HETEROGENEITY IN PREFERENCES TOWARDS COMPLEXITY

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ABSTRACT

We analyze lottery-choice data in a way that separately estimates the effects of risk aversion and complexity aversion. Complexity is represented by the number of different outcomes in the lottery. A finite mixture random effects model is estimated which assumes that a proportion of the population are complexity-neutral. We find that around 33% of the population are complexity-neutral, around 50% complexity-averse, and the remaining 17% are complexity-loving. Subjects who do react to complexity appear to have a bias towards complexity aversion at the start of the experiment, but complexity aversion reduces with experience, to the extent that the average subject is (almost) complexity-neutral by the end of the experiment. Complexity aversion is found to increase with age and to be higher for non-UK students than for UK students. We also find some evidence that, when evaluating complex lotteries, subjects perceive probabilities in accordance with Prospective Reference Theory.

Keywords: complexity aversion, complexity preferences, risk preferences, mixture models, learning.

JEL Classification Codes: C91, D03, D81.

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That complexity matters in economic decisions and other realms of human life is neither surprising nor new. Previous studies have mainly focused on understanding how complexity affects the accuracy of choices (Bruce and Johnson 1996), how this may be exploited by firms (Ellison and Ellison, 2004), how complexity leads to a lower evaluation of lotteries (Mador et al., 2000), and how complexity avoidance can lead to suboptimal portfolio selection (Sonsino et al. 2002).

Theoretical research on preferences towards complexity appears predisposed to an assumption of complexity *aversion*. Stodder (1997) uses complexity aversion to explain the Allais paradox. Gale and Sabourian (2005) show that complexity aversion can lead to a preference for competitive over non-competitive outcomes in market games. In order for these theoretical models to be at least plausible, it is important to establish how widespread the phenomenon of complexity aversion is in the population.

This is the primary aim of the present paper, in which experimental data is used to estimate the distribution of preferences towards complexity in the population. We do this in conjunction with the estimation of preferences towards risk. Thus we pursue one of the secondary goals of the paper: to assess the relationship, if any, between preferences towards complexity and preferences towards risk.

Some previous empirical work on complexity preferences appears to favour complexity aversion. Huck and Weizsäcker (1999) and Sonsino et al. (2002) both find evidence of complexity aversion in lottery choice. Bruce and Johnson (1997), however, find no evidence of complexity aversion in horse-track betting decisions. Some evidence of complexity aversion has been found in choices over products (Rouse, 2008) and choices over energy tariffs (Garrod et al., 2008; Sitzia et al., 2012). Sitzia and Zizzo (2011) find experimental evidence that consumers are exploitable (i.e. buy greater quantities at higher prices) when products are complex.

Alongside this evidence of complexity aversion, some counter-evidence exists which raises the possibility that a proportion of the population is complexity-neutral or even complexity-loving. Complexity neutrality is naturally implied by standard theories of decision making under risk, including expected utility theory. Complexity lovingness is a potential explanation for the "event splitting" effect. The event splitting effect, observed by Starmer and Sugden (1993), Humphrey (1995, 2001) and Weber (2007), is the phenomenon of a lottery becoming more appealing to subjects when one of the outcomes is presented as two different identical outcomes. Such evidence leads us to conjecture that more complex lotteries might be preferred because they are perceived as offering "more ways to win" (Weber, 2007).

To anticipate our key finding, we are able to estimate a *posterior* distribution of complexity preferences in our experimental sample while controlling for risk preferences, with some 50% of the sample being complexity-averse, 33% being complexity-neutral and 17% complexity-loving, but also with complexity-averse subjects tending to converge towards complexity neutrality with experience. We find that our preference distribution helps explain choice switches in our experiment.

The paper is organized as follows. Section 1 describes Sonsino et al.'s (2002) experiment. The reason why we focus on that experiment is because our experimental design extends theirs. Sections 2 and 3 describe the experimental method and present the experimental design. Section 4 presents exploratory data analysis, including non-parametric tests for complexity aversion. Section 5 briefly outlines the econometric model. Section 6 presents and discusses the estimation results. Section 7 concludes.

