and explains how people perceive the risk is influenced by the frames of risky choices. Following this, the *framing* effect attracts more and more economists' attention. Two lines of research deliver similar message – the people's preferences and decision-makings are not static, and they can be influenced by the decision procedure, information presentation format, context, etc.

Chapter 2 is motived by the choice overload effect, which has been widely documented as choice aversion when the decision-maker (DM) is overwhelmed by too many options. In this information exploration era, there are more and more available options. 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. 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.

Chapter 3 applies risk aversion and behaviour stochasticity. Siegenthaler (2017) proposes an ingenious solution to the lemon market adverse selection problem. He incorporates 'cheap talk' in which sellers send out costless and non-binding messages informing potential buyers of the quality of their goods; these messages could be true or false. This segments the market into several submarkets. Potential buyers need to decide which submarket to enter and what price to bid for the goods. Sellers then decide whether to accept the bid or not. He experimentally tests his model and finds that the comparative static results align with his theory, though the data does not fit exactly the model. Indeed, he does not fit the model to the data. His theory assumes risk-neutral decision-makers (DMs). Two reasons why the fit is not perfect may be that the DMs are not risk-neutral and not perfectly rational. In this note, we report the results of fitting an *Asymmetric Risk*

Averse Quantal Response Equilibrium (QRE) extension of his model to his data, and we find that the extension fits well. We show that the results are consistent with the market evidence and shed light on future research on lemon markets.

Chapter 4 examines the frame effect on menu choice. The frame effect refers to a cognitive bias wherein the presentation of choices influences DM's decisions. Several theories of decision-making in a two-stage context - one in which the decision-maker (henceforth DM) must first choose a menu from a set of menus, and secondly must choose an item from the chosen menu - have been proposed. While standard decision theory analyses this problem using backward induction (and assuming stable preferences), several new theories postulate that the DM might anticipate that his/her preferences may change and that the DM might well take this into account when deciding which menu to choose. Leading amongst such new theories is *self-control theory,* which incorporates the notion that the DM might anticipate temptation at the second stage, and hence might exercise self-control at the first stage to avoid being tempted. The other theories suggest that the DM might prefer flexibility in the second stage, and this may affect the choice at the first stage. This suggests that the composition of choices in the menus, and the *frames* of menu sets, may affect the choice of the menu. Our experiment shows that this is so.

Chapter 5 considers confirmation bias wherein the DM tends to seek evidence to confirm their own beliefs and examines herding and limited rationality to explain behaviour in a learning experiment. Specifically, this study experimentally examines how diverse information sources interactively influence subjects' decisions. Subjects are asked to take in each round a decision on how much insurance to buy to mitigate the lost (experimental) income caused by the occurrence of a (bad) event. The probability of this event varies across subjects, is unknown to the subject, and subjects have initially to learn about it through (1) *their personal experience of the event*. After 10 rounds, however, information is provided in the form of two other sources: first, an (2) *official suggestion* as to the optimal amount of insurance to buy; second, information as to the (3) *most popular decision* (the 'social consensus') amongst the other subjects in the experiment over the preceding rounds. Unlike typical social learning and belief updating studies, our information sources are multiple, and information exposure is not exogenous: subjects can select whether they want to receive the official suggestions and/or the social consensus. To test our hypotheses, we have two treatments that differ in the way that official advice is generated; the first is where the official advice is aimed at the average of the population (the 'general suggestion'); and the second is where the official advice is personalised to the individual (the 'personalised suggestion'). Our main research found an important factor: *information congruence* between the information sources significantly affects the evolution of the decisions in a group. Moreover, we surprisingly found stronger irrational herding (following the social consensus) when the official suggestions were personalised. Our results shed light on public advice mechanisms.

Chapter 2 Does the Procedure Matter?[1]

2.1 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 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

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[1] This paper has been accepted by Journal of Behavioral and Experimental Economics. This experiment was funded by the Risk, Evidence and Decision Making Priming Fund of the University of York.

[2] June 29, 2020.

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 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].

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 2.4). 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

[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.

[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.

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 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 2.2 describes the experimental design in detail, Section 2.3 contains the experimental procedures and data details, Section 2.4 discusses the estimation from econometric specifications, Section 2.5 analyses the results and insights of the data, and Section 2.6 draws conclusions.

2.2 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

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

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 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

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[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.

[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.

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]

2.2.1 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):

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

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 $r^*_{i,j}$ $(i, j = 1,2, \ldots, 24, i \neq j)$ is introduced. More specifically, for any two lotteries

[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.

$x_{i,j}$ $(1,2,\ldots,\ 24, i \neq j)$ there exists an $r_{i,j}^*$ such that $p_i u(x_i) + (1-p_i)u(x_0) = p_j u(x_j) + (1-p_j)u(x_0)$. 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:

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

that is

$$p_i\left(\frac{x_i^{1-r_{i,j}^*}-z_1^{1-r_{i,j}^*}}{z_2^{1-r_{i,j}^*}-z_1^{1-r_{i,j}^*}}-\frac{x_0^{1-r_{i,j}^*}-z_1^{1-r_{i,j}^*}}{z_2^{1-r_{i,j}^*}-z_1^{1-r_{i,j}^*}}\right)=p_j\left(\frac{x_j^{1-r_{i,j}^*}-z_1^{1-r_{i,j}^*}}{z_2^{1-r_{i,j}^*}-z_1^{1-r_{i,j}^*}}-\frac{x_0^{1-r_{i,j}^*}-z_1^{1-r_{i,j}^*}}{z_2^{1-r_{i,j}^*}-z_1^{1-r_{i,j}^*}}\right)$$

that is

$$p_i\left(x_i^{1-r_{i,j}^*}-x_0^{1-r_{i,j}^*}\right)=p_j\left(x_j^{1-r_{i,j}^*}-x_0^{1-r_{i,j}^*}\right) \quad \text{or}$$

$$p_j = p_i\left(\frac{x_i^{1-r_{i,j}^*}-x_0^{1-r_{i,j}^*}}{x_j^{1-r_{i,j}^*}-x_0^{1-r_{i,j}^*}}\right) \tag{2.1}$$

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 (2.1), are designed. We put that *j*=*i*+1, and the computation of the lotteries started from p_1=1. The experiment started with $r_{i,j}^*$ 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 of risk, the same $r_{i,i+1}^*$ was used in all seven procedures. The set of *x*

[10] Lotteries in different procedures differ but are based on the same set of *r**.

[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.

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. 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.

2.2.2 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.

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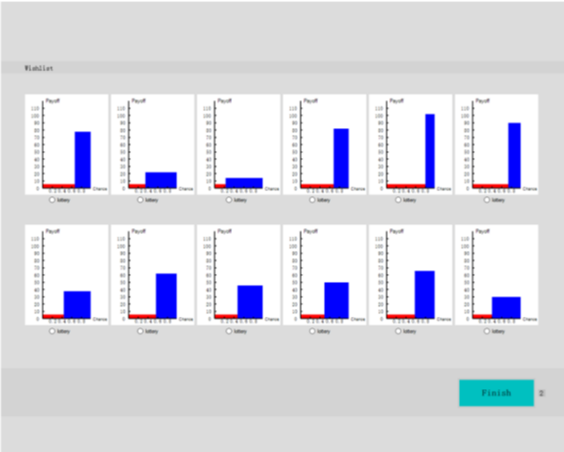
12 All the payoffs mentioned in this experiment are in Experimental Currency Units (ECUs). The exchange rate between ECUs and pounds is given as 1 ECU = £0.47

13 Ordered by r^*.

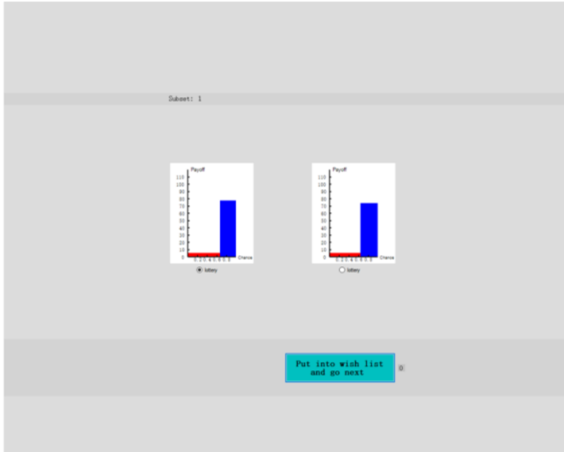
2.3 Experimental implementation[14] and data

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 2.1 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.

[14] Details of experiment instruction see appendix D1.



Screenshot of Subset stage in Procedure 2



Screenshot of Wish List stage in Procedure 2

Figure 2.1 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 $1\text{-}p$ and p. This lottery was portrayed by two columns, one blue and one red (as shown in Figure 2.2 below). The height of the red column shows the outcome x_0 and its width shows the probability $1\text{-}p$. 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.

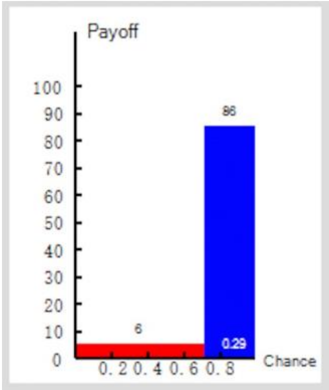


Figure 2.2 Lottery portrayal

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.

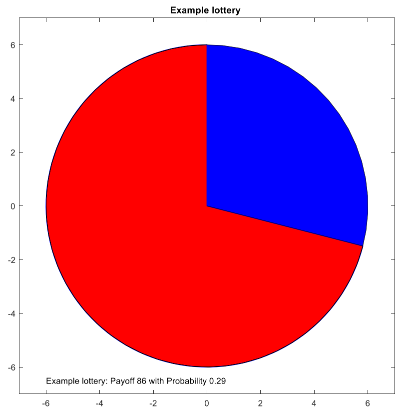


Figure 2.3 Payment disc portrayal15

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 most frequently in procedures 4 (14.8%) and 7 (17.3%). Figure 2.4 shows the frequency distribution of the chosen option in each procedure.

[15] The lottery presented in Figure 2.3 is the same as that of Figure 2.2.

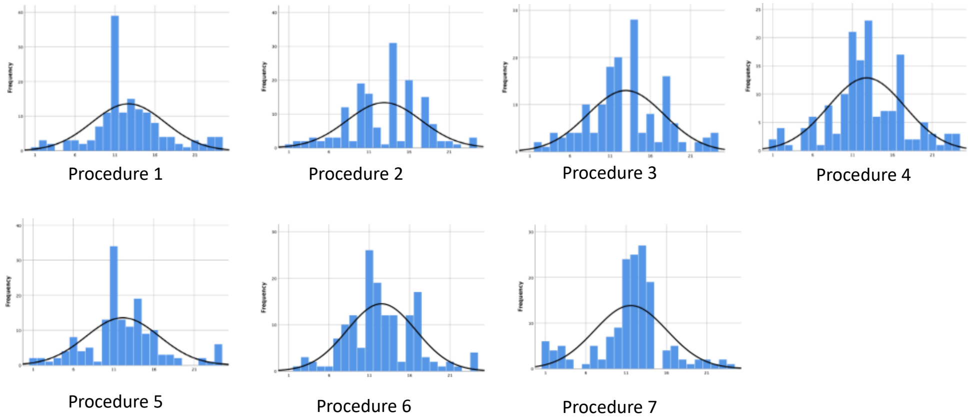


Figure 2.4 Detailed frequency distributions of final decisions

2.4 Econometric specification

The econometrics of this study focuses on risk attitude. From the choice process described in Section 2.3, 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 $\{\chi_1, \chi_2, \chi_3, \dots, \chi_N\}$. 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 $\{\chi_1, \chi_2, \chi_3, \dots, \chi_N\}$ 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_1 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

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

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

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

If it is neither the least risky nor the riskiest (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:

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

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 2.1, which shows the average time taken to make decisions, could provide some clues:

	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

Table 2.1 Average time taken to make decision

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[16]. 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

[16] 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.

Procedure 7 (36.65 seconds).

Taking these two assumptions into consideration, two weighted versions[17] 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):

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).*

Version 2 (STW): the decision made in the Wish List stage is more important.[18]

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)*.

2.5 Estimation and Discussion

Estimation of the parameters μ and σ^2 across all subjects in the RPM specification[19] was

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[17] 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.

[18] 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.

[19] 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 A.

carried out by maximum likelihood[20]. The estimation results of the unweighted version and two weighted versions are reported in Table 2.2. 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 2.3.

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.

Crucially for this paper, Table 2.2 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 2.5, 2.6, and 2.7, 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.

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

			STW weighted version		CSW weighted version		Unweighted version	
	Number of subsets	Number of options in each subset	μ	σ^2	μ	σ^2	μ	σ^2
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

Table 2.2 Estimation based on different versions

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[21], 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

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

lead to decision-fatigue.

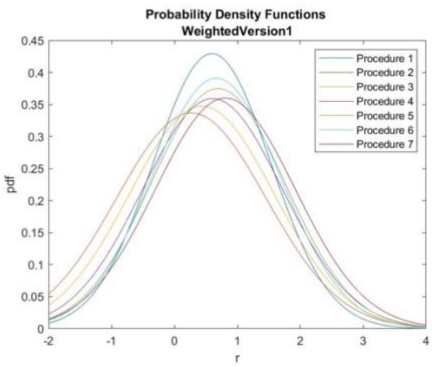

Figure 2.5 Estimated distribution based on STW weighted version

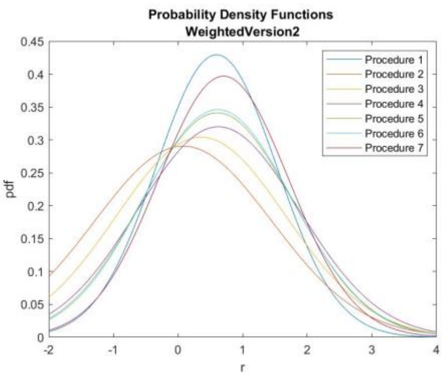

Figure 2.6 Estimated distribution based on CSW weighted version

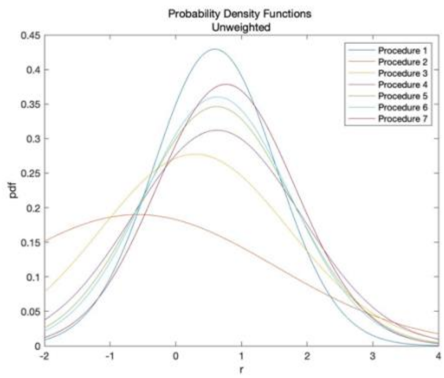

Figure 2.7 Estimated distribution based on unweighted version

			Subset		Wish list	
	Number of subsets	Number of options in each subset	μ	σ^2	μ	σ^2
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

Table 2.3 Separate estimations on the Subset stage and Wish List stage

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[22] 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.

2.6 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,

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[22] 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.

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.

Chapter 3 Does Risk-Aversion Explain Behaviour in a Lemon Market?[23]

3.1 Introduction

The problem of asymmetric information impeding trade between sellers and buyers has been a topic of interest ever since Akerlof (1970). The adverse effect of asymmetric information produces a market known as a 'lemon market'. Researchers have investigated various market mechanisms to eliminate the 'lemon problem', such as liability rules and contracts of the agent in trade (DeJong *et al.*, 1985), costly signalling (Miller and Plott, 1985), and reputation building (Lynch *et al.*, 1986). Most of these are *exogenous* mechanisms closely related to instructions and government policy. In recent years, a different perspective – in terms *of endogenous* market segmentation – has emerged (Mailath *et al.*, 2000; Fang, 2001; Kim, 2012; Siegenthaler, 2017). This perspective envisages a context in which sellers of different quality levels self-sort. Then buyers make decisions depending on the stated quality distribution. Following this line, Kim (2012) proposes an endogenous market segmentation model with cheap talk before trading; he shows an interesting result: cheap talk can effectively moderate the adverse selection problem of a lemon market.

A particular paper that follows this route is Siegenthaler (2017). His model considers a market in which there are six buyers and six sellers. Three of the sellers have a high quality good; three have a low quality good. Each seller individually claims whether their product is high or low quality. This creates two submarkets – high and low. However, there is no

[23] This paper is published by Bulletin of Economic Research. This experimental data was provided by Dr. Simon Siegenthaler. I also appreciate two anonymous referees' inspiring suggestions.

way to verify the sellers' claims, so the six buyers in the market do not know the quality of any of the sellers' products. Each buyer selects a submarket, randomly selects a seller in that submarket and offers a price to the seller according to the number of sellers claimed in the submarket high. If the seller is happy with the offer, it is accepted, and trade takes place. Note that low-quality sellers could claim their products are high quality in the hope of achieving a greater profit. The experimental results show that this cheap-talk mechanism before trading improves market efficiency and partially alleviates the lemon problem. However, the experimental data does not fit the model exactly: both the proportion of buyers choosing the low-quality submarket and the probability of sellers claiming to be low-quality exceeds the theoretical prediction. More importantly, theoretical mixed strategies predict buyers and sellers will choose submarket high more often in some cases, while the experiment observed the opposite tendency.

Two possible explanations for this departure from the theory are the assumptions in Siegenthaler's model that subjects are (1) risk-neutral and (2) perfectly rational. The fact that the data do not fit the theory *exactly* may reflect the violation of these two assumptions. As to assumption (1), we derive the equilibrium assuming that the subjects in the experiment are not risk-neutral. Risk aversion puts curvature into the utility function and hence diminishes the effects of a relatively high payoff associated with one decision. As far as (2) is concerned, this is not surprising – there is always noise in experimental data. We need to add a story about the stochastic nature of the data. To do this, we use the widely accepted Quantal Response Equilibrium (QRE) story, which builds noise around the equilibrium. We estimate this risk-averse story with QRE as our stochastic specification and see if it fits the data better than Siegenthal's risk-neutral story.

As we have already noted, we are going to assume that the subjects in the experiment were not risk-neutral. However, as we will explain in detail shortly, we found some restrictions on the normal risk-averse QRE model to explain the observation of the subjects' tendency to choose submarket low in this experiment. Inspired by the properties of the model, we consider a mental factor less investigated, namely, *asymmetric* risk tolerance towards submarkets high and low (following the spirit of contextual utility theory) to account for behaviour in this experiment. A considerable body of research has shown that attitude toward risk is stimulated by contexts, such as framing effect and mental accounting. Choosing submarket high is risky, enabling access to a high-quality product with possible loss, while submarket low presents a choice of zero loss. Some research showed that presenting outcomes as gains tends to induce risk aversion, while presenting outcomes as losses tends to induce risk-seeking (Kühberger *et al.*, 1999). In addition, the terms "good quality" and "low quality" may have different semantic sentiments for some subjects. Buying a low-quality product from a claimed high-quality market might have a lower perceived value than buying a low-quality product in the low-quality market, even at the same price. Interestingly, such asymmetries generate substantially different predictions and outperform the homogenous symmetric risk-averse models. More importantly, the results are consistent with market evidence and suggest insights into possible solutions to problems in lemon markets.

This note is organised as follows: the next section describes the experiment. Section 3.2 details the experimental and theoretical background of Siegenthaler's paper. Sections 3.3 discuss the econometric detail and the estimation of the homogeneous risk-averse QRE model in this context; Section 3.4 explores the model properties and the restrictions of the homogeneous risk-averse QRE model; Section 3.5 extends the analysis to an asymmetric risk-averse QRE and discusses the results. Section 3.6 concludes.

The core theoretical background is the same as Siegenthaler's. If a reader wants to understand the details of the whole model and the experimental design, the reader should read Siegenthaler (2017). The core of this note is centred on how the asymmetric risk-averse QRE fits the data from an econometric perspective and further reflects the prediction power and theoretical value of the cheap-talk mechanism in the lemon market.

3.2 Experiment and theoretical background

We adopt Siegenthaler's notation. The market is designed as follows: there are n_S sellers with n_L=3 low-quality sellers and n_H =3 high-quality sellers and n_B =6 buyers where n_L+ n_H = n_B. Each type of good has a reservation cost of $c_\theta = \{c_L = 0, c_H = 14\}$ and a corresponding value $v_\theta = \{v_L = 5, v_H = 19\}$ where $v_\theta > c_\theta$. The optimal strategy for both buyers and sellers is to use a mixed strategy; like Siegenthaler, we focus on the symmetric mixed strategy equilibrium. The sellers' mixed strategy is denoted by the probability $\alpha(\theta)$ to send a message θ. A submarket m_k denotes that k sellers send a message m where m={l,h}. In this case, three quality sellers will send a message l or h to form four possible market structures, i.e. l_0h_6[24], l_1h_5 , l_2h_4, and l_3h_3 . Given the announced quality distribution, the probability of a buyer choosing submarket m_k is $\beta(m_k)$.

Siegenthaler's market segmentation equilibrium is derived by starting with the buyers' choice probabilities. Sellers send messages first to claim their product types. A market structure will be formed. A buyer chooses the targeted submarket based on the sellers' messages, i.e., the observed market structure $l_k h_{n_S-k}$={ l_0h_6, l_1h_5 , l_2h_4, l_3h_3 } , considering what the other buyers will choose. The more buyers choose the same submarket, the lower the chance to match with a seller. Next, buyers offer a price based on a cumulative distribution function $F(p,\ m_k)$[25] given the submarket m_k derived from the buyers' equilibrium. Overall, a buyers' strategy is determined by the expected payoff given the probability of matching low-quality sellers in the submarket h and the probability of offer acceptance. In Siegenthaler's model, the buyers' response probability is given as the

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[24] $l_k h_{n_S-k}$ indicates there are k sellers in submarket l and $n_S - k$ sellers in submarket h .

[25] The pricing distribution is not the interest of this note. We will not go into details of the derivation.

optimal condition when they are a monopsonist. Given this, Siegenthaler shows that in equilibrium, the probability of buyers choosing submarket l is

$\beta(l_0)$=0, $\beta(l_1)$=0.29, $\beta(l_2)$=0.59 and $\beta(l_3)$=0.5[26]. In response (given these buyers' strategies), the low-quality sellers' optimal probability, $\alpha(l)$[27], that reveals their actual product type is 0.48: not all low-quality sellers reveal their actual quality. Of course, no high-quality sellers have any incentive to say that they are low quality. Overall, sellers' decisions on which submarket to enter depend on their beliefs about the buyers' and the other sellers' strategies.

The data used in this note, previously reported by Siegenthaler (2017), was obtained from 216 subjects drawn from the student population of the University of Bern. Siegenthaler's experiment consisted of four treatments, Communication First, No Communication, Matching First and Matching First II[28]. We have used the data of Communication First[29] where cheap talk is allowed. This treatment contains 1440 observations by allocating 72 subjects into 6 sessions (6 subjects as buyers and 6 subjects as sellers) and running the 20 periods of experiment for each session. In the Communication First treatment sellers

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[26] The choice probability for $\beta(m_k)$ is given by $\sum_{i=0}^{n_B-1}\beta(l_k)^i(1-\beta(l_k))^{n_B-1-i}\binom{n_B-1}{i}\left(1-\frac{1}{k}\right)^i U_l(l_k) = \sum_{i=0}^{n_B-1}\beta\left(h_{n_S-k}\right)^{n_B-1-i}(1-\beta\left(h_{n_S-k}\right))^i\binom{n_B-1}{i}\left(1-\frac{1}{k}\right)^i U_h(h_{n_S-k})$ where $U_m(m_k)$ is the expected payoff of choosing this submarket.

[27] The choice probability to send message m is derived by $\sum_{i=0}^{n_L-1}\alpha(l)^i(1-\alpha(l_k))^{n_l-1-i}\binom{n_L-1}{i}\left(1-\frac{1}{k}\right)^i U_l(l_{i+1}) = \sum_{i=0}^{n_L-1}\alpha(h)^{n_L-1-i}(1-\alpha(h))^i\binom{n_L-1}{i}U_h(h_{n_S-i})$ where $U_m(m_k)$ is the expcted payoff in submarket m when k sellers send message m.

[28] All details of the experimental design can be found in section 3.4 of Siegenthaler .

[29] The main interest of this paper is to seek a bridge between the theoretical predictions and the observed experimental behavior. The CF treatment has the same game context as theoretical models in Siegenthaler, where sellers self-claimed their products by cheap-talk, and buyers choose a submarket and offer price to a randomly matched seller. The other treatments have different contexts.

make decisions by first sending messages to announce their quality; this creates two submarkets *l* and *h.* The six buyers choose submarket *l* or submarket *h* and make bids to the sellers in that submarket. These are either accepted or rejected by the seller. A seller can accept at most one offer. A buyer whose offer price *p* is accepted earns v_m-*p* if the quality of the good is *m* where *m* ={*l*,*h*} and v_m is the value of the product. A seller of type *m* who accepts a price *p* earns *p*-c_m where c_m the cost of the product is. Buyers and sellers who do not trade earn 0. In his experiment, the observed choice frequencies of buyers choosing submarket low in l_1h_5 is 0.52 (0.29 in theory), 0.71 in l_2h_4 (0.59 in theory), 0.54 in l_3h_3 (0.5 in theory); and the frequency of sending message *l* for low-quality sellers is 0.70 (0.48 in theory). One thing that should be noted is that the data set we use here is slightly different from that used by Siegenthaler in his initial analysis: we exclude the four groups where the buyers choose submarket low when there are not any sellers that send the message low, and where the high-quality sellers send the message low because these irrationalities are not considered in our model.

Clearly, the observations deviate from the theoretical predictions. In particular, buyers show a higher tendency to choose submarket *l* in l_1h_5 and sellers have a higher tendency to send message *l*; these are opposite to the theoretical predictions. As the equilibrium is mainly influenced by their beliefs' about others' choice probabilities and the expected payoffs of choices, a higher expected payoff in submarket *l* or a lower expected payoff in submarket *h* will transform the equilibrium, leading to a greater frequency of choosing submarket *l*. Thus, we expect the noise and risk aversion to account for this discrepancy because risk-aversion puts curvature into the utility function and hence the utility of the high payoff of submarket *h* is decreased.

3.3 Risk-averse QRE and estimation

We use the standard Logit QRE formula to incorporate noise into players' expected payoff and give the actual probabilities replacing $\beta(m_k)$ for buyers and $\alpha(\theta)$ for sellers The QRE choice probabilities are denoted by $P_{\beta(m_k)}$ for buyers and P_θ for low quality sellers .We follow Siegenthaler in computing the expected payoff of buyers and sellers.

For buyers,

$$u_{l_k} = \sum_{i=0}^{n_B-1} P_{\beta(l_k)}{}^i \left(1 - P_{\beta(l_k)}\right)^{n_B-1-i} \binom{n_B - 1}{i} \left(1 - \frac{1}{k}\right)^i U_l(l_k) \tag{3.1}$$

$$u_{h_{n_S-k}} = \sum_{i=0}^{n_B-1} (1 - P_{\beta(l_k)})^i \left(P_{\beta\left(h_{n_S-k}\right)}\right)^{n_B-1-i} \binom{n_B - 1}{i} \left(1 - \frac{1}{k}\right)^i U_h(h_{n_S-k}) \tag{3.2}$$

For low quality sellers,

$$u_l = \sum_{i=0}^{n_L-1} P_{\alpha_l}^i (1 - P_{\alpha_l})^{n_l-1-i} \binom{n_L - 1}{i} \left(1 - \frac{1}{k}\right)^i U_l(l_{i+1}) \tag{3.3}$$

$$u_h = \sum_{i=0}^{n_L-1} P_{\alpha_h}^{n_l-1-i} (P_{\alpha_h})^i \binom{n_L - 1}{i} U_h(h_{n_S-i}) \tag{3.4}$$

Where the QRE choice probabilities of buyers and low-quality sellers are given by

$$P_{\beta(m_k)}(\lambda) = \frac{exp\ (\frac{u(m_k)}{\lambda})}{exp\left(\frac{u(l_k)}{\lambda}\right) + exp\ (\frac{u(h_{n_S-k})}{\lambda})} \tag{3.5}$$

$$P_{\alpha_m}(\lambda) = \frac{exp\ (\frac{u(m)}{\lambda})}{exp\left(\frac{u(l)}{\lambda}\right) + exp\ (\frac{u(h)}{\lambda})} \tag{3.6}$$

The parameter λ is the noise parameter in the Logit specification. The Logit QRE response function varies according to the noise parameter λ. This is a measure of noise/precision in the subjects' behaviour; it takes values from 0 to +∞. When λ is close to 0, the probability is close to the Nash equilibrium as detailed in Siegenthaler (2017) indicating higher precision or low noise; when λ becomes larger, the probability tends to converge to 0.5 − indicating lower precision (effectively randomness).

To investigate if risk-aversion can explain the data, we introduce a risk attitude parameter *r* to the utility function *U*(.) in equations from (3.1) to (3.6). We follow Goeree *et al.* (2003) in extending QRE to cover risk-aversion. We use a Stochastically More Risk Averse, Constant Relative Risk Aversion (SMRA_CARA) utility function defined over the payoff *x*:

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

where the utility function $\pi(.)$ takes the CARA form $\pi(x) = \frac{(1-e^{-xr})}{r}$ if $r \neq 0$ (if r=0, $\pi(x) = x$), and where z_1 and z_2 are reference points for the SMRA transformation (see below). When $r=0$, the individual is risk-neutral, when $r>0$ risk-averse and when $r<0$ risk-loving; an increase in *r* represents an increase in risk-aversion. We should note that the SMRA transformation/normalisation (given by the equation above) of the usual CARA utility function is recommended by Wilcox (2009) to ensure that "the agent is more likely to choose the relatively safe lottery in every Mean Preserving Spread pair". Wilcox's recommendation is supported by Apesteguia and Ballester (2018), who note that the usual CARA function is not monotone with respect to the riskiness. This SMRA normalisation solves this problem and enables us to rank lotteries through their riskiness, which means that a more risk averse individual prefers the less risky lottery. It is a context-dependent transformation. The parameters z_1 and z_2[30] are two arbitrary reference points.

[30] We used $z_1 = 0$ and $z_2 = 150$ as in Wilcox's example. The estimated parameters are similar if we only use CARA utility form. But the likelihood function based on SMRA_CARA is more sensitive to the changes of risk preference which is our core parameters of interest.

In this section, we use the risk-averse QRE based on logit equilibrium and a SMRA_CARA utility function to obtain structural estimates of the risk-aversion parameter (and of the noise parameters of the buyers and sellers) using the data[31] from Siegenthaler's CF treatment. We assume all subjects have the same beliefs and the same skill level.

Having obtained the choice probabilities in expressions (3.5) and (3.6) for the sellers and the buyers respectively, we construct the log-likelihood function for the observed choice frequencies and estimate the buyers' and sellers' parameters (the risk attitude and the precision). Let us denote the number of buyers in the experiment that chose submarket *l* and h in the market structure $l_k h_{n_{S-k}}$ as $n_B^l(l_k h_{n_{S-k}})$ and $n_B^h(l_k h_{n_{S-k}})$, and the number of low-quality sellers in the experiment that chose submarket l (h) as n_S^l (n_S^h) .We do not consider the buyers-sellers role differences. Thus, the observed choice frequencies and the QRE choice probabilities of buyers and sellers are put together to compute the log-likelihood function. The log-likelihood function (which is the usual observation-weighted sum of the logarithms of the probabilities) is thus given by:

$$LogL(\lambda, r) = \sum_{x=0;y=6-x}^{3} (n_B^l(l_x h_y) \ln\left(P_{\beta(l_x)}(\lambda, r)\right) + n_B^h(l_x h_y) \ln\left(P_{\beta(h_y)}(\lambda, r)\right)) +$$
$$n_S^l \ln\left(P_{\alpha(l)}(\lambda, r)\right) + n_S^h \ln\left(P_{\alpha(h)}(\lambda, r)\right)$$

The results for the risk-averse QRE are reported in Table 3.1. Subjects show a risk-averse attitude in this context when making a decision. Even though the estimated choice

[31] Siegenthaler's data incorporates the observations about which submarket buyers and sellers choose the size of bids that buyers offer under different market structures, and the rate of trade. We only use the data about which submarket buyers and sellers. The decision on entering a submarket is the crucial point of this endogenous market segmentation that will determine how the market structure is formed. The bidding behaviour is another issue that requires further investigation. From Siegenthaler's data, we see that subjects tend toward overbidding in submarket *l,* which is consistent with Goeree and Holt's (2002) results showing a tendency toward overbidding in a relative low-cost context. This note is trying to explain the overbidding behaviour in this game. We assume that the bidding strategy does have noise, and this correctly reflects the mixed strategy of buyers' and sellers' decisions on entering a submarket.

probabilities of choosing submarket low are closer to the observed values than Nash equilibrium, behaviour could be misinterpreted as tending to be fully random as they are close to and lower than 0.5, and the behavioural tendency to choose submarket *l* cannot be captured.

	Risk attitude		logit error	Log likelihood
Estimated parameters	0.43		0.89	-720.88
Choice probabilities				
The probability of choosing submarket low	Risk-averse QRE	Nash (risk neutral)		Observed
Low-quality seller	0.56	0.48		0.70
Buyers in l_1h_5	0.46	0.29		0.52
Buyers in l_2h_4	0.52	0.59		0.71
Buyers in l_3h_3	0.50	0.50		0.54

Table 3.1 Maximum likelihood estimation

3.4 Model restrictions

Our purpose is to characterize the equilibrium in such a way as to explain the observed equilibrium and find a more precise behaviour prediction. An unresolved puzzle is still the contradiction between the observations and the theoretical predictions. Models may impose unique predictions and properties on the observations. This section discusses the restrictions that the risk-averse QRE model structure imposes on the observations.

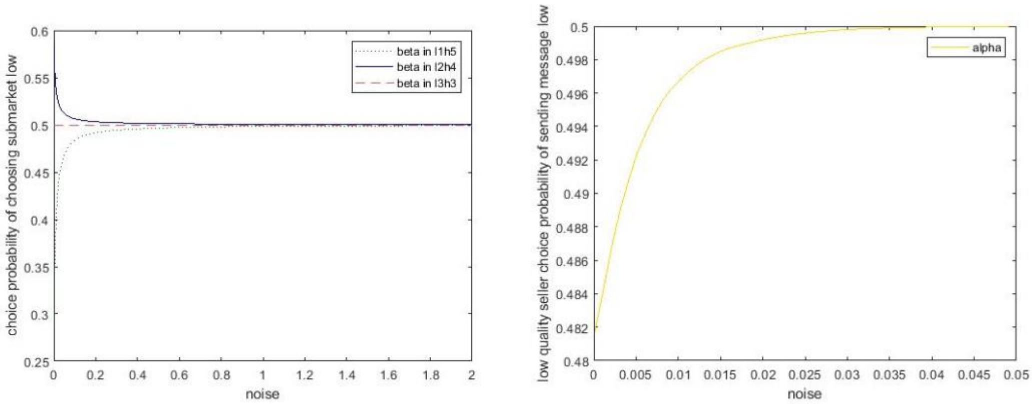

Figure 3.1 Buyers' risk-neutral QRE choice probabilities (beta) of submarket low and low-quality sellers' risk-neutral QRE choice probabilities (alpha) of submarket low

It is commonly known that the QRE value only can range from the equilibrium without noise to 0.5 (this latter indicating full randomness). If choice frequencies of submarket low are less than 0.5 without noise, the QRE cannot predict any value below 0.5. As Figure 3.1 shows, risk-neutrality predicts a choice probability between the Nash equilibrium and 0.5 (that is, totally random). Unfortunately, as Siegenthaler's experimental data shows, subjects have a higher tendency to choose submarket l. For market structure l_1h_5 the probability range (which the risk-neutral QRE can cover) for buyers to choose submarket l_1h_5 is from 0.29 to 0.5, however, the observed proportion choosing submarket l_1 in the experiment was 0.52, which is outside this range. Similarly, the percentage of buyers who chose the submarket l_2h_4 was 0.71 (0.59 in theory) and 0.54 (0.50 in theory) in l_3h_3 . For subjects who are sellers, the proportion of low-quality sellers sending message l in the experiment was 0.70; this exceeds the theoretical prediction of 0.48; it is also outside the risk-neutral QRE's prediction (Figure 3.1). This means that it is impossible to find any value of λ to fit the data. Even though we could expect that the concavity of utility with risk aversion implies a relative undervaluation of submarket high, it still has similar restriction as risk neutrality. As Figure 3.2 shows, without noise, the predicted choice probabilities of submarket low in l_1h_5 and l_3h_3 as a function of risk attitude will not go above 0.5. Hence, the probability of choosing submarket low is not covered. In other words, the model imposes a restriction on the equilibrium.

To further understand what condition could extend the predictive range greater than 0.5, Figures 3.3 and 3.4 explore the relation between utility difference of submarket low and high, and the choice probabilities. As we can see from Figures 3.3 and 3.4, the condition for an equilibrium greater than 0.5 in l_1h_5 and l_3h_3 requires a larger utility difference (between choosing the submarket low and the submarket high) than the maximum differences against a reasonable risk attitude range. In particular, the utilities of the two submarkets in l_3h_3 are always equal, whatever the risk attitude. As the equilibrium derived starting with the buyers, we investigate the properties of the buyers' choice functions. Comparing Figures 3.3 and 3.4[32], if we want the choice probabilities to cover the observed values in l_1h_5 and l_3h_3, one possible idea is to impose a different concavity in the utility function for the two submarkets low and high to further enlarge the utility differences. Assuming an asymmetric risk attitude towards the two markets seems to provide a straightforward intuition to change the concavities and hence break the equality between the two submarkets in l_3h_3. This intuition is rationalisable using the spirit of contextual utility. It assumes that choice pairs create their own "local context". We may think subjects perceive the value of the low and high submarkets differently and hold different risk tolerance toward the two markets. In the next section, we apply this intuition of assuming an asymmetric risk attitude to see if we can explain the observed behaviour in the experiment.

[32] Figure 3.3 and 3.4 mainly investigate how the choice strategy of the buyers and their risk parameters changes the utility differences between two submarkets. We can not plot the utility differences between two submarkets of sellers without assuming the form of utility function and the value of their belief on buyers' choice probabilities. But understanding the properties of buyers' choice function is sufficient to reveal the restrictions of the models.

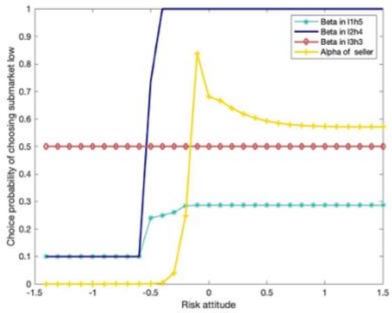

Figure 3.2 The choice probability of choosing submarket low against the risk attitude

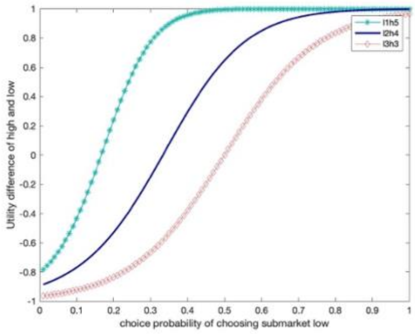

Figure 3.3 The utility difference between high and low Ul -Uh (without assuming any risk parameters, utility form and noise) against the choice probability $\beta(m_k)$

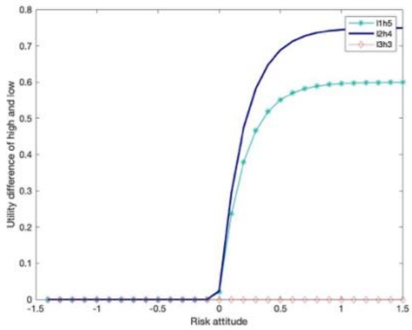

Figure 3.4 The utility difference between high and low Ul -Uh against the risk attitude with SMRA_CARA utility form

3.5 Asymmetry

As the assumption of a homogeneous risk aversion does not appear to work (in the sense of making the theoretical predictions closer to the experimental observations), we assume asymmetry between the two markets. As we have shown above, the exact nature of the mis-specification problem can be seen from the inspection of the estimation of homogeneous risk-averse QRE. Thus, if there is some difference in the risk attitude in the two submarkets, then it is possible that we would recover a higher average estimation of risk attitude and simultaneously shift the equilibrium towards the observations.

With the above goal in mind, we first assume that both buyers and sellers hold a risk attitude r_1 toward submarket low and have a risk attitude r_2 toward submarket high. We assume that risk attitudes are common knowledge.

The results for the asymmetric risk-averse QRE are reported in Table 3.2. We see that subjects have a risk-averse attitude in submarket low and a risk-loving attitude in submarket high. The estimated choice probabilities capture the tendency to choose the submarket low. Compared with the homogeneous risk-averse QRE model, the asymmetric risk-averse QRE's noise parameter is smaller (0.43 versus 0.89), indicating more precise results. It is apparent that this model does a much better job of accurately predicting choice probabilities.

	r_1	r_2	λ	-Log likelihood
Estimated parameters	0.16	-0.44	0.43	-723.48
Choice probabilities of estimation				
The probability of choosing submarket low	Asymmetric risk-averse QRE		Nash (risk neutral)	Observed
Low-quality seller	0.65		0.48	0.70
Buyers in l_1h_5	0.51		0.29	0.52
Buyers in l_2h_4	0.56		0.59	0.71
Buyers in l_3h_3	0.60		0.5	0.54

Table 3.2 Maximum likelihood estimation

Instead of interpreting the risk-aversion in the low submarket and the risk-loving in the high submarket as risk tolerance differences (different attitudes to risk in different contexts), we should remind ourselves that the phrase "more risk averse" is often interpreted as "more substitutable" or "a greater elasticity of substitution" and implies a decreasing marginal utility. As Figure 3.5 shows, the marginal utility of the high-quality product's price[33] is increasing while that of low-quality product is decreasing. This result is consistent with the common phenomenon that the high-quality product is always demanded, and the popularity of a luxury brand increases with its price. More importantly, this result gives us two key insights.

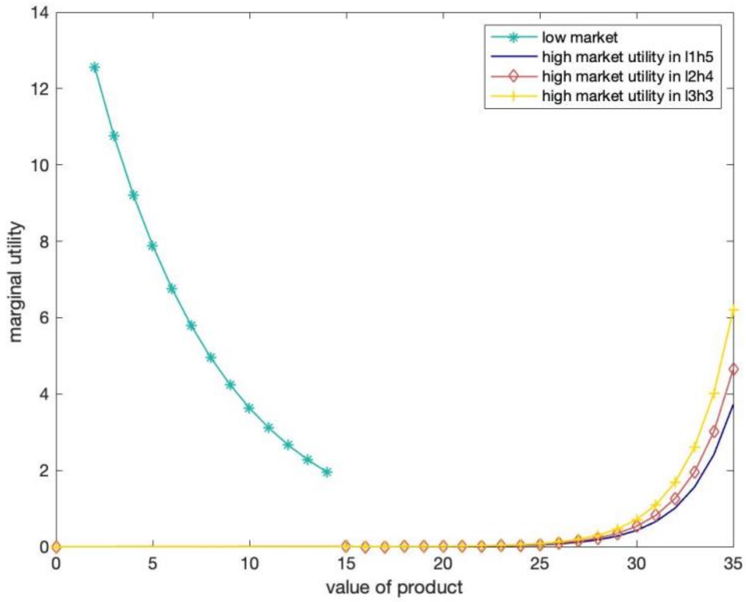

Figure 3.5 Buyers' marginal utility of each unit of product value changes
Note that the utility of low market in any market structures are the same34

First, a higher pricing strategy is one solution to stop market failure in a lemon market by

[33] Defined as the change in utility caused by an increase in the price – because the good is valued more when its price rises.