1. Sonsino et al.'s (2002) experiment

Sonsino et al. (2002) designed an experiment to study the effects of complexity on lottery choices, with complexity being measured in terms of the number of outcomes in the lottery. Lotteries all have the same expected value (107 experimental points) but different complexity levels.

Our own design (see Section 3) directly reproduces two of the choice tasks in Sonsino et al.'s design (2002, pp. 950-952; Problems 11 and 12). These two tasks are presented in Table 1 below. The first task was to choose between a sure win (labelled SW in our design) and a "simple" lottery with three outcomes (S3 in our design); the second was to choose between that same "simple" lottery (S3) and a "complex" lottery with 6 outcomes (C3 in our design). The two tasks are presented in Table 1.

(Insert Table 1 about here)

These two tasks provide a useful example for drawing attention to two important and closely related features of the design. Firstly, Sonsino et al. (2002) have used a particular procedure to derive the "complex" lottery C3 from the "simple" lottery S3. The procedure is best described by imagining that S3 is played twice in succession, with the total outcome from both plays then being divided by 2. This procedure inevitably results in a more complex lottery; however, it is also the case that the complex lottery is *less risky* than the simple lottery, in the sense of having a smaller variance. In our own design (see next section), this procedure is generalised, and used to derive "very complex" lotteries (with 27 outcomes) from "complex" lotteries.

Secondly, the presence in the design of complex lotteries that are less risky than simple lotteries is essential for separating the effect of complexity aversion from that of risk aversion. Consider the two tasks presented in Table 1. If a subject is both risk-averse and EUT maximizing, she should prefer SW over S3, and C3 over S3. If she is risk seeking and EUT maximizing, she should prefer S3 in both tasks. However, a subject who chooses SW in the first task, and S3 in the second, is signalling that she is complexity-averse, since she is apparently being put off by the complexity of C3 in the second task.

Of course, such "preference reversals" may simply be a consequence of noisiness in choice. In order to detect the presence of complexity aversion, it is necessary also to consider the number of reversals in the opposite direction (i.e. from S3 in task 1 to C3 in task 2). If the number of subjects choosing SW and S3 is significantly greater than the number choosing S3 and C3, this may be interpreted as evidence of complexity aversion in the population. A non-parametric test appropriate for making this comparison formally is the McNemar test (Siegel and Castellan, 1988). Sonsino et al. find that, of their 120 subjects, 36 switched from SW to S3, while only 19 switched from S3 to C3. The McNemar test statistic ($\chi^2(1)$) obtained from these numbers is 6.90, and the p-value is 0.0086, indicating strong evidence of complexity aversion on the basis of these two sets of choices. The McNemar test will be applied more extensively to our own data in Section 4.

2. Experiment

The experiment was run at the University of East Anglia in February 2013.[1]

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[1] The experiment was programmed and conducted with the experiment software z-Tree (Fischbacher, 2007).

A sample of 80 subjects took part in the experiment. After their arrival, subjects were asked to read the instructions and then to complete a questionnaire to check whether they understood the type of task encountered in the experiment.[2] Subjects were then given an opportunity to ask questions of clarification. Then the experiment commenced.

The experiment consisted of two phases. In each phase, subjects faced 27 tasks in which they were asked to choose between two lotteries with the same expected value of 107 experimental points (10 points = £1), but with differing degrees of complexity and risk. The same set of 27 tasks was presented in both phases; this is for the purpose of investigating the effect of experience on complexity preferences. However, the order in which the 27 tasks were presented changes between the two phases. Also, the way in which individual lotteries were presented, in terms of the order of the outcomes, changed between the two phases.

The random lottery incentive mechanism was employed. That is, at the end of the experiment one of the 54 tasks was randomly selected, and the lottery chosen by the subject in the selected task was played out to determine the earnings. Average earnings were around 11 pounds.

3.   Experimental Design

Our experimental design is built on the pair of tasks used by Sonsino et al. (2002), presented in Table 1. We chose this task because it is the simplest that Sonsino et al. employ in their paper and, in particular, it is a single period task (some of their tasks involve multi-period lotteries, which we avoid).