[34] We do not plot the case that when value of low quality and high-quality products overlap because it will change the equilibrium derivation equations. If one is interested in the changes, one could explore this case and see if the overlapping pricing strategy of two products will change the equilibrium pattern.

increasing the probability that buyers choose the submarket high. In Siegenthaler's experiment, he applied the same values to two products. Following the inspiration of increasing marginal utility of the high submarket, increasing the price of the product and the value of product correspondingly will push the equilibrium toward submarket high (Figure 3.6). However, it will create moral hazard issues for buyers and sellers, as well as motivate higher opportunistic behaviour. Opportunistic buyers use a lower price to buy high-quality products because they know there is competition between low-quality sellers and high-quality sellers, and the opportunistic sellers are motivated to send message *h* for a potentially higher price.

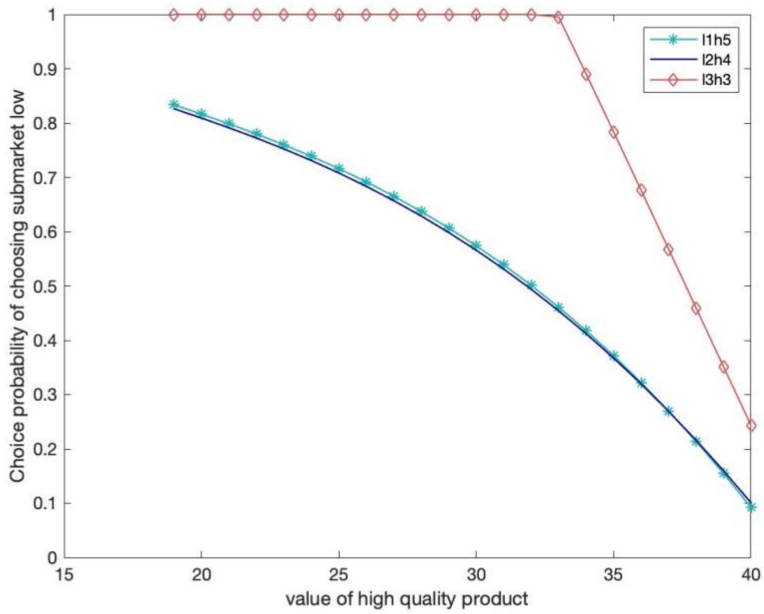

Figure 3.6 Buyers' choice probability changes given the increasing value of high-quality product

Second, the higher tendency to choose the submarket high (that is driven by the higher value of the high-quality product and buyers' opportunistic behaviour), also implies that the high-quality market needs the existence of low-quality sellers mixing in the low submarket. As shown in Figure 3.6, each unit increase in the high-quality price leads to a higher tendency to choose submarket high in l_1h_5 and l_2h_4 than in l_3h_3 . Mixing low quality sellers with high quality sellers helps opportunistic buyers to buy a high-quality good at a low price. This explains why the existence of counterfeits will not impede the development of luxury brands and indeed may raise the appeal of luxury brands (Simona et al., 2012). In future research, it will be interesting to explore the negotiation and pricing strategy.

3.6 Conclusions

This note started with the observation that there was a considerable amount of noise in the subjects' behaviour in Siegenthaler's experiment (as in any experiment). This inevitably means that the experimental results deviate from the theoretical predictions. One way of incorporating this noise is to use the Quantal Response Equilibrium (QRE) concept (McKelvey and Palfrey, 1995). However, we found that incorporating noise in this way into Siegenthaler's story, which assumes risk-neutrality of the subjects, is insufficient to explain the subjects' behaviour. Therefore, in this note, we investigated whether *incorporating risk aversion* can explain their behaviour. We conclude that it can, if we assume *asymmetric* risk aversion. Given that one cannot fit a risk-neutral QRE version to the data, it is rather trivially true that our asymmetric risk-averse QRE fits the data significantly better than risk-neutral QRE.

As we have shown, assuming asymmetric risk aversion enables the explanation of the experimental observations. The asymmetry may be caused by the perceived probability of getting different product types and the perceived probability of competing with other buyers from the two types of submarkets. The former is evaluated as a risk of possible loss, and the latter is a possibility of getting nothing. The sensitivity to risk (because of a perceived difference of context in the two markets) differs in the two markets.

However, we do not claim that this asymmetry explanation is the only possible explanation. Other behavioural factors, such as loss aversion, bias in beliefs (Weizsäcker, 2003), and skill heterogeneity (Rogers *et al.*, 2009), may be equally plausible explanations. Other possible explanations include the dual theory (where agents take decisions using two systems) and rank-dependent expected utility (where the agents weigh the probabilities). These possibilities could be explored in the future. In the meantime, it is encouraging to note that Siegenthaler's game theoretic story, once noise and asymmetric risk aversion are incorporated, does explain the data.

Chapter 4 Can the frame of menu influence how people make the decision?

4.1 Introduction

Consider an everyday decision problem: in the morning, the decision-maker (DM) has to choose a restaurant (from a set of restaurants) to go to in the evening; in the evening, the DM arrives at the chosen restaurant and has to choose an item from the menu.

Standard economic theory provides a clear solution to the problem (assuming that the DM has well-defined preferences over all menu items in all restaurants under consideration and that the quality of the cooking is the same in all restaurants): the DM should work backwards. First, the DM should imagine herself [35], for each restaurant under consideration, arriving at that restaurant in the evening, and choosing the best item from that restaurant. Then (in the morning) she should choose the restaurant where the best item is the most preferred. All that matters is the best menu item at each restaurant; any other items (and the numbers and types of them) are irrelevant.

One thing that follows is that if one restaurant has a larger menu than another has (and contains the same menu items as the other), then the former will be chosen in the morning. However, this ‘solution’ appears to be unrealistic: for example, a would-be vegetarian might want to avoid restaurants that serve both meat and fish, for she might fear that she would be tempted in the evening by a meat item (which she is trying to avoid).

A number of recent theory papers have tried to construct models that are more realistic.

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[35] For ‘herself’ read ‘herself’ or ‘himself’, and similarly, *mutatis mutandis*; for ‘she’ and ‘her’.

Common to many of these new theories is the idea that the DM does not have unique well-defined preferences over all menu items in all restaurants under consideration, and instead may have preferences different from her preferences in the morning when she arrives at the restaurant in the evening. These latter are called by some theorists 'temptation preferences'. If this is the case, then the thing of interest to theorists is how the conflict between her '*ex-ante*' (morning) preferences and her temptation preferences is resolved.

The literature in this new field is commonly referred to as the literature on self-control problems. Most of this literature is axiomatic. A leader in this field is Gul and Pesendorfer (2001), who models the DM as anticipating her dilemma in the evening and taking into account the cost to herself of exercising self-control. This may lead to a desire for commitment at the choice of menu stage. An earlier contribution by Kreps (1998), suggests that uncertainty about future preferences may instead lead to a desire for flexibility. Both behaviours can be observed in the same context. The existence of tempting choices will affect the individual's desire for current versus future consumption (that is, time inconsistency) or the uncertainty about future preferences, which we term as a taste shock. Time-inconsistent preferences generate demand for commitment, but uncertainty about future preferences generates demand for flexibility.

This paper applies the above two lines of literature to experimentally study how menu frames influence consumer behaviour. Our analysis focuses on the following questions: (1) how does the frame of the menu influence the decision-making rules on the choice of the menu; (2) will choice probabilities on ex-ante undesirable choices be increased by placing the same choice options within different menus? To answer these questions, we design an experiment to investigate how menu frames influence subjects' decision rules by identifying which of the various stories (the standard model, self-control, and flexibility) best describe subjects' decision rules. We assume that subjects differ in their preferences, so we first infer subjects' ex-ante preferences. We then observe the choices of our subjects in this two-stage decision problem (from which we can infer whether they suffer from temptation and how they resolve the temptation). Menu sets are carefully designed so we can identify the demand for flexibility and commitment. Lotteries are used as the final objects of choice, allowing us to measure quantitatively temptation and the decision rules of the subjects.

Research on marketing, economics, and decision science shows considerable evidence of how decision-making can be influenced by the frame of decision problems (Darke and Chung, 2005) and the availability of choices (Weissmann and Hock, 2021). But few investigate these phenomena from the choice of menu perspective. Menus can be interpreted either literally or as an action concerning an opportunity set, such as signing up for a contract, choosing a service package (product bundles that will affect subsequent opportunities), or choosing from a product assortment. Our research mainly contributes to product assortment strategies incorporating consumer heterogeneity. There is growing evidence that consumers tend to focus on the set of options they happen to observe in a particular context (for example, the items on the shelf) and use that set to determine which, if any, of the options are attractive (Simonson, 1999). This tendency can have significant implications for retailers since consumers typically consider only a subset of the entire product assortment. Accordingly, the configuration of subsets can be the key determinant of purchase decisions.

This paper is organized as follows. Section 4.2 discusses the main literature in this field. Section 4.3 describes the framework and gives motivating examples for our research. Section 4.4 describes the experimental design and section 4.5 the econometric specifications. Section 4.6 discusses and interprets the experimental results. Section 4.7 concludes with a summary of the results, and a discussion of findings and implications.

4.2 Related literature

Our analysis relates primarily to a class of preferences over menus that addresses the role of temptation within a menu in the presence of self-control and flexibility.

An early paper on the role of temptation in menu choices is that of Gul and Pesendorfer (2001). This models a decision maker who anticipates being tempted and executes self-control to resist the temptation at the choice of menu stage, thus incorporating the disutility of temptation. There are other models following this line but adopting different assumptions. A generalization of GP is Chatterjee and Krishna (2000) - henceforth CK. While GP incorporates a cost of self-control when the DM deliberately excludes possible temptations, CK incorporates a cost from the risk of succumbing, that is, from 'random indulgence' rather than costly self-control: the DM implements a dual-self-evaluation which is determined by the long-term normative preference and the temptation-driven preference incorporating the fact that the individual considers the possibilities of both selves. Most models in this line derive the idea of a commitment demand that allows the DM to exclude temptations from the menu.

Empirical evidence shows that excluding *ex-post* opportunities is not always desired; a preference for flexibility is also widely observed. A preference for flexibility corresponds to strictly preferring a restaurant that serves two options to a restaurant that serves only one or the other. This preference for flexibility was first modelled by Kreps (1979). Kreps modelled this preference by considering the agent's choices over menus of options by anticipating the possibility to choose from the chosen menu, where the chosen menu will be her choice set at a future date. Dekel, Lipman, and Rustichini (2001; henceforth DLR) enriched Kreps's domain of choice from menus of deterministic alternatives to menus of lotteries. The key feature of self-control (as distinct from flexibility) is the desire to keep commitment and eliminate possible temptations.

These two lines of research have been applied to optimal contract design. Even though they suggest opposite behaviours, both of them are observed in real life: hence, the value of commitment and flexibility should both be considered. Manuel and Iván (2006) state that the DM can act upon the taste shock driven by temptation and the trade-off between commitment and flexibility. Philip and Gustav (2013) analyze a contract on a consumption-saving problem considering the demand for commitment and demand for flexibility. But few investigate how the menuset design influences the choice rules regarding the demand for commitment and the demand for flexibility, nor answer how sellers should respond to this demand heterogeneity (though this latter will not be our main concern, our research shed light on this question).

Our research context is close to that of Esteban and Miyagawa (2022) who examine the optimal design of menusets when investigating the pricing strategy of sellers, and how they can benefit from offering multiple menus and adding temptation to menus. However, we do not try to find the optimal design of menusets; instead, we are interested in whether the composition of menusets influences consumer behaviour. This has a similar spirit to Yuval's research on 'contracts with frames'. Yuval (2018) justified product menusets with frames as temporarily increasing the attractiveness of some products and deriving an optimal menuset design leading to higher profits. However, their context focuses on a choice *of* menu situation. Ours explores the frames of menus and the final choice *from* the chosen menu. We are not trying to answer whether nor not one theory would be best to explain the data than the other. We are interested in whether different menu configurations will more likely trigger particular decision rules. If it will, we expect to find some insight into whether anyone can benefit from this menu configuration from the sellers' and buyers' perspectives.

4.3 Framework

We consider an environment where sellers produce a variety of goods. They produce a collection of goods {e_1, e_2, ..., e_l} which are differently preferred by different customers. They also produce some goods that are less desirable to most customers {t_1, t_2, ..., t_l} but could be considered desirable under some circumstances. Let us term these as *temptation goods*.

In our experiment, we need to choose some particular goods for our subjects to choose from. Moreover, we need to be able to measure the attractiveness of these goods to our subjects. We, therefore, chose our 'goods' *lotteries*. The relative attractiveness of the goods is given by their riskiness; if we know the risk attitude of our subjects, we can rank the goods/lotteries by their risk attitude. We assume that our subjects differ in terms of their risk attitude: there is preference heterogeneity amongst our subjects.

In response to this heterogeneity, sellers often use product assortment[36] strategies to offer consumers different menus or service packages. Buyers need to choose a particular choice set first and make a decision from this choice set.

Consider two motiving examples.

Case 1:

Consider a frugal traveller who is planning a trip and needs to choose a hotel room. During her trip, she expects to use the room only to sleep. Hence, she prefers a standard-level room $C = \{e_1, e_2\}$. So, she only checks this category and books one and wants to avoid the

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[36] Product assortment sometimes referred to as merchandise mix, refers to the variety of products that a retailer stocks and sells.

luxury type $T = \{t_1, t_2\}$, as she is worried that she will be tempted by luxury fancy rooms. The hotels want to increase the chance of selling a luxury room, so they offer another flexible service package allowing travellers to delay commitment, that is a menu $F = \{e_1, e_2, t_1, t_2\}$. The hotel hopes that travellers can be tempted to choose one of t_1 or t_2, and therefore offers her the menu $F = \{e_1, e_2, t_1, t_2\}$ to enable her possibly to be attracted by the luxury types after arriving at the hotel.

Case 2:

Consider a big vehicle company owning three stores and which wants to promote a new artificial intelligence automobile. It is a new technology with lots of fancy functions. But it is an early stage for this kind of technology, and consumers may feel it is too risky to buy them. If the company's strategy is to arrange the products in three stores: $C=\{e_1,e_2\}$, $T=\{t_1,t_2\}$ and $F=\{e_1,e_2,t_1,t_2\}$, consumers may not go into $T=\{t_1,t_2\}$ so that this store will not be profitable. But if the company places the new products in every store: $C= \{e_1, t_1\}$, $T= \{e_2, t_2\}$ and $F=\{e_1,e_2,t_1,t_2\}$, consumers will get information about the new model whichever store they visit.

The trade-off for sellers is different consumers' preferences for given assortment schemes and the profitability of sellers. The exact nature of this trade-off is whether and how buyers' behaviour (choice of menu and choice from the menu) differs in the two cases. To answer these questions, we should understand different buyers' decision-making rules in these cases.

Buyers: in our context, we assume that the buyers have preferences over lotteries and that their preferences are uniquely described by their *risk attitude*[37] *r*. We need to

[37] Later we will assume that their utility function is of the CRRA form with parameter *r*.

distinguish between their *ex-ante* (or long-term, or normative) preferences with parameter r_u, and their temptation (or *ex-post* or *ex-ante* undesirable) preferences with the parameter r_v. It is the fact that these may be different that causes possible conflicts in their decision-making. We define the preferences *outside* the menu-choosing context r_u , as their *ex-ante* normative preferences. These can be understood as the buyer's long-term goal before making choices in a menu context. However, when facing a choice in a menu-choosing context, a taste shock may be induced by the existence of some tempting choices. We assume that tempting choices are *ex-ante* unattractive, but they are attractive under r_v. For instance, a DM says *ex-ante,* that she is not a fan of beef steak and prefers to avoid it: but, in the restaurant, she is tempted to choose steak by the smell in the restaurant. We understand the menusets themselves create an environment in which the individual's desires conflict with their initial desires. When they make a choice of menu from the available menus, they apply different decision rules and a different menu utility function to evaluate menus.

Different types of buyers have different rules; let us use θ to denote the type of a buyer (we give specific cases below). We introduce some notation: let $U(r_u, r_v, \theta)$ denote the utility function of a buyer of type θ, in the choice of menu stage with *ex-ante* preference r_u and ex-post preference r_v.. We identify three different types. We label these as those who follow standard theory (ST), those who care about flexibility (PF), and those who follow self-control theory (SC). We get the following three decision rules over menus:

Standard theory (ST): The **DM** applies standard backward induction to solve the two-stage problem: first, decide what is optimal to do at the second stage (given what has been decided at the first stage), and then, in the light, of that decide what is optimal to do at the first stage.

Preference for flexibility (PF): The **DM** anticipates the probabilities of each choice she will make in future and how much utility these choices will provide. This implies that the menu with more possible choices under DM's consideration may be more preferred.

Self-control (SC): The **DM** will anticipate a preference conflict driven by temptation and will tend to avoid the temptations on the menu. It implies that a smaller menu size without temptation may be preferred, as the existence of temptation in the menu will decrease its utility of the menu.

Menusets

We need some preliminaries. Let us denote the lotteries to be inserted into the menus in the menusets by l_i (*i=1,…,*I). The *ex-ante* preferences will determine a ranking of these; we suppose that this is a complete ranking and we denote the lotteries ranked in this way by e_i (*i=1,…,*I). (It follows that, *ex-ante,*$e_1 \succ e_2 \succ \cdots \succ e_I$, where $\succ$ indicates strict preference. Similarly, the *ex-post* preferences will determine a ranking of the lotteries; let us suppose again this is a complete ranking and denote the lotteries ranked in this way by t_i (*i=1,…,*I). (It follows that *ex-post* $t_1 \succ t_2 \succ \cdots \succ t_I$)

Now, let us talk about *menusets*. We define a menuset as a collection of menus. We restrict ourselves here to menusets of size three, so that there are three menus in each menuset. A menu contains 2, 3 or 4 lotteries. The composition of a menuset depends upon the *frame*.

Let us denote a menuset of the frame by *f .* The frames *f* differ in terms of their flexibility and the location of the *ex-ante* undesirable choices in different menus. We define a menu containing more choices as one with a higher degree of flexibility. Motived by two typical cases, we consider four possible menusets (the rationale for which we will explain later):

Two of them are designed following the two above-mentioned motivating examples, that is, $f_1 = [\{e_1, e_2\}, \{t_1, t_2\}, \{e_1, e_2, t_1, t_2\}]$ and $f_2 = [\{e_1, t_1\}, \{e_2, t_2\}, \{e_1, e_2, t_1, t_2\}]$[38]. The others consider higher flexibility cases, with more *ex-ante* undesirable choices, which are $f_3 = [\{e_1, e_2\}, \{t_1, t_2, t_3\}, \{e_1, e_2, t_1, t_2\}]$ and $f_4 = [\{e_1, t_1\}, \{e_2, t_2, t_3\}, \{e_1, e_2, t_1, t_2\}]$.

Our notation implies that e_1 and e_2 are the two most attractive lotteries according to *the ex-ante* preferences r_u; and that t_1, t_2 and t_3 are the three most attractive lotteries according to the *ex-post* preferences r_v. t_1, t_2 and t_3 are different sources of *temptation* to the DM.

The choice of the menu from the menuset is determined by the *type* of DM. We can use the types to produce the Table 4.1. If there is a single entry, then that is the optimal choice; if there are two or more entries the DM is indifferent between them and can be presumed to choose at random. If the Table says 'depends' then the optimal decision depends upon the magnitudes of the risk-aversion parameters, and may vary from individual to individual.

Frame	f_1	f_2	f_3	f_4
Sets of menus	$[\{e_1,e_2\},\{t_1,t_2\},\{e_1,e_2,t_1,t_2\}]$	$[\{e_1,t_1\},\{e_2,t_2\}\ \{e_1,e_2,t_1,t_2\}]$	$[\{e_1,e_2\},\{t_1,t_2,t_3\}\ \{e_1,e_2,t_1,t_2\}]$	$[\{e_1,t_1\},\{e_2,t_2,t_3\},\{e_1,e_2,t_1,t_2\}]$
ST	$\{e_1,e_2\}$ $\{e_1,e_2,t_1,t_2\}$	$\{e_1,t_1\}$ $\{e_1,e_2,t_1,t_2\}$	$\{e_1,e_2\}$ $\{e_1,e_2,t_1,t_2\}$	$\{e_1,t_1\}$ $\{e_1,e_2,t_1,t_2\}$
PF	$\{e_1,e_2,t_1,t_2\}$	$\{e_1,e_2,t_1,t_2\}$	$\{t_1,t_2,t_3\}$ $\{e_1,e_2,t_1,t_2\}$	$\{t_1,t_2,t_3\}$ $\{e_1,e_2,t_1,t_2\}$
SC	$\{e_1,e_2\}$	Depends on risk-aversion parameters	$\{e_1,e_2\}$	Depends on risk-aversion parameters

Table 4.1 The different frames and the menu choice of each type

Let us start by explaining the first column, f_1: given that an ST type uses backward induction, she starts by deciding the best choice from each menu: these are e_1 from

[38] Some may wonder why not design the menus following more common examples in most papers like $\{e_1\}, \{t_1\}, \{e_1, t_1\}$. The reason we design in our way is so that subjects were given a richer and more realistic choice set, and so that we can distinguish between the different decision rules.

$\{e_1,e_2\}$, either t_1 or t_2 from $\{t_1,t_2\}$, and e_1 from $\{e_1,e_2,t_1,t_2\}$. However, as e_1 is preferred to either or both of t_1 and t_2, it is best to choose either the first or third menu. The PF type prefers $\{e_1,e_2,t_1,t_2\}$ because it contains two other menus. The SC type chooses $\{e_1,e_2\}$ to avoid the utility cost of resisting being tempted.

As regards the second column, the decisions of the ST and PF types follow with a similar argument to the first column. However, the decision for an SC type is not trivial. The menuset under f_2 does not offer any menu choices that exclude *ex-ante* inferior options (that is, the commitment menu $\{e_1,e_2\}$), thus the disutility of resisting temptation needs to be included in every menu evaluation. A SC DM needs to trade off the utility of the *ex-ante* most preferred option in the menu and the disutility of resisting temptation. In the other words, menu utility and hence the menu choice depends upon the difference between the utility of the *ex-ante* most preferred option in the menu and the disutility of resisting temptation.

Frames f_3 and f_4 are analogous to frames f_1 and f_2 respectively, with only one difference: that one menu has more temptations. Adding *ex-ante* inferior options into menus will not influence their menu utility for the ST and SC decision maker. However, as flexibility is increased (by adding new options), the PF decision-maker may behave differently. Either $\{t_1,t_2,t_3\}$ or $\{e_1,e_2,t_1,t_2\}$ may be preferred conditional on the anticipated possibility distribution to choose these options and the corresponding utility of each option.

Overall, the fundamental difference between the three different types is the DM's attitude towards the role of temptation goods (i.e, *ex-ante* undesirable choices) and the possible conflict between r_u and r_v. Both PF and SC types perceive a preference conflict triggered by the presence of *ex-ante* undesirable choices (but choices preferred by r_v). The PF *type* positively perceives them as flexibility for future opportunities; the SC typ*e* negatively responds to them by excluding future possibilities, while the ST type does not perceive preference conflicts.

Hence, three decision *types* rule out three responses to different frames of menu depending upon the perceived preference conflict triggered by the presence of *ex-ante* undesirable choices in the menu: (1) perceiving the preference conflict in a positive way leads to a preference for flexibility; (2) perceiving the preference conflict as negative temptation leads to self-control behaviour; (3) perceiving the preference conflict in a neutral way leads to menu frame-free decision rule.

These develop our first *hypothesis*. Inspired by context-dependent effect research, the perception of preference conflicts can be shaped by the frame of menus. For example, attraction effect rules out a situation that adding an alternative to choice sets makes DMs shift their weight of alternative evaluation (Huber et al., 1982; Bhatia, 2013). Huber et al. (1982) suggested that the difference between alternatives is perceived as smaller with the presence of an added attraction alternative, which widens the range of the choice set. Comparing the frame f_1 with f_3 ,and f_2 with f_4 , adding one more *ex-ante* undesirable choice widens the range of the diversification. While considering frame f_1,and f_2 , three menu choices are more similar to f_2 than f_1. A similarity effect may happen. In the similarity effect, when alternatives are similar, they tend to be eliminated together or remain together (Tversky, 1972).

Following the research evidence, we construct our main hypothesis as follows.

Hypothesis 1*: Placing ex-ante undesirable choices following different frames can reverse the perception of preference conflict which leads to different behaviour rules (i.e, ST, SC and PF) as consequence.*

Choice from menu – f_1 and f_3 satisfy the flexibility and commitment demand for PF and SC decision makers respectively. While f_2 with f_4 mixes temptation choices with normatively preferred choices and makes the commitment menu *{e_1,e_2}* unavailable. In this context, the DM has entered an environment where tempting choices always exist. As theoretical prediction (Table 4.1), the choice of menu is uncertain for SC subject under frame f_2 with f_4. According to research evidence indicating that DM with Self-control problems has stronger demand for commitment earlier, we developed our second hypothesis as follows.

Hypothesis 2: *DM who perceives the preference conflict negatively performs worse without the commitment menu than that frame with the commitment menu.*

4.4 Experimental design

4.4.1 Experimental Procedure[39]

Our experiment consisted of two parts. In the first part, we identified the subjects' *ex-ante* preferences using (our slight modification of) Holt-and-Laury's price list[40] method and hence estimated the subjects' *ex-ante* risk attitude. (We assumed throughout that all preferences were CRRA Neumann-Morgenstern.) In the second part, subjects were asked to choose one menu from a set of menus, and then choose an option from the chosen menu[41]. Importantly, we gave different subjects different sets of menus and different menus depending on their *ex-ante* risk preferences; this embodies the idea of a personalized offering based on an *ex-ante* market survey (as current online shopping websites do).

Part 1 consisted of 28 tasks, and Part 2 consisted of 60 tasks (30 tasks on choice *of* menu, and 30 tasks on choice *from* menu). As we shall discuss, the menus and menusets offered

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[39] Details of experiment procedures see the instruction in appendix D2

[40] Details of Holt-and-Laury's price list see appendix B

[41] Subjects need to finish 30 tasks on choice of menu first, then procedure to choose from 30 chosen menu at a random order. The purpose of this design is to stop subjects memorizing tasks, and repeatedly making the same choice without thinking.

to subjects in part 2 varied across subjects according to their evaluation of the singletons in part 1. At the end of the experiment, one of the totals of the 88 tasks was chosen at random, and the subject's decision on that task was 'played out'.

As we have already noted, we used lotteries as the menu items. All the lotteries in the experiment were simple ones, each with just two outcomes. We used the representation of Figure 1, to help the subject better visualize the risk of each choice.

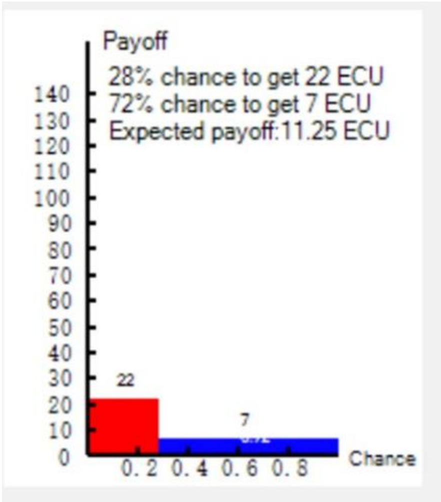

Figure 4.1 The representation of lotteries

4.4.2 Temptation

We need to implement possible temptations in our menusets. We employ two different types of temptations: risk-free lotteries and very-risky lotteries. Both may create a conflict between the *ex-ante* preferences[42] and menu choices in Part 2. We refer to very risky lotteries as gamble temptations, as they may stimulate an urge to gamble.

Both risk-free and very-risky menu items have a lower expected payoff than the other menu items. Risk-free items are a certainty of £8, £9 or £10. The very-risky items' high

[42] In Part 1 none of our subjects were extremely risk-averse or completely risk-loving.

payoffs are triple of the high payoffs for the other items, and they have a low probability (less than 0.05); while the low payoffs are lower than any normal items' low payoffs.

We designed the menusets in a particular way so that the *ex-ante* preferred choices and the *ex-ante* unpreferred choices can be clearly determined. Risk is the single measurement of the attractiveness of lotteries. We generated 30 sets of lotteries (each set has 7 lotteries) for 60 menu choice tasks according to particular riskiness. It follows that each set of 7 lotteries can be ranked according to a particular value of risk preference r.

4.4.3 An illustration of the lotteries included in different menusets

We start with a 7 by 210 matrix, each cell referring to a lottery. These lotteries are used in Part 1 and allocated into menusets according to frame and subjects' *ex-ante* preference. The attractiveness of lotteries *in each row* is ranked according to each subjects' r_u. There are 7 entries/lotteries in each row; each row defines the lotteries to be put into a menuset (the actual construction of the menusets is described later). The rows are constructed in blocks of 10. The first block of 10 rows is all of the same type, though the actual lotteries differ (but the five e's are still defined as the five most preferred according to the *ex-ante* preferences) and the t's are all *very risky* lotteries (but differ from row to row). Similarly, the second block of 10 rows are all of the same type, though the actual lotteries differ (but the five e's are still defined as the five most preferred according to the *ex-ante* preferences) and the t's are all *risk-free* lotteries (but differ from row to row). Likewise, the third block of 10 rows are all of the same type, though the actual lotteries differ (but the four e's are still defined as the four most preferred according to the *ex-ante* preferences) and one of the t's is a *risk-free* lottery and the other two are *very-risky l*otteries (but differ from row to row).

$$
\begin{pmatrix}
e_{1,1} & e_{1,2} & e_{1,3} & e_{1,4} & e_{1,5} & t_{1,1} & t_{1,2} \\
 & & & \cdots & & & \\
e_{11,1} & e_{11,2} & e_{11,3} & e_{11,4} & e_{11,5} & t_{11,2} & t_{11,3} \\
 & & & \cdots & & & \\
e_{21,1} & e_{21,2} & e_{21,3} & e_{21,4} & t_{21,1} & t_{21,2} & t_{21,3} \\
 & & & \cdots & & &
\end{pmatrix}
$$

We note that though there are repetitions within each block since the actual lotteries differ; this was to stop subjects from memorising the lotteries. We summarise the construction of the menusets: (1) Menusets with very-risky temptations; (2) Menusets with risk-free temptations; (3) Menusets with multiple temptations

Now we discuss the different *frames.*

The implied menusets (depending on the *frame*) are

The others consider higher flexibility cases, with more *ex-ante* undesirable choices, which are $f_3 = [\{e_1, e_2\}, \{t_1, t_2, t_3\}, \{e_1, e_2, t_1, t_2\}]$ and $f_4 = [\{e_1, t_1\}, \{e_2, t_2, t_3\}, \{e_1, e_2, t_1, t_2\}]$.

Frame 1: $f_1 = [\{e_1, e_2\}, \{t_1, t_2\}, \{e_1, e_2, t_1, t_2\}]$

Frame 2: $f_2 = [\{e_1, t_1\}, \{e_2, t_2\}, \{e_1, e_2, t_1, t_2\}]$

In this, e_1 and e_2 are the most preferred according to Part 1 preferences, and t_1 and t_2 are two risk-free items in a menuset with risk-free temptations and are very-risky items in a menuset with very-risky temptations. The difference between the two frames is cosmetic according to Standard Theory but may have an effect on one of the non-standard theories. These are both repeated ten times with different lotteries.

Now we need to include menusets with multiple temptations. This leads to two more frames:

Frame 3: $f_3 = [\{e_1, e_2\}, \{t_1, t_2, t_3\}, \{e_1, e_2, t_1, t_2\}]$

Frame 4: $f_4 = [\{e_1, t_1\}, \{e_2, t_2, t_3\}, \{e_1, e_2, t_1, t_2\}]$

In these, t_1, t_2 and t_3 are one of the certainties and two of the riskiest lotteries. As these are possible temptations, we denote these with a '*t*'.

4.5 Econometric specification

4.5.1 Menu utility function

We used three different menu utility functionals to identify different types of DM in our experiment. The simplest, of course, is that with Standard Theory: an individual with a standard function simply uses their normative preference to evaluate all available options among the three menus, and then the utility of menu is given by the maximised utility of lotteries in the menu, which is the one she plans to choose from the menu.

Standard theory (ST):

$U_{ST}(A) = max_{x \in A} u(x)$ where *x* is an option in menu *A.* (4.1)

Recall that we assume CRRA utility. Thus, utility is determined by the single parameter of risk preference. We assume that standard theory subject has consistent preferences across stages and the inconsistency in behaviour is interpreted as noise. So, the *ex-ante* preference r_u which is inferred from part 1 will be applied to measure the menu utility.

As for the self-control, there is rich research in this vein. They offer different solutions to model the preference over menus. One of the most popular is GP's costly self-control model. Their axioms yield a representation that identifies the conflict between *ex-ante* *preference u* and anticipated *ex-post temptation preference v* and incorporates a cost of self-control. To some extent, our experiment context is more general without addressing the cost of self-control as in most self-control experiments. For example, Toussaert (2018) who designed an experiment to test GP, implements the cost of self-control by offering additional earnings to read a sensational story during a tedious attention task for which subjects received payment. In our experiment, the self-control and demand of commitment are triggered by preference conflicts driven by designed temptation where the DM anticipates the risk to succumb to temptation. Alternatively, another model in terms of self-control emphasizing the anticipated risk of departure from normative preference is the dual self with a stochastic story proposed by Chatterjee and Krishna (2000)(CK). In contrast to using strong self-control with the cost involved, DMs are modelled to evaluate the possibility of being tempted in the future. This model interprets temptation as a systemic mistake in which the second-stage choice could be interpreted as being made by an "alter ego" who appears randomly; DMs at the first stage take into account the probability of being tempted at the second stage.

Self-control functionals (SC)

$$U_{SC}(A) = (1-p)max_{x \in A} u(x) + pmax_{y \in B_v(A)} u(y) \quad (4.2)$$

Where $B_v(A)$ is the set of v maximisers in A.

Here p is the probability of being tempted. CK refer to their model as a dual-self model, where u is the utility function of the long-run self and v is the utility function of the other self. When making the choice of menu, the DM believes she has p probability that the other self will dominate at the choice from the menu stage; that is, giving in to the temptation. Following the spirit of self-control, the representation could be interpreted as an internal battle for self-control with the alter ego where p is the probability to lose self-control.

The parameters to estimate in this function are the anticipated probability p and the preference r_v.

A class of preference over menu representations, which mainly originates from Kreps's preference for flexibility, says that expanding menus by adding alternatives is always desirable. He models a DM who is uncertain about her future preferences and anticipates the probabilities of each choice she will make in future and how much utility these choices will provide.

Preference for Flexibility functionals (PF)

$$U_{PF}(A) = \sum q\,(s) \max u_s(x) \quad \text{where} \quad x \epsilon A \tag{4.3}$$

Where $s \epsilon S$ is the subjective state and the $q(s)$ are the probabilities of anticipated future preferences. Specifically, the utility of a menu A is equal to the expected utility of the best option in A, with expectations taken over the different possible utility functions indexed by the state S, which we refer to as the belief about the preferences at the second stage.

Here the parameters to be estimated are the anticipated probability distribution across states. The estimation difficulties are that the subjective state and the belief on probability cannot be directly observed. Following the spirit of CK's dual self and given the design of our experiment which offers two types of options, we assume there are two states, s_u the normative preference state where has a maximizer determined by r_u and s_v the temptation indulgence state where has a maximizer determined by r_v (that is, the taste shock driven by temptation). Without losing generality, this binary-states assumption does not change the nature of preference for flexibility. For example, a DM makes choice from the menusets $f_1 = [\{e_1, e_2\}, \{t_1, t_2\}, \{e_1, e_2, t_1, t_2\}]$. She knows she normally prefer choices e to the choices t. But a choice t (such as an extremely high possible payoff) may seem attractive from another perspective. Even though she is unsure about what will be her mood when making final choices, she thinks the s_u is more likely than s_v. Let us say $q(s_u)$=0.8. Note that two options in $\{e_1, e_2\}$ and two options in $\{t_1, t_2\}$ have close riskiness levels. But r_u and r_v will determine a unique maximizer. For instance, if s_u is realized, e_1 is the maximum one with $u_{s_u}(e_1)$=1 while $u_{s_u}(t_1)$=0 and $u_{s_u}(t_2)$=0.01; if s_v is realized, t_1 has the maximum utility with $u_{s_v}(t_1)$=0.9 while $u_{s_v}(e_1)$=0.2. So, the expected utility of menu $\{e_1, e_2\}$ becomes 0.8, that of $\{t_1, t_2\}$ is 0.72, however, the menu $\{e_1, e_2, t_1, t_2\}$ has a utility of 1.52, and so $\{e_1, e_2, t_1, t_2\}$ will be preferred to other menus.

So, the main parameters of interest of PF are r_v and the state probability $q(s)$[43].

4.5.2 Extensions

In our experiment, one menu of f_3 and f_4 contains two different temptations, gambling and risk-free lotteries. We are interested in whether the presence of temptation diversity will influence decision-making. We assume there is a case that a DM is tempted by gambling and risk-free lotteries at the same time. Thus, the above utility functional of self-control and flexibility should be extended into more exogenous states. For the PF, the extension is straightforward. We assume there are three states, s_u the normative preference state which has a maximizer determined by r_u, the temptation state s_{v1} evoked by risk-free temptation which has a maximizer determined by r_{v1} (that is, when the state happens, the risk-free lottery will be preferred) and s_{v2} the temptation state evoked by gambling temptation where has a maximiser determined by r_{v2} (that is, when the state happens, the gambling lottery will be preferred). The probabilities of each state are measured by the $q(s)$ as equation (4.3). Therefore, the parameters of this case are r_{v1} , r_{v2}

[43] Indeed, a more general method is to assume the belief on future preference contingency is continuous distribution, that is, the anticipated risk preference is distributed normally with certain mean and standard deviation. The probability of choosing each available option will be determined by the density distribution function of preference distribution. But it requires larger data sample.

and corresponding anticipated probabilities $q(s_{v1})$ and $q(s_{v2})$.

As for the SC, we can follow CK's extension to finite exogenous states, which is similar to the flexibility. We assume two states of world $S = \{s_{v1}, s_{v2}\}$ with the probability that the state occurs given by $q(s)$. Each state determines which is option is most tempting given the v of this state. As CK's argument, DM's utility function does not change across states nor does her alter ego. The only thing that changes is the probability of getting tempted. Following the equation (4.2), if subjects are tempted by multiple temptations, the utility of menu can be written as

$U_{SC}(A) = \sum_{s \epsilon S} q(s)((1 - p_s) max_{x \epsilon A} u(x) + p_s max_{y \in B_v} u(y))$ where p_s is the probability of getting tempted under the state s and $q(s)$ is the probability of state realization .

The parameters here are r_{v1} , r_{v2} , the corresponding anticipated state probabilities $q(s)$, and the probability p_s of getting tempted in each state.

4.5.3 Luce model

The choice *of* menu stage in all models are deterministic stories, identifying a particular optimal menu. In any experiment, however, there is behavioural noise. This fact implies that we have to model choices *of* menus in a stochastic fashion; otherwise, no model can explain the data. We use the multinomial logit model (or Luce model) to incorporate stochasticity. According to this model, the DM evaluates the problems with some noise. If the noise in the evaluation is additively separable and independently distributed according to the extreme value distribution, then the multinomial logit model emerges. This model implies that the *probability* of selecting one menu over another from a set of many menus is not affected by the presence or absence of other menus in the same context. The choice probability formula is given by the equation below.

$$P_i = \frac{e^{\lambda U_i}}{\sum_{j \in \Theta} e^{\lambda U_j}}$$

Here U_i is the expected utility of the menu i, j is any other menu in the menuset Θ and λ is a precision parameter which measures the amount of experimental noise and reflects the variance of the unobserved portion of utility.

4.5.4 Type identification

Decision rules are the private information of the DM. If instead, they were observable and verifiable by an outside party, one could simply contract upon them in a way given their decision rules. Indeed, decisions under different decision rules will differ in some cases. But as Table 4.1, indicates, sometimes different types' choice of menu could be identical. For example, within a limited sample, we may observe one DM keeping on choosing $\{e_1, e_2, t_1, t_2\}$ all the time. We cannot simply make a conclusion as to whether the decision is more likely to be coming from PF since a SC decision maker would randomly choose between two menus for which she is indifferent. The Luce model enables us to better identify the types based on maximum likelihood estimation. Essentially, the fundamental differences between each type are how subjects respond to temptation. Their attitude toward temptation will be incorporated into the menu utility. As disused, flexibility subjects respond to them by delaying commitment, thus the existence of temptation will increase the utility of the menu; self-control subjects respond to them by commitment themselves at choice of menu stage, thus the existence of temptation will create disutility, while the standard decision makers will not be influenced by the temptation. Whether the subjects are tempted, and are facing preference conflict, cannot be directly observed by the experimenter, but the choice probability distribution over menus is identifiable by our quantitative estimation. As long as subjects are tempted, the preference conflict will be measured by the parameters r_v and anticipated probabilities of Kreps and CK.

We assume that subjects are different. We therefore fit each of three preference functionals discussed above for each of the 82 subjects individually by maximum likelihood estimation. For every subject with the n observations of menu choices i from the menusets $S(f)$, recall that each menuset has three menus formed in particular way , the likelihood function can be written as $LogL(\lambda, \omega) = \sum_{n=1, i\in S(f)}^{N} \ln{(P_{i,n})}$ where ω is the parameters in each menu utility functionals which will determine the choice probabilities $P_{i,n}$. With the same observation, the likelihood of different types will be different, as the $P_{i,n}$ is determined by utility functional *U.* We demonstrate identifiability with our Luce stochastic specification[44] through a simulation (see the Appendix C).

4.6 Results

In this section, we present the experimental results from the experiment conducted at EXEC, the Centre for Experimental Economics at the University of York, in 2022. There were 81 subjects (mainly students from university of York) participating in the experiment. The mean earnings were £17.32 per subject (including a £2.50 show-up fee).

We started with the data from Part 1 of the experiment. There we effectively elicited the certainty equivalents of 28 lotteries. We assumed that the preferences of the subjects were Neumann-Morgenstern with an SMRA-CRRA[45] utility function with risk-aversion parameter r_u and we estimated the value of r_u for each subject. We assumed that noise (in the expressed certainty equivalents) was an additive normal distribution with mean zero and standard deviation 1/s. We also estimated s – the precision. The average estimated r_u is 0.04 with a standard deviation of 1.06 among subjects and the average estimated s is 0.04 with a standard deviation of 0.007 among subjects.

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[44] Of course, this assumes that our subjects are noisy in their responses.

[45] CRRA – Constant Relative Risk Averse; SMRA – Stochastically More Risk Averse (see Wilcox,2011)

4.6.1 Overall menu frames effect

Our key fundamental research purpose is to understand whether different frames of menusets influence the choice of the menu and the choice from the menu. We start with some descriptive statistics.