(Insert Tables 2a and 2b about here: if possible facing each other)

Tables 2a and 2b show the 18 lotteries, other than the sure win SW of 107 points, that we used in the experiment. Six lotteries are simple (S), 6 are complex (C), and 6 are very complex (VC). We derived the complex and the very complex lotteries from the simple lotteries using the same procedure as used in Sitzia and Zizzo (2011), which is an extension of the procedure used by Sonsino et al. (2002). An intuitive explanation of the procedure, in terms of averaging the outcomes from two independent plays of the same lottery, was provided in Section 2. The importance of this procedure is that it provides a way of making a lottery considerably more complex, while at the same time making it *safer*. This feature of the design – complexity and risk (sometimes) moving in opposite directions – is what enables us, in estimation, to separate the effect of complexity aversion from that risk aversion.

A formal explanation of the procedure is as follows. We will first show how we can generate, from a simple lottery S_a with 3 outcomes, a complex lottery C_a lottery with 9 outcomes, and then how we can generate a *very complex* lottery from the same simple lottery. Consider the following simple lottery:

$$S_a = (\mathbf{p}, \mathbf{x}) = \left((p_1 \; p_2 \; p_3)', (x_1 \; x_2 \; x_3)' \right)$$

Note that **p** and **x** are 3×1 (column) vectors of probabilities and outcomes respectively. **p** is such that $\sum_{j=1}^{3} p_j = 1$. A more complex lottery C_a can be generated from S_a using the following formula:

$$C_a = \left(vec(\mathbf{pp'}); vec\left(\tfrac{1}{2}\mathbf{xi_3}' + \tfrac{1}{2}\mathbf{i_3 x'} \right) \right) \qquad (0)$$

where $\mathbf{i_3}$ is a 3×1 (column) vector consisting only of ones, and vec(A) is the function that transforms a n×n matrix A into a n^2×1 (column) vector consisting of the elements of A. Note that this complex lottery is equivalent to playing the simple lottery twice in succession and using the arithmetic mean outcome from the two plays as the outcome. Note also that the expected value of C_a is the same as that of S_a: $E(C_a) = E(S_a)$.

From a complex lottery, using a procedure similar to the one just described, it is possible to create very complex lottery, with 27 outcomes. Let us consider the following complex lottery, C_b, similar to C_a defined in (0), but with different (smaller) weights in the second argument:

$$C_b \equiv (\mathbf{q}, \mathbf{y}) = \left(vec(\mathbf{pp'}); vec(0.03\,\mathbf{xi_3'} + 0.07\,\mathbf{i_3 x'}) \right)$$

Intuitively, C_b is equivalent to two independent plays of S_a, with a weighted average being taken of the two outcomes, with weights 0.07 and 0.03. However, note that, because the weights sum to 0.10, $E(C_b) = 0.1 \times E(S_a)$. We then combine S_a and C_b, with the weights 0.9 and 1, to obtain the very complex lottery VC_b:

$$VC_b = \left(vec(\mathbf{qp'}); vec(0.9\,\mathbf{i_9 x'} + \mathbf{yi_3'}) \right)$$

where $\mathbf{i_9}$ is a 9×1 (column) vector consisting only of ones. Note that the two vectors defining VC_b are of order 27×1, implying that this very complex lottery has 27 outcomes. Note also that $E(VC_b) = E(S_a)$.

Note that the procedure employed to generate complex and very complex lotteries does not guarantee that the actual numbers of outcomes are 9 and 27 respectively. The reason for this is that some outcomes may be the same. This is in fact the case for the complex lotteries (where the number of outcomes is 6 instead of 9) while for the very complex lotteries this does not happen and the number of outcomes is always 27.

Table 2a shows the 3 simple lotteries, S1, S2 and S3, and the lotteries derived from them. As previously noted, S3 is identical to one of the lotteries in Sonsino et al. (2002). S1 and S2 have been designed by us. They have the same expected value as S3 but more extreme lowest and highest outcomes, and also different middle outcomes. The procedures described above were used to obtain 3 complex (C1-C3) and 3 very complex (VC1-VC3) lotteries from the three simple lotteries (S1-S3).