Table 4.2 illustrates average individual choice *of* menu choice frequencies across menus under different frames. As shown in this table, f_2 significantly increases individual choice frequencies of menu $\{e_1,e_2,t_1,t_2\}$ compared to f_1 in both the gamble temptation and the risk-free temptation context (f_1 and f_2 with gamble temptation p<0.05; f_1 and f_2 with risk-free temptation p <0.05).f_3, Adding one risk-free temptation into the menu $\{t_1,t_2\}$ significantly increases the choice frequency of the pure temptation menu $\{t_1,t_2,t_3\}$ than $\{t_1,t_2\}$ in f_1 with both gamble (p=0.00) and risk-free (p=0.05)temptation cases. While the significance changes (p<0.05) are only observed between the choice frequencies of $\{e_2,t_2\}$ in f_2 with gamble temptation and $\{e_2,t_2,t_3\}$ *of* f_4. Overall, we can observe choice frequencies differences between *frames*.

	f_1			f_2		
	$\{e_1,e_2\}$	$\{t_1,t_2\}$	$\{e_1,e_2,t_1,t_2\}$	$\{e_1,t_1\}$	$\{e_2,t_2\}$	$\{e_1,e_2,t_1,t_2\}$
Gamble	0.53	0.09	0.38	0.24	0.10	0.66
Risk	0.33	0.15	0.52	0.09	0.18	0.73
	f_3			f_4		
	$\{e_1,e_2\}$	$\{t_1,t_2,t_3\}$	$\{e_1,e_2,t_1,t_2\}$	$\{e_1,t_1\}$	$\{e_2, t_2,t_3\}$	$\{e_1,e_2,t_1,t_2\}$
Multiple	0.45	0.22	0.32	0.31	0.19	0.50
All the choice frequencies of each subject are based on 10 observations.						

Table 4.2 Choice frequencies under different frames and temptations

Result 1: *Allocating the same set of choices into different menus dramatically alters the decision patterns of menu. Particularly, menu choices with similar structure (f_2 and f_4) nudge preference for more flexibility.*

For the choice *from* the menu, we are interested in the frequencies of choosing temptation choices under different frames. Table 4.3 shows the average individual choice frequencies of choosing temptation (that is, t_1,t_2,*or* t_3) as the final choice and choosing *ex-ante* preferred choices (that is, {e_1 or e_2} Overall choice frequencies of choosing temptations are not significantly different among different frames even though the frequencies of choosing menus $\{e_1, e_2, t_1, t_2\}$ are higher under f_2 in the gamble temptation context. However, the frames have an effect on the frequencies of choosing risk-free temptation and multiple temptation options. Subjects have a significantly higher tendency to choose temptations in f_2 than in f_1. Note that all the temptation choices are designed with a lower expected payoff than any other lottery. To some extent, the gamble and risk-free temptations have different effects on choice frequencies of choosing temptation. Risk-free temptation cases increase the frequencies of choosing temptation choices than gamble temptation cases under the same frame. There is strong evidence showing that the frequencies of choosing temptation with multiple temptations are higher than with gamble temptation. While the differences are not prominent between menu frames with multiple temptations and with risk-free temptation.

	f_1		f_2	
	Temptation	*Ex-ante* preferred choice	Temptation	*Ex-ante* preferred choice
Gamble	0.13	0.87	0.15	0.85
Risk-free	0.27	0.73	0.34	0.66
	f_3		f_4	
	Temptation	*Ex-ante* preferred choice	Temptation	*Ex-ante* preferred choice
Multiple	0.26	0.74	0.35	0.65

Table 4.3 Choice frequencies of choosing temptation under different frames and temptations

Result 2: Widening the range of temptation diversification induces higher frequencies of choosing temptations when facing gambling choices (f_3 and f_4).

4.6.2 Type identification through Menu preference

Even though a frame effect has been observed, our two main postulates are that different types of subjects react to temptation differently; and different frames of menu have different effects on each type. We investigated whether any frames will increase the attractiveness of some *ex-ante* undesirable choices. Thus, our analysis starts with *types* identification by fitting the choice *of* menu with three menu utility functionals. We take as given the estimated value of r_u, the risk-aversion of the u function. We estimated, by Maximum Likelihood, each of the 3 choice *of* menu functionals for the 81 subjects subject-by-subject, using the data on the choice *of* the menu, obtaining estimates of the parameters of the functional (particularly the implied CRRA level of risk-aversion r_u of the v function) and the maximized log-likelihood. In order to compare the relative goodness-of-fit of the model, we need to correct the log-likelihoods for the different number of parameters (Kreps has 2, CK has 2 and Standard Theory has none). As the parameters of each function differ and the sample size for each subject is limited, we calculate the corrected likelihood value by the AICc[46] (Akaike Information Criterion). We define which type the subjects are more likely to be according to the model with the lowest AIC.

Table 4.4 shows the fraction of each type under different frames with different temptations. Each *column* reports the *type* distribution under particular menu frames. Starting from the f_1 with gamble temptation subsets, 50% subjects are identified as PF type, 35% as SC type, and 15% as ST type. Comparing with the fraction of SC type in f_1, only 19% of subjects are identified as ST under f_2 with gamble temptations. The PF types have opposite changes. A larger fraction of subjects (68%) is identified as PF type under

[46] In small samples, AIC tends to over-fit. To address overfitting, AICc adds a size-dependent correction term that increases the penalty on the number of parameters (Burnham et al, 2002).

f_2 with gamble temptation. A similar pattern of the fraction of ST and PF types is observed between the f_1 and f_2 with risk-free temptation. We interpret this as *context-dependence menu preference*: subjects are more likely to respond to the temptation as PF when mixing the temptation with normatively preferred lotteries such as f_2, that is , $[\{e_1,t_1\},\{e_2,t_2\}\{e_1,e_2,t_1,t_2\}$.

Now the multiple temptations, adding risk-free temptation into one menu of f_1 and f_2 with gamble temptation, shows a different pattern. Recall that the f_3 is analogous to the menusets under f_1 with gamble temptations; and f_4 is analogous to that of f_2 with gamble temptations. If subjects will not be tempted by the two temptations, *risk-free and gambling lotteries* at the same time, adding one risk-free choices into menu will not make any difference. However, comparing the fraction under f_3 to the fraction under f_1 with gamble temptation, more subjects are identified as ST type (74% vs. 35%). Similarly, 97% of subjects are identified as SC under f_4 while only 19% under f_2 with gamble temptations. Subjects do feel tempted by two extreme temptations simultaneously. It implies subjects are more likely to react to temptation in a self-control way if the context evokes more conflicting preferences.

	f_1		f_2	
	Gamble	Risk-free	Gamble	Risk-free
PF	0.5	0.58	0.68	0.68
SC	0.35	0.10	0.19	0.02
ST	0.15	0.32	0.13	0.31

	f_3	f_4
	Multiple temptation	Multiple temptation
PF	0.26	0.03
SC	0.74	0.97
ST	0	0

Table 4.4 Fraction of types under different frames with different temptations47

Result 3: *Mixing temptation choices with ex-ante desirable in each menu (f_2 and f_4) shapes the perception of preference conflict more positively than bracketing temptation choices as $\{t_1,t_2\}$ in (f_1 and f_3), as consequence leads lower tendency of behaviour rules of PF in the latter frame.*

4.6.3 Frame effect on different types' decision-making

How does the menu frame influence different types' choice frequencies of choice of menus? In Table 4.5, we investigate each the *type* difference on choice *of* menu and choice *from* menu respectively. Comparing columns shows the observed choice frequencies differ across different types of subjects. It is consistent with the theory that PF types of subjects have a higher tendency to choose the flexibility menu $\{e_1,e_2,t_1,t_2\}$. Not surprisingly SC types tend to choose the menu $\{e_1,e_2\}$. Interestingly, the choice frequency distribution of SC types shows different patterns between f_1 and f_2. SC subjects have significantly ($p<0.05$) higher tendency to choose menu $\{e_1,e_2,t_1,t_2\}$ under f_2 than f_1 with gamble temptation cases. However, the significance is not observed in the risk-free cases. One of the main

[47] This table is constructed after identifying the best-fitting type of subject column by column – as described above; note that the entries in the columns add up to 1.

reasons is that only one subject is identified as SC.

The PF *type* under f_3 with multiple temptations shows a higher tendency to choose *{t1,t2,t3}* in f_3 (51%) than with a similar menu *{t1,t2}* under f_1 (8%). Given the utility function of Kreps, the possible explanation is subjects feel tempted by risk-free and gamble temptations simultaneously and perceive a higher possibility to choose the risk-free temptations than the choice of normative preference, that is, e_1 *or* e_2 at the second stage. The ST type subjects show similar choice frequency pattern between f_1 (f_2) with gamble temptation and f_3 (f_4) with multiple temptations. When the commitment menu, *{e1,e2}* is available, they will tend to choose this menu to exclude the temptation.

		f_1			f_2		
		$\{e_1,e_2\}$	$\{t_1,t_2\}$	$\{e_1,e_2,t_1,t_2\}$	$\{e_1,t_1\}$	$\{e_2,t_2\}$	$\{e_1,e_2,t_1,t_2\}$
Gamble	PF	0.36	0.08	0.56	0.26	0.09	0.65
	ST	0.59	0.21	0.20	0.24	0.24	0.53
	SC	0.74	0.05	0.21	0.18	0.03	0.79
Risk-free	PF	0.28	0.08	0.69	0.00	0.20	0.80
	ST	0.35	0.32	0.33	0.24	0.15	0.61
	SC	0.9	0	0.1	0.8	0	0.2[48]
		f_3			f_4		
		$\{e_1,e_2\}$	$\{t_1,t_2,t_3\}$	$\{e_1,e_2,t_1,t_2\}$	$\{e_1,t_1\}$	$\{e_2, t_2,t_3\}$	$\{e_1,e_2,t_1,t_2\}$
Multiple	PF	0.10	0.51	0.39	0.30	0.20	0.50
	ST	-	-	-	-	-	-
	SC	0.58	0.12	0.3	0.46	0.22	0.31

Table 4.5 Menu choice frequencies of each type under different frames and temptations

As for the choice *from* the menu, Table 4.6 shows each types' subjects' choice frequencies of choosing temptations and normal choices. Comparing PF and SC in f_1 with that of f_2, the frequencies of choosing temptation do not show a significant difference, while $f_2's$ ST subjects have a significantly increased frequency to choose temptation than $f_1's$ ST

[48] Only 1 subject has been identified as a CK type.

subjects for both menusets with gamble temptation and risk-free temptations.

Given the observation of PF type's higher tendency to choose menu *{t_1,t_2,t_3}*, it is not surprising to observe the frequencies of choosing the temptation for PF type under f_3 with multiple temptation menu is significantly higher ($p<0.05$) than that under f_1. However, the significance cannot be found between f_2 and f_4. We can conclude that the PF subjects are more likely to give in to the temptation in the multiple temptation frame.

		f_1		f_2	
		Temptation	*Ex-ante* preferred	Temptation	*Ex-ante* preferred
gamble	PF	0.14	0.86	0.13	0.87
	SC	0.05	0.95	0.2	0.8
	ST	0.27	0.73	0.21	0.78
Risk-free	PF	0.37	0.63	0.13	0.87
	SC	0.03	0.96	0.2	0.8
	ST	0.37	0.63	0.21	0.78
		f_3		f_4	
		Temptation	*Ex-ante* preferred	Temptation	*Ex-ante* preferred
Multiple	PF	0.55	0.45	0.3	0.70
	SC	0.16	0.84	0.26	0.74
	ST	-	-	-	-

Table 4.6 Choice from menu frequencies of each type under different frames and temptations

Result 4: *Subjects who is identified as SC type are more likely to give into temptation choices under the menu frame without the commitment menu than that frame with commitment menu.*

4.7 Conclusions

We report on an experimental investigation into two-stage decision-making, particularly examining the influence of temptation and flexibility on behaviour. The preference for menus problem has been studied extensively in self-control, commitment demand and flexibility theories, but to a much lesser extent, in experiments. Moreover, we are unaware of any previous work that discusses the existence and effect of the desire for flexibility and self-control in the same context. This paper contributes to the small but growing literature by applying insights and formal models from behavioural economics to the study of frame effects. In addition, our experimental design enables us to measure the importance of preference conflict and to identify the possible behavioural principles of subjects under different frames of menusets. Designing the experiment to make the preference conflict identifiable, and behaviour patterns distinguishable, while following the basic structure of the models, was challenging, and we are aware of no other published experiment in which this behaviour has been demonstrated.

To identify the self-control, flexibility and standard theory types, the experiment was carefully designed. The identification strategy relies on the varied riskiness of lotteries to define the *ex-ante* preferred choices and the *ex-ante* unfavourable choices in menusets, and the corresponding construction of menus. We elicited each subject's *ex-ante* risk preference in a menu-free context. We constructed four different frames of menusets, designed to identify different types of decision makers. Then, we placed the *ex-ante* preferred lotteries on different menus with *ex-ante* unfavourable lotteries (which we term as gambling temptations and risk-free temptations). With this design and with the application of the Luce stochastic choice model, the directly unobservable preference conflict can be captured.

Our menu designs are not just for econometric convenience, but also offer real world business insights into how a firm can present its products in a particular manner, hence leading to framing effects and thus manipulating consumers' decisions (Kamenica, 2008). Our principal conclusions can be summarised as follows. First, we show that menu frames that mix the normatively preferred choices with *ex-ante* undesirable choices can lead more subjects to behave according to a preference for flexibility and consequently significantly increases the choice of the flexibility menu. However, it does not influence the final choice from the menu: most subjects still choose from the menu according to their *ex-ante* normative preferences. This answers the store allocation problems of the vehicle company in our motivating examples - placing the new automatic car in every store will not increase the sales; it tends to attract more buyers to visit the more flexible store, thus causing a profit maintenance problem for the other two stores. This suggests a direction for future research – the optimal allocation strategy to achieve the overall profit maximization and increase the sales of *ex-ante* unpopular products. From a different perspective, this result sheds light on competitive strategies – when products are similar among suppliers, offering more flexible choice sets attracts more consumers.

Second, the frame does have a significantly adverse impact on the self-control type subjects. As the theory predicts, subjects with self-control problems have a stronger commitment demand. Removing the commitment menu will not only lead to higher possibilities of choosing the more flexible menu but also, self-control subjects have a higher tendency to give in to the temptation. The self-control subjects' average payoffs of the chosen lotteries are all lower under the menu set choices where the commitment menu is not available; for example subjects who are identified as self-control subjects have an average payoff of £11.18 under the frame with commitment menu (f_1) compared with £9.53 under the frame without commitment menu (f_2) in the gamble temptation context; and earned £13.69 on average under f_1 compared with an average of £11.40 under f_2 in the risk-free temptation context. Offering menu choices without commitment menu lead self-control subjects to perform worse.

Third, adding a risk-free temptation into a menu with a gamble temptation (that is, f_3 and f_4), (which we term as higher flexibility) shows a different impact on self-control subjects than on flexibility subjects. Multiple temptations create more preference conflicts, and leads more subjects to exclude the presence of temptations. However, increasing the flexibility has a stronger effect on the decision maker with a preference for flexibility. This kind of behaviour is common in real life: when choosing an insurance scheme, people are more likely to be convinced if there is some minimum guaranteed amount; when choosing a risky investment portfolio, people are more likely to be convinced if they are told the minimum return. It gives some insight to companies wanting to launch a new product, or to policymakers who want consumers to accept more risk, by offering safe options in a risky bundle.

Chapter 5 How are individuals' decisions influenced by incongruence between information sources?[49]

5.1 Introduction

The initial stage of the Covid pandemic is a good example of the problem we are investigating. Initially, individuals had to make their decision concerning the preventative measures that they would take solely on their personal experience of the disease. After a while, however, the government provided advice ("wear masks, practice social distancing etc.") and also people, through social media, could get information about what other people are doing.

It is not clear what people 'should' be doing, and what they would do. Some may base their decisions solely on their personal experience; some may follow the official suggestion; some may follow the social consensus ("follow the herd"). Previous research finds that individuals adjust themselves to match the decisions of others in their group even if there is no explicit requirement for such unanimity (Staats *et al*, 2018). Society could be misled if the desire to follow others is intrinsically prevalent among the population. In this case, the effectiveness of the official suggestions is crucial. A considerable body of research has discussed how individuals respond to others' decisions and expert suggestions (Schotter,2003; Schepen and Burger, 2022). However, few of them discuss two information sources in the same context.

[49] This experiment was funded by LUISS Rome.

In this paper, we experimentally study how individuals learn from their own experience and the other two sources of information (an official suggestion and social consensus). We address three research questions: (1) whether the interest in the official suggestion and the social consensus is rational; (2) to what degree individual's decisions are influenced by their own experience, the official suggestions and the social consensus; (3) whether contradictory information between information sources matters and if it does, how individuals adjust their responses accordingly.

To answer these questions, we design an experiment considering a situation in which individuals, in a situation of learning under ambiguity, make decisions on an insurance decision mitigating the effect of the financial loss caused by some bad event. The risk of the bad event varies across subjects; this leads to diverse experiences. In the first 10 rounds, subjects do not have any suggestions for the optimal decision and must take their insurance decision using their own past experience of the bad event. We shall call this their *personal experience*. From period 11 and onwards, however, *an official suggestion* and information on *the social consensus* are available for consultation[50]. After that, two decisions are required; first, subjects need to decide which information source they want to check; second, subjects are asked to make a decision on the amount of insurance they want to buy. Exposure to information is chosen by the individual, and subjects are allowed to choose none, one or both of the two sources without any cost. Only the final decision on insurance is financially incentivized, while the information-usage behaviour is endogenously triggered by the demand for information. This design reflects a real-world environment where an individual searches information from multiple sources online and converts information into decisions endogenously.

[50] Subjects do not have to consult them, but they can without cost.

The ultimate goal of this research is to find out possible insights for official guidance. The experiment focuses on how the decision distribution evolves within a group under the interactive intervention of information sources. We elicit final decision instead of individual's beliefs, because the decision distribution in society is a way of measuring policy effectiveness (and it is this that we are interested in). Inspired by the application of cheap-talk mechanism to public communication research, the official suggestion can be seen as a generalization of the cheap- talk mechanism in society, which sends a costless and non-binding message to any agents. Following cheap-talk research regarding private (individualized) messages and public messages, we have two treatments concerning the official suggestion with different levels of informativeness to examine the information source bias and the rationality of the responses to information. In the first treatment, the official suggestion is the optimal insurance decision based on the (past) occurrence of the bad event for the whole population (henceforth general suggestion); in the second treatment, the official suggestion is personalised for each individual with the suggestion for an individual being the optimal insurance decision based on the (past) occurrence of the bad event *for that particular individual* (henceforth personalised suggestion). The motivations of the two designs are discussed in more detail in the hypotheses section.

This experimental design is different from those conventionally used in classic social learning research. However, the literature relating to our experiment can be briefly traced following information choices and social learning studies. Similar to our spirit of understanding when information is chosen and how it is used, Duffy *et al*. (2019) studied the rationality of choosing private information and social information and how that information is subsequently used in guessing the state of the world. But subjects in their experiment are only allowed to choose one information source each time. Our design tries to capture the interaction of two information sources, and we are interested in whether the interactive effects of information sources might jointly aggregate in a somehow rational manner. Most prior experiments on social learning, such as Anderson and Holt (1997), Celen and Kariv (2004), Goeree *et al* (2007), Ziegelmeyer *et al* (2009) and De Filippis *et al* (2017), required subjects to take decisions with a private signal and social information on the prior choices of others. We focus on the effect of social consensus. People's belief in the "wisdom of crowds" has been documented by some research (Surowiecki, 2014). The internet and social media make us more likely to access a broader range of information sources. Hence, it is meaningful to examine what will happen if these sources go wrong and whether this can be corrected. Our main analysis is close to Davis *et al* (2018)'s research on how consumers learn from their experiences and social information. They elicit a final decision after learning from different types of information in a repeated interaction and analyze the value of different kinds of information and how subjects combine information.

We focus our analysis on the issues raised above. We first study the information-checking pattern in two treatments where the informativeness of information sources differs. We next built a simple partial decision-adjustment model to examine how subjects might adjust their decisions in responding to the available information. An EU Bayesian DM (decision maker) using noisy beliefs is used to model subjects' self-learning through experience. We further investigate the interaction effect of information sources. Lastly, we explore a counter-intuitive observation from our experiment that more informative suggestions (the personalised suggestions in treatment 2) fail to guide individuals in our experiment and examine possible explanations. Our results reveal that subjects treat others' decision in the group as verification of official suggestion reliability rather than considering information independently. An official suggestion diffusion model incorporating information congruence and imitation behaviour was built. These results shed light on a possible situation where the official suggestion can use the intrinsic behaviour of herding to improve the effectiveness of the recommendation.

This paper is organized as follows. Section 5.2 presents three hypotheses that serve as the basis for the design and analysis of our experiment, Section 5.3 describes the experimental design, Section 5.4 presents our data analysis strategy and results, and Section 5.5 provides a conclusion and interpretation of our findings.

5.2 Hypotheses

Three hypotheses serve as the primary guides for this paper's experimental design and analysis. These hypotheses originate from research evidence on cheap-talk as public persuasion and herding behaviour. The first hypothesis concerns how individuals convert information into decisions. The second and third hypotheses investigate two types of official suggestion mechanisms and derive the possible interaction effect of the social consensus.