Table 2b shows our "safe" versions of the lotteries shown in Table 2a. These are designated by the subscript "s" in the lottery name. The "s"-type lottery is derived by decreasing the spread of the extreme outcomes while leaving unchanged the middle outcome. Complex and very complex lotteries are then derived from the "s"-type simple lotteries using the procedures described above, and they are also given the "s" label. The "s"-type lotteries are only used in

following choice tasks: S_s-S, C_s-C, VC_s-VC. The reason for using them in this way is to investigate whether risk attitude is influenced by task complexity. For example, if the propensity to choose VC_s over VC is higher than that of choosing S_s over S, this would simply indicate that subjects become more risk-averse when tasks become more complex.

Risk is sufficiently measured in our setting in terms of variance of the lotteries. For the time being it suffices to say that, for every simple lottery S, and the complex (C) and very complex (VC) lotteries derived from it, it is the case that $0=V(SW)<V(C)<V(VC)<V(S)$.

4.   Exploratory Data Analysis

In this section we will present some descriptive statistics, ahead of the more rigorous econometric modeling in the later sections.

Our sample consists of 80 subjects. Table 3 contains information about the sample. Almost 2/3 of our subjects are female (last column in Table 3). We also notice (last row in Table 3) that about 37% are from China, 25% from the UK, 10% from Hong Kong and the remainder from other countries (the proportions are sufficiently small for these countries to be grouped together). It is interesting to see that most of our Chinese participants (83%) are female, and this is true also for other nationalities except participants from Hong Kong, of which there is an equal number of males and females, and participants from the UK, of which 60% are male. The sample is spread over many different fields of study, with the most commonly observed fields being Accounting and Finance (11% of sample) and Political, Social and International Studies (8%). Finally, 53% of our participants are enrolled in Bachelor's degrees, 38% in Master's degrees, with the remaining 9% in other postgraduate programs. The average age of our sample is 22.63.

(Insert Table 3 about here)

There are 9 types of choice problem; these are defined in the second column of Table 4. All choice problems are represented as two lotteries separated by a hyphen, with the first lottery being the safer. Each of the 9 types consists of 3 particular choice problems (for example, type 1 is labelled SW-S, and consists of the 3 choice problems: SW-S1; SW-S2; SW-S3). This explains why the total number of tasks (within each phase) is 27.

The third column of Table 4 shows the total number of decisions made for each of the 9 types of choice problem. For most problem types[3] this is 480, being the product of: the number of different lotteries within the type (3); the number of subjects (80); and the number of phases (2).

The final column of Table 4 shows the proportion of decisions in which the safe choice is made. This information is also presented in Figure 1, with white bars used for tasks involving the sure win, black bars for tasks with lotteries of the same complexity level, and grey bars for the remaining tasks.

(Insert Table 4 about here)
(Insert Figure 1 about here)

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[3] Note that task types 1 and 5 have only 440 observations, while all other task types have 480. The reason for this difference is a minor programming bug that led to the loss of data on 40 of the 80 subjects' choices on each of the two choice problems: VC3-S3 and SW-S3.

With respect to Table 4 and Figure 1, a number of comments are in order. Firstly, on more than 70% of occasions the sure win (SW) is preferred to the other lottery (white bars in Figure 1) and this does not appear to be affected by the complexity of the latter. When lotteries have the same complexity level (black bars), the safe lottery is chosen more frequently than the riskier one, indicating overall risk aversion, but these bars are not as high as the white bars, indicating that risk aversion is highest when one of the alternatives is a sure win. Note also that the black bars do not appear to be very different from each other, indicating that risk attitude does not change when task complexity increases. However, when lotteries of differing complexity levels are employed (grey bars), the proportion of safe choices seems to fall as the complexity level of the *task* (i.e. again taking both complexity levels into consideration) rises. Taken together, these results lead us to conclude that there is mixed evidence on the relationship between task complexity and risk aversion.

Some of the individual tasks can be paired in such a way as to allow pure tests of complexity aversion, in the manner of the example used in Section 2. The results of these tests are presented in Table 5.