First, we consider how an individual's decision is influenced by personal-experience and different sources of information. The information defined in our design is action from various information sources, but not the direct signal regarding the truth of the state (they are not told the true probability of the bad event). The purpose of this design is motivated by the situation that more emerging and unpredictable events happening around the world nowadays, such as the first global pandemic, bitcoin development, wars between Russia and Ukraine, etc., require individuals to make a choice without fully understanding the information. Behind each question is a large body of research that few of us will thoroughly evaluate the research report. Instead, we rely on doctors, government agencies, or other trusted sources to tell us what to do. Inevitably, sometimes we do not fully follow suggestions immediately as source reliability is ambiguous, and contradictory information is common. Therefore, individuals in real life do not just make decisions according to professional suggestions but also social information. For example, people decide whether or not to take the vaccine not only by receiving professional advice but also by noticing how many people have taken the vaccine. There is a wealth of literature on both the value of public suggestions and herding in social learning, but few have discussed two information sources (professional advice and social information) in the same context; this is closer to reality where many information sources are readily available.

The information structure we investigate in our experiment is not presented as a signal regarding the truth of the world. Instead, the information is about action. Research on advice and social experience both show a common research finding of both types of information sources. Both are presented as indirect information (action) rather than a signal that can influence decision making. One crucial line in terms of professional recommendation is the application of cheap-talk to public persuasion. The official suggestion in our design is similar to cheap-talk message from experts. Research shows that an outside expert's strategic message manipulates voters with heterogeneous preferences and prevents them from making decisions according to their private information, even if individuals know the advice is biased (Jeong, 2017). Adjustment to match others in the group is instinctive behaviour, as illustrated by evidence on investment decisions, voting behaviour and consumption (Janis 1991,Whyte 1993).

In the design that we consider, described in Section 5.3, subjects face a complicated decision task on insurance expenditure. Initially, personal experience is the only way to infer the probability of the bad event. After several rounds of personal experience, subjects can check official suggestions and the social consensus before deciding what to do. Therefore, personal experience and observed indirect information might reasonably be expected to influence jointly the individual's decision in each round. Decision adjustments with the intervention of information are expected to be observed. When the information from different sources is inconsistent, the amount of investment adjustment relies on the weight given by the DM to the information source. The Hypothesis is stated informally below and given a precise specification in Section 5.4.

Hypothesis 1*: Decision is a function of information available to DMs. Individuals adjust their decision each round in response to observed diverse information using a weighted average of what they learn, even if the information is not relevant to the true state.*

With Hypothesis 1, a society with a certain proportion of the population overly weighting others' decisions could mislead the society's welfare and prevent the diffusion of the official suggestion. The efficiency of herding relies on a majority of the population updating their choices toward an optimal decision (Juang 2001). As mentioned above, we investigate a decision task facing a complicated and unprecedented environment where learning to find the optimal decision requires high rationality and cognitive cost. The central question in this case, which most policymakers and researchers have widely discussed, is the efficiency of the official recommendation and how official recommendation guides majority of the population toward optimal decision. Different features of cheap-talk messages from the expertise and the persuasion efficiency have been examined by extensive research (Feddersen and Pesendorfer, 1997; Crawford and Sobel, 1982). Caillaud and Tirole (2007) propose a communication strategy to improve the proposal approval probability by convincing a qualified majority of members in a group to approve the proposal. Following their results, the second Hypothesis developed as follows.

Hypothesis 2*: The extent of congruence between the official suggestion and the social consensus improves the willingness to adjust toward the official suggestion.*

Hypothesis 2 describes a public communication mechanism by generating a suggestion in line with the majority population's state and is expected to persuade the majority of members in the group to adopt the suggestion and prevent inefficient herding. The intuition behind this is simple. People who doubt the official suggestion could check what other people have done to decide whether adopt the suggestion, such as whether to take the vaccine. In the real world, individuals face heterogeneous states with distributed optimal choices. Hence, this is an inevitable situation that general suggestions based on the whole population may not benefit minority groups. For example, vaccines might not be optimal for a small group with the potential disease. In Bardhi and Guo (2018), they compare a general expert message in which a signal depends on the states of all decision-makers and a personalised message in which each decision-maker's signal depends only on their state, and their research shows that the two types of messages have a different value from the standpoint of the message senders.

This motivates us to design two treatments with different official suggestions: treatment 1 with a general suggestion based on the incidence of the bad event for the whole population; and treatment 2 with a personalised suggestion based on the incidence of the bad event for that individual; If subjects are rational, a personalised suggestion is more informative than a general suggestion. However, one who puts excessive weight on others' decisions might perform worse as the relevance of the two information sources differs in the personalised suggestion setting. In treatment 1, the social consensus can reveal most subjects' attitudes toward official suggestions. Assuming the subject doubts the official suggestion, he or she might check if most subjects have adjusted their decision toward the official suggestion (Hypothesis 2). While in treatment 2, the suggestion for each subject varies, and so the social consensus is not informative for a rational decision maker. One Hypothesis based on treatment 2 is developed as follows.

***Hypothesis* 3**: *Personalised suggestions can better persuade individuals to adjust their decision if subjects are rational.*

5.3 Experimental Design and Procedures

To test our hypotheses, we designed a decision environment and problem with the following features:

(1). We wanted to create a situation in which personal experience is costly and the optimal decision difficult to solve without a full understanding of the problem and the relevance of the information. In this situation, the demand for information is strong, but the quality of the information is ambiguous.

(2). We wanted a situation in which information from two sources are possibly contradictory. This allows us to better distinguish the effect of information sources and examine how the decision distribution evolves when facing contradictory information.

(3). We felt it was desirable to have a decision-making environment with a heterogeneous true state of world. This structure is in fundamental ways mirrors the real-world, where different people in society face a different situation.

5.3.1 Decision problem

There were 40 decision rounds in the experiment, identical in structure and each independent of the others. In each round, subjects were asked to take a decision on the amount of money they would spend in that round in insurance to mitigate the effects of the occurrence of some bad event. Formally, in each round

The Stochastic Structure: Denote the outcome space by $S = \{S_1, S_2, \pi\}$, where π is probability that S_1 will happen, and 1- π is the probability that S_2 will happen. If S_1 happens, subjects lose a proportion p of their experimental endowment; If S_2 happens they lose nothing. Rather obviously, we refer to S_1 as the *bad event*.

Insurance structure: each unit of insurance costs c; each unit of insurance will compensate k per cent of the loss if the bad event happens to them.

In this design, the optimal decision on insurance investment for a rational risk-neutral decision maker is determined by the probability of the bad event. Denote by e the experimental endowment of each subject in each period. Then, the optimal decision[51] is:

$$n_{optimal} = \frac{c-(pc+ke)\pi}{2kc\pi} = \frac{1}{2k\pi} - \frac{pc+ke}{2kc} \qquad (5.1)$$

To incentivise personal-experience and the demand for information, subjects do not know the probability π that S_1 will happen to them. Hence, the perceived optimal value is determined by the subject's beliefs about the probability π. (The other parameters e, c and p are fixed, and are told to the subjects).

The parameters were carefully selected after extensive simulation. The endowment of each subject in each round was e= 40 euro; if the bad event happened, (p=) 90% of the experimental endowment, net of spending on insurance, will be lost. We fixed each unit of insurance's compensation k = 0.2 and the cost of each unit c = 4.5 euro. The high possible payoff and potential loss, and relatively high cost of insurance incentivises subjects to carefully consider their insurance expenditure decision. Rather obviously, this depends upon their perception of π. Note that with k=0.2, the possible decisions on insurance are {0,1,2,3,4,5}, where 5 units of insurance is full insurance with a cost of 22.5. The large decision space not only increases the difficulty of the decision problem but also reduces the possibility that an optimal decision is achieved with a random guess. In contrast with designs with a binary decision, a larger decision space is more informative and helps us to answer our research questions. One of our main analyses is to try to explain the insurance decision-adjustment across rounds and the adjustment direction, and look at

[51] Assuming risk-neutrality.

the relationship of these with the information sources that they consulted. The observed decision on insurance may be correct or wrong – resulting from a variety of mistakes or randomness. It could result from Bayesian updating, statistical inference, rational reasoning, or some behavioural bias. Such mistakes are difficult to disentangle in the standard binary choice design, as one mistake might offset a second mistake, so that a subject making two mistakes might end up behaving in a manner that appears to be the same given the observed information. We fixed the probability π to be normally distributed over the subjects in a particular session with a mean of 0.47 and a standard deviation of 0.2, which means that the optimal amount of insurance for the majority of subjects is either 2 or 3. This is designed to support the justification of our *Hypotheses 2 and 3.* Why this design matters will be discussed in the following shortly.

5.3.2 Experiment Procedure

Subjects were given written Instructions[52], which were read aloud by an experimenter. In the Instructions, subjects were told about the structure of the experiment, the consequence of the bad event, the insurance scheme and the differences between subjects.[53] However, they were not told the true probability π that the bad event will happen to them. This means that initially, they had to learn it through experience. After each round, subjects are told whether the bad event S_1 happened to them and how much they had earned. For the first 10 rounds, subjects need to take the insurance decision themselves; however, from 11 round and onwards, subjects are informed that an official suggestion and the social consensus are available. They could decide to check neither, either, or both information sources without any cost, in any round (after the 10th round).

[52] Instruction details see appendix D3.

[53] Subject only know probability of the bad event slightly varies from subject to subject but does know the true distribution.

The computer recorded which information source (if any) they consulted in each round, the decision they made, and their payoff in that round[54]. Note that the payoff in each round is determined by their decision on insurance in that round and on whether the bad event happened to the subject in that round. The final payment to a subject for the experiment as a whole was the payoff in a randomly chosen round plus a 5 euro participation fee.

5.3.3 Information structure

In addition to the problem structure, a key feature of our experiment is the design of the information sources that subjects could consult. We had two information sources, namely, (2) the official suggestion and (3) the social consensus on the insurance decision.

The official suggestion generation rules are different according to Hypothesis 2 (Treatment 1) and 3 (Treatment 2). The official suggestion in both experiments is an actuarial (statistical) calculation regarding the optimal units of insurance for subjects using equation (5.1). However, the estimate[55] of the probability π in equation (5.1) is different in the two treatments. In Treatment 1, the official suggestion is the solution to equation (5.1) using an estimate of the probability of the bad event π, based on the frequency of the bad event *over* ***all the preceding rounds for all subjects***. In Treatment 2, the official suggestion varied from subject to subject, being the solution to equation (5.1) using an estimate of the probability of the bad event, π, based on the frequency of the bad event ***over all the preceding rounds for that particular subjec****t*. As the true probability of bad event differs over subjects, this means that the official suggestion in Treatment 2 differs over subjects. With a decision space of {0,1,2,3,4,5}, subjects are very likely to

[54] If S_1 happens their payoff *is (e-nc)-p(e-nc)+knp(e-nc)*; If it does not happen, theirpayoff is *e-nc,* where *n* is their decisision on the unit of insurance.

[55] While the computer obviously knows the true value of π, the official suggestion is based on the observed frequency of the bad event in the experiment, and the subjects knew this.

observe contradictory information between the two sources (for example, the official suggestion can be zero while the social consensus is 4). Note that the social consensus is a summary of all subjects' decisions showing how many units of insurance was the most popular among all subjects in the preceding round; this may change from round to round. Similarly, the official suggestion may vary from round to round, as more evidence of the occurrence of the bad event is obtained.

5.4 Econometric specification and Results

Data was collected in six experimental sessions (three sessions for each treatment), carried out in the CESARE laboratory at LUISS in Rome. A total of 140 subjects participated in the experiment. Treatment 1 had 71 subjects and treatment 2 69 subjects. On average, each session had 23 subjects; each individual participated in only one session. Parameters were chosen so that the distribution of the optimal decision was approximately the same in each session: for 56% of the subjects the optimal decision was 2 or 3; for 20% it was 1, for 14% it was 0 and for 10% it was 4; full insurance was not the optimal decision for any subject. This design was to capture the existence of any extremely irrational subjects. As mentioned, each session consisted of 40 rounds; no subject could proceed to the next round until all subjects in the session submitted their decision. Each session lasted approximately one hour. The average payment to subjects was 21 euros.

5.4.1 Descriptive summary of the Data

We first present the overall information usage pattern, decision evolution and convergence patterns in the two treatments, and examine the differences between the treatments.

Table 5.1 shows the information-checking frequencies in the two treatments. Subjects in treatment 2[56] checked the official suggestion more frequently than subjects in treatment 1, while the frequencies of checking the social consensus were lower in treatment 2 than in treatment 1. This is consistent with our intuition that rational subjects are more likely to pay attention to the personalised suggestion. We classify the information-checking patterns into four types: (1) checking only the official suggestion, (2) checking only the social consensus, (3) checking both, and (4) checking neither. Table 5.2 shows the information-checking pattern distribution of subjects. Subjects are more likely to pay attention only to the official suggestion in treatment 2 than in treatment 1. Few subjects *only* check social consensus. To some extent, this shows that the social consensus by itself does not play a crucial role in our experiment. However, the social consensus and official suggestion are more likely to be checked together: on average subjects paid attention to both information sources 12.7 times in treatment 1; this is significantly higher than the 10.4 times in treatment 2. This is consistent with our Hypothesis 2, indicating that subjects use the social consensus as complementary information to verify the official suggestion.

	Treatment 1	Treatment 2
Frequencies of checking the official suggestion	18.6	20.2
Frequencies of checking the social consensus	13.7	10.8

Table 5.1 Average information-checking frequencies across subjects

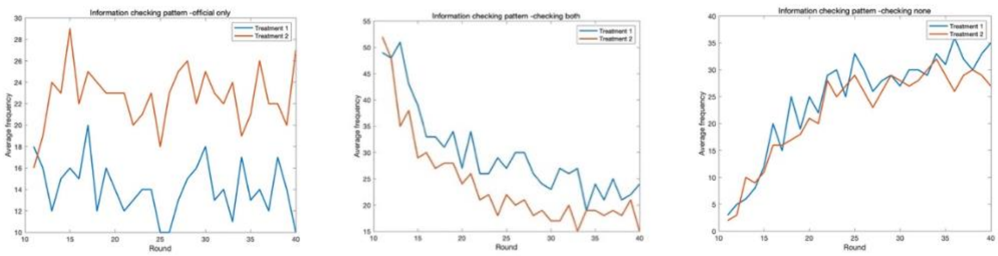
	Official only	Social consensus only	Both	None
Treatment 1	6.0	1.0	12.7	10.4
Treatment 2	9.8	0.4	10.4	9.4

Table 5.2 Average information-checking pattern distribution across subjects

We further explore the interaction of the two information sources. Information

[56] In Treatment 2, official suggestions were personalised; in Treatment 1 they were the same for all subjects, irrespective of their personal probability.

exploration is a self-selection procedure that reflects subjects' willingness-to-learn. Figures 5.1 a, b and c show how information-checking pattern frequencies change over time. The two treatments show a similar information-checking pattern over time. As can be seen in Figure 5.1 a, the number of subjects checking only the official suggestion shows a stochastic pattern without an obvious trend; this is the same in both treatments. However, the frequencies of checking both information sources and checking nothing show opposite trends over time. The number of subjects checking the official suggestion and the social consensus decreases as they gain experience (Figure 5.1 b); and more and more subjects are likely not to check any information source as they gain experience (Figure 5.1 c).



a *b* *c*

Figure 5.1 Information checking patten trend across time

Result 1: The personalised suggestion attracts more attention than the general suggestion; the social consensus is more likely to be used alongside the official suggestion; this is consistent with our **Hypothesis** ***2.***

Now we turn to the decisions. Figure 5.2 depicts the evolution of the observed frequencies of the decision on insurance from unit 0 to 5 in each session. Darker green indicates that more subjects have chosen the same unit of insurance. In rounds 1 to 10, the distribution of subjects' decisions is very dispersed. After the introduction of the official suggestion and the social consensus information, the decisions are distributed more centrally. Even though no clear convergence emerges, treatment 2 has a more prominent convergence pattern than treatment 1. This is counterintuitive. In treatment 1, the official suggestion ranges from 2 to 3 across time since 2 and 3 are the optimal decisions for the majority of the subjects. In treatment 2, the official suggestion varies according to each subject's individual probability. Intuitively, treatment 2 with more diverse official suggestions, should show less convergence than treatment 1. Even though treatment 1 does not converge toward the official suggestion, the overall decision is centrally distributed around the official suggestion. Looking at the information-checking patterns, it seems to be the case that subjects use the information in different ways. In treatment 2, subjects show higher frequencies to check the official suggestion than subjects in treatment 1. However, the higher information exposure does not indicate a higher tendency to *follow* the official suggestion. In treatment 1, subjects show a higher tendency to check *both* the official suggestion and the social consensus, it confirms our intuition of ***Hypothesis 2*** that the social consensus influences subjects' responses to the official suggestion. But we cannot simply reach a conclusion on how information sources influence subjects' decision from these patterns: several questions arise here: why a convergence pattern appears when facing diverse personalised official suggestions; whether subjects are more willing to follow the official suggestion when more subjects have done so in treatment 1; and whether subjects use the social consensus information in the same way in treatment 2 even this is irrational. There are many possible explanations of this observed pattern. In the following sections, we first build an econometric model to examine how information accounts for the adjustment of the decision, to outline behaviour stochasticity, rationality and information source bias. Then, we further investigate the interaction effect of information on decision.

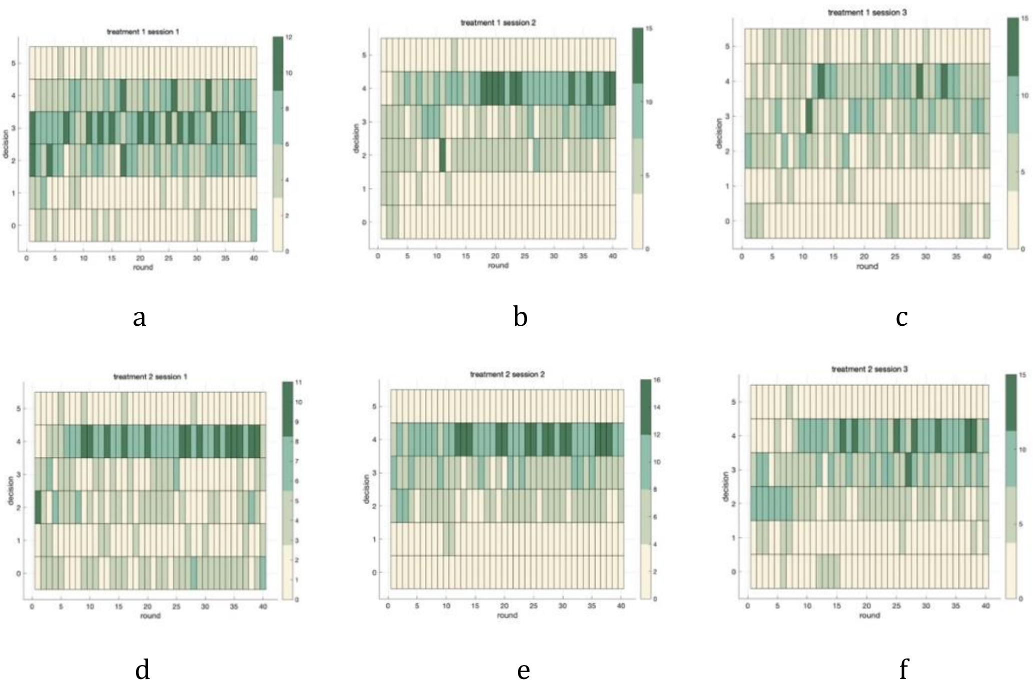


Figure 5.2[57] Group decision frequency distribution evolution across time

5.4.2 How can information account for the decision adjustment?

Hypothesis 1 states that the adjustment of the decision in each round is a simple weighted average of the information available to them. To assess to what extent the adjustment of the decision is responsive or susceptible to personal-experience, the official suggestion, and the social consensus, we build an estimation model based on a simple decision-adjustment rule[58].

To explain this, we start with an adjustment rule in the absence of the official suggestion and the social consensus, and then build in the possible influences of these two

[57] The horizontal axis (labeled 'decision') indicates units of insurance from 0 to 5, and the vertical axis (labeled 'round') indicates the round of decision. The color bar indicates the number of subjects; a darker color indicates more subjects have made the same decision.

[58] We follow several articles in the literature which have modeled the demand for stock investment, money and consumption (Aschheim and Tavlas,1988; Kennan, 1979) using such a partial adjustment framework.

information sources.

Our model specifies a rule for subjects' each round adjustment of their decision on insurance depending on the gap between the updated decision based on the newly arrived information (the latest occurrence or not of the event) and the decision in the preceding round.

In general, a rational subject in this experiment should mainly rely on personal experience (based on the observed frequency of the event), rather than on either the official suggestion or the social consensus. Our simple rule to model the adjustment of the decision between rounds, without the intervention of this outside information, is given by equation (5.2).

$$d_{t,i} = \partial d_{t-1,i} + (1-\partial)\left(d_{t-1,i} + \left(n_{t-1,i}^{self} - d_{t-1,i}\right)\right) + \varepsilon_i \tag{5.2}$$

Here we denote by $n_{t,i}^{self}$ the optimal decision calculated by subject i in round t based on the occurrence of the bad event for this subject. The adjustment parameter ∂ is expected to between 0 to 1, since the decision-adjustment may be incomplete due to inertia, self-confidence, and rationality. This adjustment speed parameter reflects subjects' willingness to respond. The parameter ε_i is subject-specific noise which we assume to be normally distributed with a mean of 0 and standard deviation of λ.