(Insert table 5 about here)

The first two columns of Table 5 show the two tasks used in the test. For example, the first test compares the choices made in the two tasks SW-VC1 and VC1-S1. Using the same reasoning as used in the example of Section 2, if any subject switches from SW (the sure win) in the first task to S1 (the simple lottery) in the second task, they are signalling complexity aversion, because S1 has a higher variance than VC1 despite being less complex. Such a subject is committing a "safe-to-risky" (SR) reversal. The direct test of complexity aversion simply compares, for each task-pair, the number of SR reversals with the number of RS reversals (shown in the 5th and 6th columns of Table 5). If the number of SR reversals is significantly greater, there is evidence of complexity aversion. As with the example in Section 2, the McNemar test (Siegel and Castellan, 1988) is used to formalise this comparison. The last three columns of Table 5 show the test statistic, the p-value, and the conclusion of the test. We see that around half of the tests result in either evidence or strong evidence of complexity aversion. We also see that the evidence of complexity aversion appears to be weaker in the second phase (since p-values in the second round tend to be larger than the corresponding ones in the first round). The exception is the last two pairs, but here the evidence is stronger in the second round because the test is based on 80 observations instead of 40. The difference between phases suggests a reduction in complexity aversion with experience.

These simple tests clearly provide some evidence of complexity aversion. In the next section we go a step further, by allowing complexity aversion to vary between individuals, and in particular we allow a positive proportion of the population to be complexity-neutral. This is achieved within the context of a finite-mixture random-effects model. The framework also allows estimation of the correlation between complexity aversion and risk aversion, and (formal) estimation of the effect of experience on complexity aversion.

7

5. Econometric Models of Complexity Aversion

In this section we outline the econometric models whose estimates are reported in the next section. Technical details, such as the construction of the log-likelihood, are provided in Appendix B.

The modeling strategy is similar in some ways to that of Sonsino et al. (2002). Let the two lotteries in the choice problem be defined as:

riskier: $\qquad (\mathbf{p}, \mathbf{x}) = (p_1 \cdots p_J, x_1 \cdots x_J)$

safer: $\qquad (\mathbf{q}, \mathbf{y}) = (q_1 \cdots q_K, y_1 \cdots y_K)$

Importantly in the context of measuring complexity aversion, the two lotteries are permitted have different numbers of outcomes (J and K). The two lotteries have expected values:

$$E(\mathbf{p}, \mathbf{x}) \equiv \mu_{(\mathbf{p}, \mathbf{x})} = \sum_{j=1}^{J} p_j x_j$$

$$E(\mathbf{q}, \mathbf{y}) \equiv \mu_{(\mathbf{q}, \mathbf{y})} = \sum_{j=1}^{K} q_j y_j$$

$\qquad\qquad\qquad\qquad\qquad\qquad (1)$

and variances:

$$V(\mathbf{p}, \mathbf{x}) \equiv \sigma_{(\mathbf{p}, \mathbf{x})}^2 = \sum_{j=1}^{J} p_j \left(x_j - \mu_{(\mathbf{p}, \mathbf{x})} \right)^2$$

$$V(\mathbf{q}, \mathbf{y}) \equiv \sigma_{(\mathbf{q}, \mathbf{y})}^2 = \sum_{j=1}^{K} q_j \left(y_j - \mu_{(\mathbf{q}, \mathbf{y})} \right)^2$$

$\qquad\qquad\qquad\qquad\qquad\qquad (2)$

The riskier lottery is defined as the one with the higher variance. Hence:

$$\sigma_{(\mathbf{p}, \mathbf{x})}^2 > \sigma_{(\mathbf{q}, \mathbf{y})}^2 \qquad\qquad (3)$$

Since all lotteries have the same mean, but differing variances, a natural and convenient basic framework in which to operate is that of the mean-variance utility function. We will assume that the choice between two lotteries is based on the difference between the (mean-variance) utilities of the two lotteries. Within this framework, we assume the existence of four types. Indexing individuals by i, and letting U_i be the utility function for individual i, the four types are defined as follows:

Type 1 (RN and CN): $\qquad U_{i,1}(\mathbf{p}, \mathbf{x}) = \mu_{(\mathbf{p}, \mathbf{x})} \qquad$ (4a)