Up to now, we have assumed that subjects' decisions are based solely on their experience. We now build in subjects' possible responses to the information sources. Our Hypothesis 1 suggests that subjects' decision-adjustment will be influenced both by the observed official suggestion and by the social consensus; the effect of these will depend upon by the weights attached to the different information sources. We denote the weight placed by the subject on personal experience by w^{self}, that on the official suggestion by $w^{offical}$, and that on the social consensus by $w^{consensus}$. Incorporating these into equation (5.2) we get

$$d_{t,i} = \partial d_{t-1,i} + (1-\partial)\big(d_{t-1,i} + w^{self}\big(n^{self}_{t-1,i} - d_{t-1,i}\big) + D_{t,i}w^{official}\big(n^{official}_{t,i} - d_{t-1,i}\big) + M_{t,i}w^{consensus}(n^{consensus}_{t,i} - d_{t-1,i})\big) + \varepsilon_i \tag{5.3}$$

$$D_{t,i} = \begin{cases} 1 & if\ checked\ official\ suggestion \\ 0 & if\ not\ checked\ \ official\ suggestion \end{cases}$$

$$M_{t,i} = \begin{cases} 1 & if\ checked\ social\ consensus \\ 0 & if\ not\ checked\ social\ consensus \end{cases}$$

The parameters w_s capture the relationship between information and decision. One can also interpret these as the information source bias, for example if $w^{consensus}$ in treatment 2 is larger than that in treatment 1, we can conclude that subjects irrationally weigh the social consensus in treatment 2 where the consensus is uninformative.

As Figures 5.1 and 5.2 suggest, there is obvious stochasticity in the decision. We introduce a parameter tremble w to capture randomness. If the tremble happens, subject makes decision randomly. Based on above equations, a likelihood function across subjects can be obtained:

$d_{t,i} = 0$

$$P\big(d_{t,i}\big) = (1-\omega)cdf(-\big(\partial d_{t-1,i} + (1-\partial)\big(d_{t-1,i} + w^{self}\big(n^{self}_{t-1,i} - d_{t-1,i}\big) + D_{t,i}w^{official}\big(n^{official}_{t,i} - d_{t-1,i}\big) + M_{t,i}w^{consensus}(n^{consensus}_{t,i} - d_{t-1,i}))\big), 0, \lambda\big) + \frac{\omega}{6}$$

$0 < d_{t,i} < 5$

$$P\big(d_{t,i}\big) = (1-\omega)pdf(d_{t,i} - \big(\partial d_{t-1,i} + (1-\partial)\big(d_{t-1,i} + w^{self}\big(n^{self}_{t-1,i} - d_{t-1,i}\big) + D_{t,i}w^{official}\big(n^{official}_{t,i} - d_{t-1,i}\big) + M_{t,i}w^{consensus}(n^{consensus}_{t,i} - d_{t-1,i}))\big), 0, \lambda\big) + \omega/6$$

$d_{t,i} = 5$

$$P(d_{t,i}) = (1-\omega)cdf(5 - (\partial d_{t-1,i} + (1-\partial)(d_{t-1,i} + w^{self}(n_{t-1,i}^{self} - d_{t-1,i}) + D_{t,i}w^{official}(n_{t,i}^{official} - d_{t-1,i}) + M_{t,i}w^{consensus}(n_{t,i}^{consensus} - d_{t-1,i}))), 0, \lambda) + \omega/6$$ [59]

Hence,

$$logL = \sum_{i=1}^{n}\sum_{t=1}^{T} P(d_{t,i})$$

So far so good, but there is a problem: $n_{t,i}^{self}$ is a latent variable, which can not be directly observed. We propose a noisy *Bayesian rule* to model subjects' calculation of $n_{t,i}^{self}$. For **Bayesian rules**, subjects form their belief on probability by learning from experience and calculate the optimal utility using equation (5.1). To model randomness in probability inference in a simple way we assume that subjects form a belief on probability according to a Beta distribution, which is determined by subjects' experience after *t* rounds with $a_{t,i}$ times of event happening, and t- $a_{t,i}$ times of the event not happening. For round *t+1*, the probability of the bad event for subject *i* is

$$f(\pi_{t+1,i}^{self}) = \beta(\pi_{t+1,i}^{self})^{a_{t,i}}(1-\pi_{t+1,i}^{self})^{t-a_{t,i}} \text{ where } \beta \text{ is a normalization constant.} \quad (5.4)$$

As we observed from Figure 5.2, subjects tend to over-purchase the insurance (tend to purchase 4 units) during the first 10 periods (when the other two sources are not provided). This could be because subjects overestimate the probability of the bad event, or because they are risk averse. We introduce a parameter α to reflect this over-perception of the frequency of the bad event and assume that it decays in magnitude over time (to allow for learning); that is, that subjects more precisely perceive the probability of the bad as they gain experience. We incorporate this as follows.

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[59] *cdf* and *pdf* are the parameter ε_i's cumulative distribution function and probability density function which is a normal standard distribution.

$$\hat{a}_{t,i} = (1 + e^{\alpha(t-1)})a_{t,i} \tag{5.5}$$

We expect the parameter α to take a negative value. One can interpret this parameter α as a subjects' learning rate. The larger it is in magnitude; the faster learning will be. We postulate that subjects apply equation (5.4) based on $\hat{a}_{t,i}$to estimate the probability of event.

Given our equation (5.1) and our design of the insurance structure, a discrete approximation of $n_{t,i}^{self}$ can be defined[60] . We can classify five different intervals for the perceived probability of the bad event, each interval leading to a different optimal insurance decision[61].

Probability of event happening	Optimal unit of insurance
$0 \leq \pi \leq 0.37$	0
$0.37 \leq \pi \leq 0.44$	1
$0.44 \leq \pi \leq 0.53$	2
$0.53 \leq \pi \leq 0.68$	3
$0.68 \leq \pi \leq 1$	4

Hence, the probability of $n_{t,i}^{self}$ can be easily obtained by integrating equation (5.4) over the corresponding interval. We call $n_{t,i}^{self}$ the decision based on **Bayesian learning** .We denote the five intervals as *X=[X₀, X₁, X₂, X₃, X₄, X₅]*

$$p_{baye}\left(n_{t,i}^{self}\right) = \int_{X_{n_{t,i}^{self}}} f(\pi_{t+1,i}^{self})$$

It follows that we can write the likelihood function in the following form:

[60] Note to derive equation (5.1), we assuming that subjects are risk neutral.

[61] Note that we leave the unit 5 as an complete irrational decision to capture any irrational decision makers.

$$logL = \sum_{i=1}^{n} \sum_{t=1}^{T} \sum_{n_{t,i}^{self}=0,1,\dots,5} p_{baye}(n_{t,i}^{self}) P(d_{t,i}|n_{t,i}^{self})$$

We obtain the following maximum likelihood estimates of the various parameters:

	∂	λ	ω	α		w^{self}	$w^{offical}$	$w^{consensus}$	$-Log\ L$
Treatment 1	0.71	0.79	0.20	-0.15	D=1，M=1	0.38	0.59	0.03	3120.39
					D=1，M=0	0.39	0.61	0.00	
					D=0，M=1	0.94	0.00	0.06	
					D=0，M=0	1.00	0.00	0.00	
Treatment 2	0.57	0.74	0.16	-0.05	D=1，M=1	0.58	0.20	0.22	2811.47
					D=1，M=0	0.75	0.25	0.00	
					D=0，M=1	0.73	0.00	0.27	
					D=0，M=0	1.00	0.00	0.00	

Table 5.3 Across subject estimation

Table 5.3 presents the estimated weights of information in our decision-adjustment model; this is derived from the estimation conditional on the information-checking states (checking official suggestion, D=0 or 1; and checking social consensus, M=0 or 1 in round t) of subjects according to equation (5.3)[62]. In treatment 1, subjects' decision-adjustment is mainly accounted for by the official suggestion, then the noisy EU Bayesian EU personal-learning, and finally the social consensus. In treatment 2, the estimation is consistent with Figure 5.2. Subjects in treatment 2 put more weight on the social consensus than in treatment 1. The parameter ∂ indicates subjects' willingness to adjust decision in two treatments. Treatment 1 shows a lower adjustment speed ($\partial = 0.71$) than treatment 2 ($\partial = 0.57$). Combining ***Result 1*** with the results shown in Table 5.3, regarding treatment 2, subjects show a more active official suggestion checking behaviour, but decision-adjustment is less responsive to the official suggestion. Subjects' decision-adjustment is

[62] We assume the weight of information is independent of the information checking states. The weights are standardised.

mainly interpreted by Bayesian personal-learning in treatment 2 based on a lower learning rate (α=-0.05) than subjects in treatment 1 (α=-0.15). In other words, subjects in treatment 2 tended to over-estimate the probability of the bad event and learnt to adjust the estimated probabilities precision more slowly, which leads to a higher optimal unit based on Bayesian rules.

Results 2: In the general suggestion treatment (treatment 1), subjects place most weight on the official suggestion, followed by personal-learning (based on Bayesian Updating) and put the least weight on the social consensus to adjust their decision in each round. While in the personalised suggestion treatment (treatment 2), subjects place most weight on personal learning (based on Bayesian updating), less weight on the social consensus, and the least on the official suggestion. Comparing the two treatments, subjects are less responsive to the personalised suggestion than the generalised suggestion.

This is a surprising result. More active self-selection of official information reflects subjects are aware of the value of personalised information, so why do subjects decide not to *respond* to the official suggestion? Furthermore, subjects are more responsive to the social consensus in treatment 2 than in treatment 1; does this mean that herding is intrinsic even it is not rational? To explore possible explanations, we consider information congruence (1) between official suggestion and the social consensus, and (2) between official suggestion and personal learning (based on noisy Bayesian updating).

5.4.3 Does congruence between official information and the social consensus matter?

Hypothesis 1 can be verified by estimation results showing that Individuals adjust their decision each round in response to observed diverse information using a weighted average of what they learn, even if the information is not relevant to the true state. Our

Hypothesis 2 and Hypothesis 3 can possibly explain these results. In treatment 1, subjects can verify the quality of the official suggestion by checking the social consensus. It is reasonable to be convinced by the official suggestion if more and more subjects move towards the official suggestion. While in treatment 2, subjects who are uncertain about the official suggestion will face more contradictions between the social consensus and the official suggestion. To evaluate Hypothesis 2 and Hypothesis 3, and verify this explanation, we run a probit regression to examine how observed congruence between the official suggestion and the social consensus influences the adoption of the official suggestion.

$$p\left(adopted \middle| y_{t,i}\right) = \Phi(\beta_0 + \beta_1 y_{t,i})$$

$$y_{t,i} = \left|n_{t,i}^{official} - n_{t,i}^{consensus}\right| \quad (5.6)$$

Here $y_{t,i}$ is subject *i's* observed absolute difference between latest checked official suggestion and the latest checked social consensus up to round *t*.[63] The symbol *Φ* denotes the *cdf* of a standard normal distribution. The coefficient parameter β_1 captures the idea that higher congruence between official suggestion and the social consensus may lead to a higher probability of the adoption of the official suggestion.

We estimate the parameter β_1 with the data generated after round 10. Table 5.3 shows that higher incongruence between the official suggestion and the social consensus significantly decreases the adoption of the official suggestion in both treatments. This is consistent with our Hypothesis 2. The extent of congruence between the official suggestion and the social consensus improves the willingness to adjust toward the official suggestion. Furthermore, this effect still exists in treatment 2, even though the

[63] For example, a subject only checked official suggestion and observed $n_{t-1,i}^{official}$ at round *t-1,* and only checked the social consensus $n_{t,i}^{consensus}$ at round *t.* Then, the observed difference at round t will be $|n_{t-1,i}^{official}$-$n_{t,i}^{consensus}|$.

relationship in treatment 2 is weaker than that in treatment 1. The significant adverse impact of incongruence between the official suggestion and the consensus suggests that some subjects intrinsically reference the social consensus to decide whether to adopt the official suggestion. This may potentially explain why the official suggestion accounts for a smaller decision-adjustment in treatment 2 than in treatment 1, as subjects in treatment 2 are more likely to observe incongruence between the official suggestion and the social consensus.

	β_1	β_0	$-Log\ L$
Treatment 1	-0.29 (0.06)***	-0.61 (0.04)***	1152.73
Treatment 2	-0.11 (0.03)***	-0.7 (0.06)**	1057.28

*** indicates p<0.001

** indicates p<0.05

Standard deviation is presented within the parentheses

Table 5.4 Congruence effect

We find that a higher observed incongruence between the official suggestion and the social consensus reduces the probability of adopting the official suggestion in both treatments (see Table 5.4). This incongruence effect in treatment 1 is almost twice that of treatment 2. It is more sensible to observe this effect in treatment 1. Subjects who doubt the official suggestion would check what others have done to decide whether the official suggestion is reliable. This rationale does not exist in treatment 2.

Results 3: The incongruence between the official suggestion and the social consensus impedes the willingness to adopt the official suggestion, even though the information sources are irrelevant.

5.4.4 Doe congruence between official suggestion and self-belief matter?

Confirmation bias, defined as a decision-maker's tendency to seek for evidence supporting their own belief, and refuse to accept contradictory information, has been widely discussed in research on decision-making under uncertainty (Rabin and Schrag.,1999; Charnessa and Dave, 2017). In our experiment, we do not elicit subjects' beliefs on the probability. However, the decision during first ten rounds must be based on their belief. Of particular interest is if first observed information congruence influence the further attitude toward information. For example, suppose a subject make a decision to buy 4 units before first checking the official suggestion (which turns out to be 0). This huge difference shocks the subject's belief, leading either to the subject adjusting their decision toward the official suggestion, or to build an aversion to the official suggestion. In this case, subject may tend to search for evidence to support their own decision by checking the social consensus. If the consensus happens to be consistent with the decision from personal-learning, subjects with confirmation bias will be more confident with their own decisions and less likely to adopt the official suggestion. Hirshleifer *et al*.,(2020) present the first impression bias in finance professionals. Rabin and Schrag (1999) studied how first impression matters regarding confirmation bias. The prevalence of confirmation bias of first impression reflects real-world circumstances. In early stages of covid 19, people in different countries show polarized attitudes toward the official suggestion of wearing a mask. For Asian countries, such as China, wearing a mask is usual behaviour, while it is uncommon in western countries. The mask policy triggers debate and more doubts in western countries than in Asian countries. The confirmation bias in first impression may explain this phenomenon.

To examine this, the first observed congruence between the official suggestion and the self- decision $B_i^{official}$ is measured as follows. $B_i^{official} = |d_{m-1,i} - n_{m,i}^{official}|$where m[64] denotes the first-time that subject i checked the official suggestion.

Hence,

$$p(adopted|y_{t,i}) = \Phi(\beta_0 + \beta_1 y_{t,i} + \beta_2 B_i^{official})$$

$$y_{t,i} = |n_{t,i}^{official} - n_{t,i}^{consensus}|$$

This will be added into the regression equation (5.6).

The coefficient of interest regarding the effect of confirmation bias in first impression is β_2, which is expected to be negative. A lower negative value of β_2 indicates stronger adverse impact of perceived incongruence formed in first impression on the willingness to adopt the official suggestion.

The results are presented in Table 5.5. Consistent with the research conclusion of Hirshleifer *et al*., (2020), Rabin and Schrag (1999) and confirmation bias research (Alemanni et al.,2020), the negative coefficient β_2 indicates that the congruence in first impression matters. In both treatments, the coefficient β_2 shows that a higher incongruence between the first observed official suggestion and the personal-learning decision decreases the probability to adopt the official suggestion in later rounds. Compare the coefficients in treatment 1 and treatment 2, the initial willingness to adopt official suggestion in treatment 2 is more vulnerable to be shocked by first observed conflict between official suggestion and personal learning. It is the same as Table 5.4, the coefficient β_1 maintains negative indicating the existence of adverse effect of

[64] The majority of the subjects started checking the official suggestion at round 11 except for 2 subjects who never checked the official suggestion. These two subjects' observations were not included in this estimation.

incongruence between official information and the social consensus. Interestingly, the official suggestion adaptation in treatment 2 is more significantly influenced by the incongruence between first observed official suggestion and the personal-learning decision ($\beta_2 = -0.23$) than that between official suggestion and the social consensus ($\beta_1 = -0.02$). One can interpret the first impression as a mediator intervening the adverse impact of information incongruence between consensus and official suggestion. This explains why subjects in treatment 2 put less weight on the official suggestion in the decision-adjustment estimation results (Table 5.3). Subjects who have a lower learning rate ($\alpha = -0.05$ in Table 5.2) end up with an extreme decision on insurance (for example, over-purchasing shown in Figure 5.2). Later on, they observe different official suggestions being contradictory to their self-experience. For example, some subjects will be suggested with 0 unit of insurance. They begin to doubt the official suggestion, however they do not have any method to verify the quality official suggestion except for carrying on using self-experience. Rational subjects may quickly adjust their decision through personal-experience while limitedly rational subjects may end up with biased belief and bad decisions.

	β_1	β_2	β_0	$-Log\ L$
Treatment 1	-0.15 (0.06)***	-0.17 (0.03)***	-0.30 (0.06)***	1223.88
Treatment 2	-0.02 (0.03)	-0.23 (0.03)***	-0.06 (0.05)	1314.54

*** indicates p<0.001
** indicates p<0.05
Standard deviation is presented within the parentheses

Table 5.5 Congruence effect

Results 4 : Confirmation bias in the first impression has an adverse impact on willingness to adopt the official suggestion; meanwhile the first impression mediates the impact of information incongruence between official suggestion and social

consensus on the willingness to adopt the official suggestion.

5.4.5 How is the diffusion of the official suggestion influenced by information congruence and imitative behaviour?

The above results suggest that the congruence between the official suggestion and the social consensus influences subjects' willingness to adopt the official suggestion. This behaviour could adversely affect the evolution of society's decisions. The intuition is straightforward. Imagine more subjects who are not capable of learning from their own experience make bad decisions without official guidance. Then subjects see what others have done to decide whether to follow the official suggestion. In this case, if the proportion of this type of subjects is large, it will impede the diffusion of the official guidance. In this section, we examine how the official suggestion diffuses in the two treatments, and whether imitation is prevalent in both treatments.

We follow an early model of diffusions proposed by Bass (1969). His model considers two influencing factors on the fraction of populations in a society who adopt a behaviour through time. They are: (1) The rate at which populations adopt one behaviour spontaneously; and (2) the rate at which they imitate others or adopt because others have.

Follow Bass's framework, consider time period t, and let $F(t)$ be the fraction of subjects in a society who adopted the official suggestion by time t. Then p is the rate of spontaneous adoption and q is the rate of imitation. The growth of fraction $F(t)$ is described by a difference equation as equation (5.7). The first term $p(1- F(t-1))$ describes spontaneous adoption subjects among subjects who have not adopted the official suggestion, which is $p(1- F(t-1))$; and the second term $q(1- F(t-1))F(t-1)$ captures the tendency of imitation behaviours is influenced two factors which is how many subjects have adopted the official suggestion $F(t-1)$ and therefore can be imitated; and how many subjects have not adopted the official suggestion and can be potential imitate $q(1- F(t-1))$.

$$F(t) - F(t-1) = p\big(1 - F(t-1)\big) + q\big(1 - F(t-1)\big)F(t-1) \tag{5.7}$$

The simple equation captures the idea that the more the population has adopted the official suggestion the larger the growth of the adoption of the official suggestion. In our design, the subjects only know the majority decision, but they do not know *how many* subjects have adopted the official suggestion where the *F(t-1)* in the equation can not be applied. Meanwhile, the decision space is not binary. Following the ideas of Bass, we extend equation (5.7) given our design.

$$F(t) - F(t-1) = p\big(1 - F(t-1)\big) + q\big(1 - F(t-1)\big)C$$

$$C = \frac{1}{NA}\sum_{i}^{NA}\frac{1}{1+e^{|n_{t,i}^{official} - n_{t,i}^{consensus}|}}$$

Here we define *NA* as the group of subjects who did not adopt the official suggestion at round *t-1. C* is to measure the average observed information congruence of these non-adopters. As our regression analysis shows, the observed information congruence influenced individual's probability of adopting official suggestion. We aim to measure parameters *p* and *q* and see to what extent the diffusion of official suggestion can be explained by imitation.

	p	*q*
treatment 1	0.12	0.99***
treatment 2	0.35***	0.63***

Regression based on OLS regression
*** indicates p<0.001
** indicates p<0.05

Table 5.6 Information diffusion

In both treatments, imitation plays a crucial role in the diffusion of the adoption of the official suggestion. Spontaneous adoption is lower in treatment 1 than in treatment 2 (see

Table 5.6). The personalised suggestion is more valuable for rational subjects, but it cannot eliminate imitation. Our results show that imitation is intrinsic.

Results 5: Imitation is prevalent. The imitation rate is higher than the spontaneous adoption rate in both treatments.

5.5 Conclusion

In this paper, we investigated how an individual's decisions are affected by the interaction of the official suggestion and the social consensus. To learn more about a possible public recommendation mechanism, two types of official suggestions (that is, a general suggestion and a personalised suggestion) were examined in two treatments. We also explored how the information congruence influences the attitude toward the official suggestion. Understanding the relationship between information sources and how individuals respond to them is difficult, due to the complexity and unobservability in the real world. In our experiment, however, a relationship between information sources is constructed in which the fundamental structure is known, what information has been checked, and the corresponding decision in response to information is measured. This design guarantees our identification strategy.

Our results show that the social consensus plays a crucial role in the adoption of the official suggestion. It seems that subjects perceive the social consensus as a kind of verification of the official suggestion. More interestingly, we found this kind of verification by the social consensus is prevalent even when the official suggestion and the social consensus are essentially irrelevant. In our treatment 2, subjects were given personalised suggestions. However, more herding is observed in treatment 2 (with a personalised suggestion) than in treatment 1 (with a general suggestion).

Our results show that the congruence between information sources matters. The information sources will interactively influence individual's decision making. The adoption of the personalised suggestion requires higher rationality in the population so that they can personally learn to judge the quality of the information. However, when the environment is ambiguous and the truth of the state is hard or too costly to learn, the reputation of suggestion generation should be high enough to make people initially trust it. Otherwise, society can be easily misled by a biased social consensus. Further research based on the current experiment design could provide further information showing how subjects adopt the official suggestion and see how it influences the effect of the social consensus on the adoption of the official suggestion.

To our knowledge, our paper takes the first step toward studying the interactive effect of different information sources. Our setting captures real-world decision-making features, such as information quality ambiguity, decision space richness, and individual heterogeneity. Our results point out an important factor: information congruence influences the diffusion of the official suggestion. Our research sheds light on research on experts' cheap-talk mechanisms. One interesting further question arises here as to how cheap-talk equilibrium will be changed after considering information congruence. For example, as we mentioned, our information design in two treatments is inspired by Bardhi and Guo (2018). They investigate senders' benefit based on a general suggestion (advice given all decision-makers' states) and a personalised suggestion (advice given individual's state). One can extend the research by adding extra information sources.

Importantly, our results also show that the congruence or the incongruence between the self-learning decision, the official suggestion and the social consensus in period 11 (the "first impression") has a significant effect on future decisions, with the effect lingering for a long time. So, behaviour in the first 10 periods before exogenous information arrives is crucial. Also, important seems to be the *timing* of the release of other information.

Perhaps, it is in society's interests in the long run for the information that is published initially to be 'manipulated'. Or for governments not to allow the social consensus to be published until after the publication of the official guidance. We would need further experiments to test for this.

Appendix

Appendix A : 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 $N(0,\sigma^2)$, 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 σ^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.

	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

Table A Estimation on RUM

Appendix B Eliciting the *ex-ante* preference by Holt-and-Laury's price list

The evaluation of the *ex-ante* preference, which is a key component in most models under consideration, cannot be observed from the two choices (choice *of* a menu and choice *from* the menu) in the second part of the experiment. Thus, we elicited the *ex-ante* risk attitude r_u in Part 1 using (our slight modification of) the Holt and Laury price-list mechanism. In Part 1, we elicited each singleton valuation by showing a particular lottery on the left of the screen and a drop-down list of numbers on the right. Subjects indicated their valuation of the lottery on the left by comparing the lottery with a series of amounts of money and ticking to indicate whether they preferred the lottery or the amount of money. An example of a screenshot is in Figure B. Their indicated preference depends on their own *ex-ante* risk attitudes in part 1. This elicitation came before the subjects began to make decisions in Part 2 of the experiment.

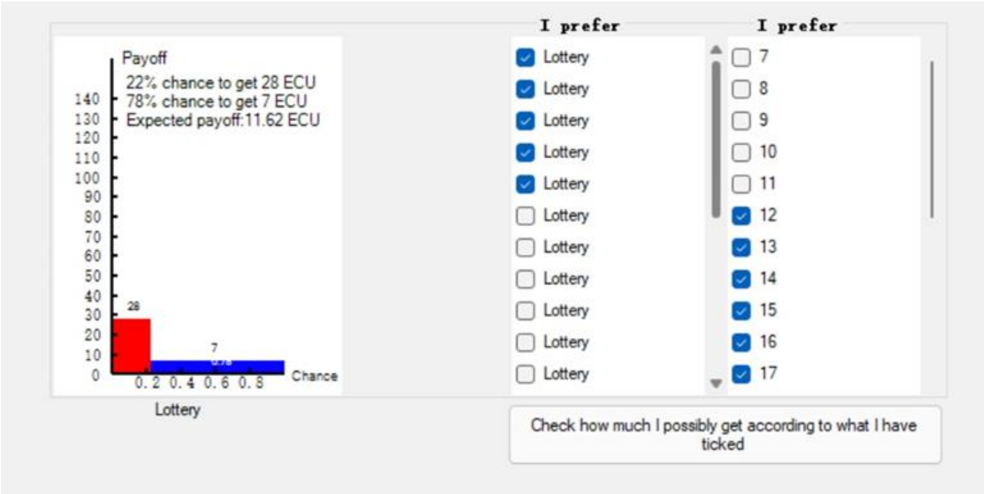


Figure B Holt-Laury Price List Method

To provide them with an incentive to reveal their true preference, we used the following method to pay subjects if one of these lotteries was played out at the end of the experiment. We randomly selected one of the rows from the drop-down list; if the subject had ticked the lottery in this row, we played out the lottery on the left; if subject had ticked the amount of money in this row, their payment was the amount of money in this row.

Appendix C Simulation

In this simulation we have assumed that r_U=1.73 and have used the corresponding menusets generated as in our experiment as described above. We first generated 100 sets of observations on the choice *of* a menu under frame f_1 with gamble temptations for the different models assuming Luce noise. We then estimated the parameters of the different models. This was to see if the maximum likelihood estimation can identify the true model that was used to generate the decisions, and if the true parameters can be estimated. We use the AICc criterion to determine the best-fitting model.

True model is ST with r_u=1.73			
Models	r_v	p	Corrected likelihood
PF	2.6	0	11.99
SC	2.4	0.16	12.03
ST	-	-	11.98

Table C1 Average estimated parameters and corrected likelihood value (AICc)

True model is PF with r_u=1.73, r_v=-2, p=0.8			
Models	r_v	p	Corrected likelihood
PF	-2.23	0.85	13.9
SC	-3	0.98	15.27
ST	-	-	15.44

Table C2 Average estimated parameters and corrected likelihood value (AICc)

True model is SC with r_u=1.73, r_v=-2, p=0.8			
Models	r_v	p	Corrected likelihood
PF	-5	0.95	14.15
SC	-2.4	0.79	1.95
ST	-	-	18.22

Table C3 Average estimated parameters and corrected likelihood value (AICc)

The above tables show that using the different menu utility functional with Luce model are tractable and identifiable.

Appendix D experiment instructions

D.1 instruction for Chapter 2's experiment

Preamble

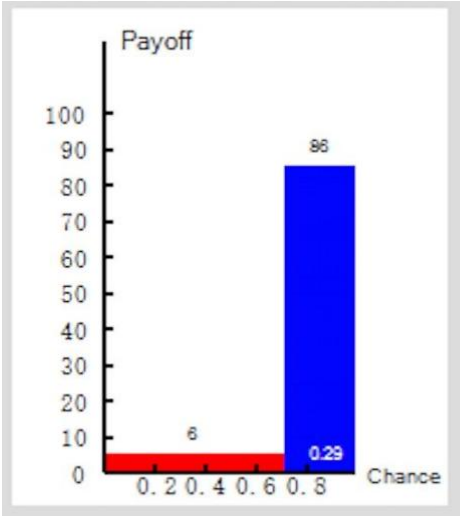
Welcome to this experiment. These instructions are to help you to understand what you are being asked to do during the experiment and how you will be paid. The experiment is simple and gives you the chance to earn a considerable amount of money, which will be paid to you in cash after you have completed 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.

D.2 instruction for Chapter 4's experiment

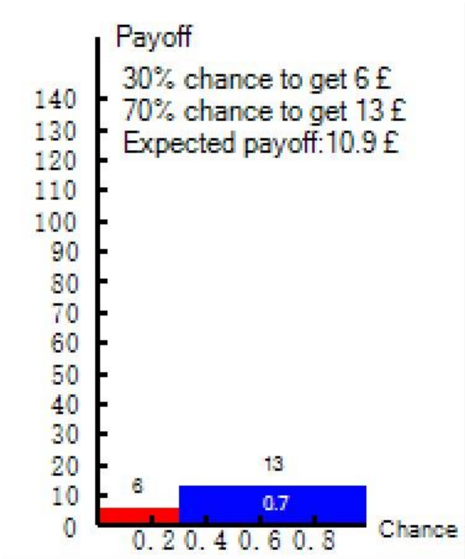
Instructions

Welcome to this experiment. Thank you for participating. It is an online experiment and hence different from an experiment in the lab. The differences are explained in a separate document. This document is solely about what you are being asked to do in the experiment.

Please read this document carefully. If you have any questions, send direct messages to the host or co-host and an experimenter will answer your question privately. Please switch off our mobile phone, and concentrate on the experiment; your payment depends upon your answers.

Lotteries

This experiment is all about *lotteries*. Lotteries have random outcomes. All lotteries in this experiment have the same format. A typical lottery is shown below.



The vertical dimension shows the possible payoffs, denominated in £. The horizontal dimension shows the probabilities of the possible payoffs. So, the lottery shown in the figure above has a 71% chance of resulting in a payment of 6 £ and a 29% chance of resulting in a payment of 86 £. Note that in this example, there are just two possible outcomes, a low one and a high one. In all lotteries, the low outcome will always be 6 £, while the high outcome (in this example, 86 £) and the chance of the high outcome will vary from lottery to lottery. The red part of the figure relates to the low outcome, the blue part to the high. You should note something very important about the lotteries that you will be presented with; the higher the high outcome, the lower is its chance.

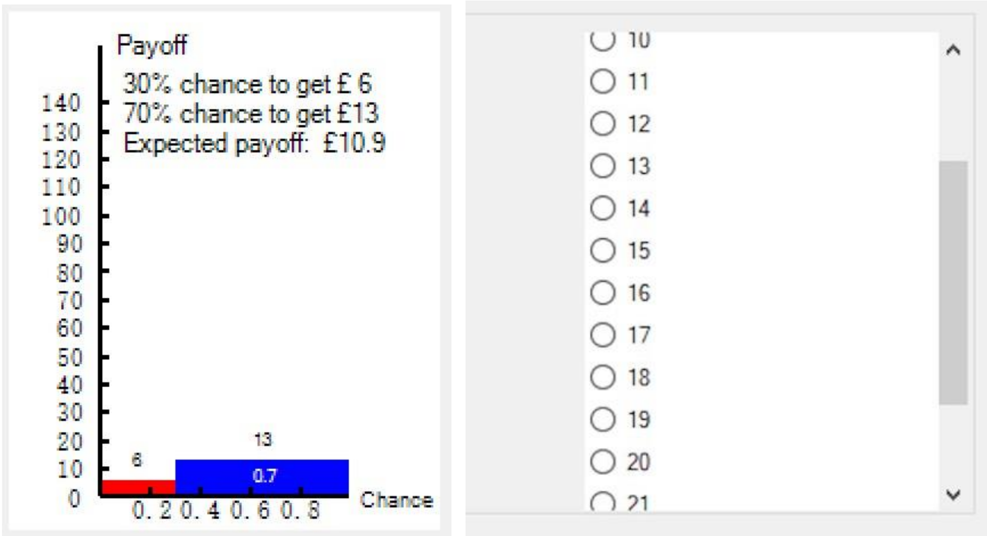
Playing out a lottery

When we come to determine your payment, we may need to play out a lottery. This will be done as follows. We use the lottery above as an example. This lottery has a 71% chance that the outcome will be 6 £ and a 29% chance that the outcome will be 86 £. To determine the outcome, the computer will generate a random number between 0 and 1. If this number is less than 0.71 (that is, between 0 and 0.71), the outcome will be 6 £; if this number is equal to, or greater than 0.71 (that is, between 0.71 and 1) the outcome will be 86 £. This guarantees that there is a 71% chance that the outcome is 6 £ and a 0.29 chance that it will be 86 £.

The experiment

It has two parts: Part 1 and Part 2. Part 1 consists of 27 problems, and Part 2 consists of 30 problems. They are described below. Your choices on the part 1 will influence what you will choose on the part 2. At the end of the experiment, one of the total of 57 problems will be chosen at random, and your decision on that problem will be 'played out'. How this will be done is described in 'The Payment Procedure' below.

Part 1



In this part, each problem has the same purpose: we want to elicit **your valuation** of a lottery, that is, how much **you** value the lottery. As this is an important concept, we should explain it carefully. One way to think about it is as follows: imagine you own the lottery and are thinking of selling it, your valuation is the *smallest* amount of money **you** would happily accept to sell it. Alternatively, imagine that you do *not* own the lottery and are thinking of buying it; then your valuation is the *largest* amount of money **you** would happily pay to buy it. Note crucially that **your** valuation (which is what we want you to tell us) is entirely personal: it depends on **you** and on **your** attitude to risk.

We will elicit your valuation as follows. We will show a particular lottery on the left of the screen and a drop-down list of numbers on the right. We want you to indicate your valuation of the lottery on the left by ticking one of the numbers on the right. To provide you with an incentive to reveal your true evaluation, we will use the following method to pay you if one of these problems is played out at the end of the experiment:

> *We will randomly select one of the numbers from the drop-down list. If that number is less than the number you have ticked, we will play out the lottery on the left; if that number is equal to or greater than the number you have ticked, your payment will be the number that you have ticked.*

Note that it is in your interest to tick the right number. Suppose, for the example above, your valuation of the lottery is 15. If you tick a number lower than your valuation, say 12, then when the random number generated by the computer is greater than 12, your payment would be 12, whereas in fact you would prefer to play out the lottery (since you value the lottery at more than 12). If you tick a number greater than your valuation, say 19, then when the random number generated by the computer is less than 19, you would have to play out the lottery, whereas in fact you would prefer the sum of money since you value the lottery less than 19)

Part 2

Each problem in this Part has two stages. In the first stage, you will be presented with a set of *menus*, each menu consisting of a set of lotteries, and you will be asked to choose *one* menu. In the second stage, you will be asked to choose *one* lottery out of your chosen menu. If one of the problems in Part 2 is chosen for payment, we will simply play out your chosen lottery.

The Payment Procedure

When you have completed the experiment, the software will take you to the payment stage. This will proceed as follows. First, the computer will select at random one of the two Parts; it will tell you which Part it has selected, and then the computer will select at random one of the problems in that Part. Depending upon which Part it has selected the procedure will be different.

If it is a problem from Part 1, the computer will recall your answer. Then, as we described above, the computer will randomly select one of the numbers from the drop-down list. If that number is less than the number that you ticked, we will play out the lottery on the left; if that number is equal to or greater than the number that you ticked, your payment in £ will be the number that you ticked.

If it is a problem from Part 2, the computer will recall your choice. This will be a lottery. We will then play out the lottery.

The show-up fee of £2.50 will be added to the payment as described above. You will be paid with an Amazon Voucher.

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

Thank you for your participation.

D.3 instruction for Chapter 5's experiment

Instructions for Treatment 1[65]

PREAMBLE

Welcome to this experiment. Thank you for participating. This document tells you what you are being asked to do in this experiment. Please read this document carefully. If you have any questions, please ask one of the experimenters. Please switch off our mobile phone, and concentrate on the experiment; your payment depends upon your decisions.

THE EXPERIMENT

The experiment consists of 40 *rounds* each requiring you to take one decision. They are described below. At the end of the experiment, one of the 40 rounds will be chosen at random, and your payment for the experiment will be the payoff on that round, plus a €5 participation fee.

THE BAD EVENT

[65] The instructions for two treatments are almost the same except for the paragraph in terms of official suggestion.

Central to this whole experiment is a *bad event*, which may or may not happen to you in each and every round. The chance of it happening to you in any one round is determined probabilistically and independently by the computer; the computer knows the probability[66] of it happening to you. However, you will not be told the probability, and you will have to learn about it through observations. Each round, after you have taken your decision (see below) you will be told whether the bad event happened to you in that round and what your payoff was in that round. You can use that information to estimate the probability. You can also get information from two other sources, which will be described to you below.

THE ROUNDS

There will be 40 rounds; all rounds have the same structure. In each round, you will be given €40 in money. In each round, the bad event may happen to you: if it does NOT happen to you, nothing changes, and your payoff for that round will be €40 minus the amount you have spent on insurance (see below); if it DOES happen to you, you will lose some of your money (for the precise amount, see below). However, you can take out insurance against the bad event happening – by spending some of your money. *This is the decision that you will be asked to take in each round – that is, deciding how much you want to spend on insurance.* For **each unit** (which costs €4.5) of your money you spend on insurance, the insurance will compensate you 20% of the loss caused by the bad event (so, for example, if you buy 5 units (costing you €22.5) you will be compensated 100% of the

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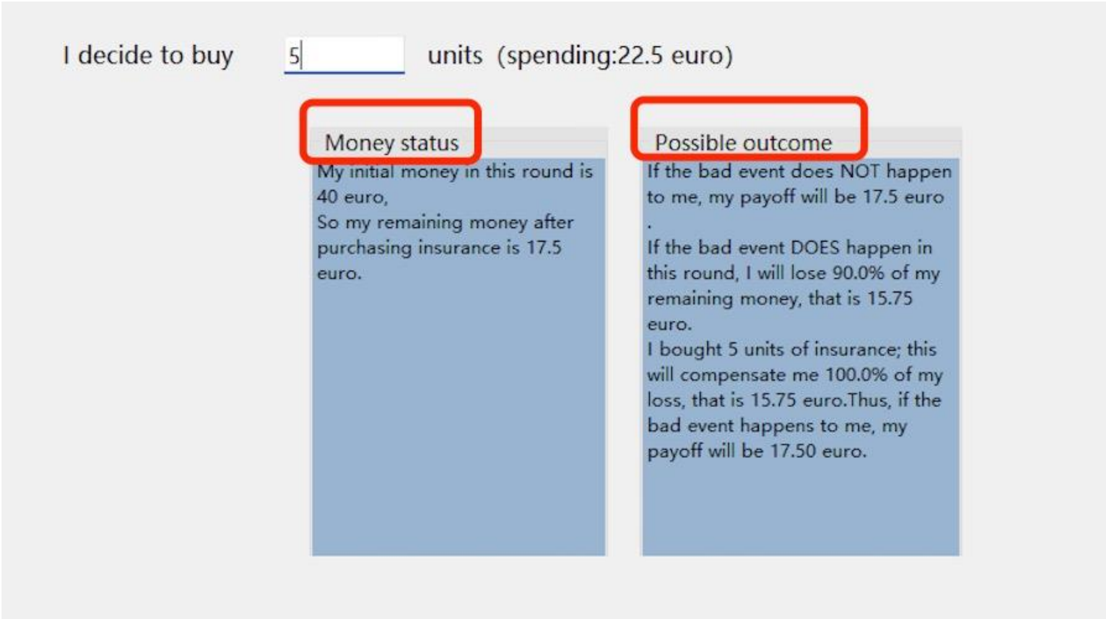
[66] If you are not familiar with the concept of probability, and as the probability of the bad event happening is clearly important to your decision-making, we should explain it more fully. It is simply the chance of the bad event happening: if we observe whether the bad event happens or not, this probability is simply the proportion of times that it happens. If, for example, half the time it happens, and half the time it does not, this probability is ½. If three-quarters of the time it happens, and one-quarter of the time it does not, this probability is 3/4, and so on. We should note that the chances across rounds are independent, so whether it happens in one round does not affect whether it happens in the next round.

loss). The actual amount of loss caused by the bad event is equal to 90% of how much you have left after buying insurance. So ***your payoff*** *for a round in which the bad event happens is the initial money (€ 40) less the amount you spend on insurance minus (if the bad event happens) the loss net of the compensation.* You will note that buying insurance has two effects: first, it reduces the amount of your loss caused by the bad event; second, it increases the percentage of your compensation. After your decision in each round, you will be told whether the bad event happened to you or not, and what your payoff in that round was.

You should note that the probability of the bad event slightly varies from participant to participant. Your personal probability (which is known to the computer) is drawn from a distribution centered on the population probability; so that the average probability (across all participants) is equal to the population probability. This means that your personal probability may differ from that of other participants, but the majority of participants' probabilities will be similar.

The picture below shows what you will see on your screen. Once you input your decision into the top left-hand box, the screen will automatically tell you how much you would spend on insurance and what your payoff would be if the bad event happens to you and if it does not.



Your own probability is initially not known to you. You need to learn it through observation, and through information that you will be given in rounds 11 to 40. In these latter rounds, there will be two sources of information available to you to aid your decision-making. The first source is an ***official suggestion*** on how many units of insurance you should buy. The second source is a ***summary of other subjects' 'insurance decisions*** in the previous round.

We should explain these more fully. The **official suggestion** [67]is based on an actuarial (statistical) calculation that determines your *optimal decision* given an estimate of the probability of the bad event based on the frequency of the bad event over all the preceding rounds *and* ***over all participants***. Note that the official suggestion will vary from round to round as evidence is accumulated, and the observed frequency of the bad event changes.

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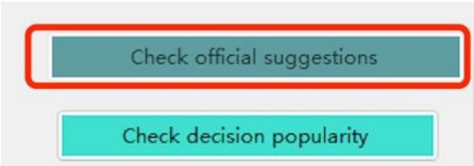
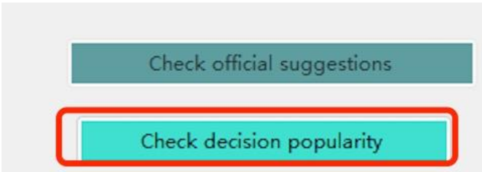
[67] In treatment 2, the introduction regarding official suggestion is written differently, which is "The **official suggestion** is based on an actuarial (statistical) calculation that determines your *optimal decision* given an estimate of the probability of the bad event based on the frequency of the bad event happened to you over all the preceding rounds."

The official suggestion will get more and more precise through the rounds as the number of observations increases. If you want to check the official suggestion, you should click the button “Check official suggestion”.



Click the green button

The summary of the other subjects' decisions will tell you how many units of insurance was the most popular among all subjects in the preceding round. If you want to see this summary, you should click the button “Read the summary”.



Click the green button

THE PAYMENT PROCEDURE

The software will record for every round the decision you made and your payoff in that round.

You will be asked to draw at random a number from 1 to 40 – the draw will determine on which round your payment will depend. We will then pay you your payoff in that round (this, of course, being determined by your decision on insurance and whether the bad event happened to you in that round).

The show-up fee of €5 will be added to the payment as described above. You will be paid in cash, asked to sign a receipt, and then you will be free to leave.

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