Type 2 (CN): $\qquad\qquad U_{i,2}(\mathbf{p}, \mathbf{x}) = \mu_{(\mathbf{p}, \mathbf{x})} - \alpha_i \sigma_{(\mathbf{p}, \mathbf{x})}^2 \quad$ (4b)

Type 3 (RN): $\qquad\qquad U_{i,3}(\mathbf{p}, \mathbf{x}) = \mu_{(\mathbf{p}, \mathbf{x})} - \gamma_i C(\mathbf{p}, \mathbf{x}) \qquad$ (4c)

Type 4 (neither RN nor CN): $U_{i,4}(\mathbf{p}, \mathbf{x}) = \mu_{(\mathbf{p}, \mathbf{x})} - \alpha_i \sigma_{(\mathbf{p}, \mathbf{x})}^2 - \gamma_i C(\mathbf{p}, \mathbf{x}) \qquad$ (4d)

8

RN stands for "risk-neutral", that is, non-responsive to variance; CN stands for "complexity-neutral", that is, non-responsive to complexity. The parameter α is closely related to the coefficient of absolute risk aversion (see Chavas and Pope, 1983). $C(\mathbf{p},\mathbf{x})$ is the chosen measure of the complexity of the lottery (operationalized as: C=0 for Sure Win; C=1 for Simple; C=2 for complex; C=3 for very complex). γ is a parameter representing the degree of complexity aversion. We expect $\gamma > 0$. Note further that we will be assuming between-subject heterogeneity both in risk aversion (α) and in complexity aversion (γ); hence the *i*-subscripts on these parameters.

The distribution we will assume for risk aversion (α) and in complexity aversion (γ) is:

$$\begin{pmatrix} \alpha \\ \gamma \end{pmatrix} \sim N\left[\begin{pmatrix} \theta_1 \\ \theta_2 \end{pmatrix}, \begin{pmatrix} \eta_1^2 & \rho\eta_1\eta_2 \\ \rho\eta_1\eta_2 & \eta_2^2 \end{pmatrix} \right] \qquad (5)$$

Hence the parameters of principal interest are the two means, θ_1 and θ_2, the two standard deviations, η_1 and η_2, and the correlation ρ. We shall also allow the means (θ_1 and θ_2) to depend on experience and subject characteristics. Since there are four types (defined in 4a-4d), we also require the estimation of a set of mixing proportions which we shall label π_1 - π_4. There is also a parameter φ, whose sign will indicate whether the magnitude of computational errors increases ($\varphi > 0$) or decreases ($\varphi < 0$) over the course of the experiment. The former will be interpreted as a "boredom" effect, and the latter as an "experience" effect.

Finally, we will allow for the possibility that agents do not take the stated probabilities at face value.[4] One hypothesis that is of particular relevance for compex lotteries is that agents act as Bayesians, and view the prior probability of each outcome as *1/J* (where *J* is the number of outcomes in the lottery). A way of modelling this is to assume that agents act on transformed probabilties ($\tilde{p}_j$), given by:

$$\tilde{p}_j = \frac{\delta \frac{1}{J} + p_j}{\delta + 1} \quad j = 1, \cdots, J \; ; J > 1 \qquad (6)$$

(6) is, in fact, a form of Prospective Reference Theory (Viscusi, 1989). The important quantity in (6) is the parameter δ. If $\delta = 0$, probabilities are correctly interpreted ($\tilde{p}_j = p_j$ for all *j*). If δ is large and positive, all probabilities[5] become equal ($\tilde{p}_j \to (1/J)$ for all *j*). Hence, in order to test this form of Prospective Reference Theory, we shall incorporate (6) in our model, and test the null hypothesis $\delta = 0$ against the alternative $\delta > 0$.

The likelihood function is constructed by appending a stochastic term to the utility difference pertaining to each choice problem and deducing choice probabilities. Estimation is performed using the method of Maximum Simulated Likelihood (MSL) (Train, 2003). See Appendix B for

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[4] We thank Kip Viscusi for suggesting this extension to our model.

[5] It is important to realise that (6) does not apply when *J=1*. In this case, $\tilde{p}_1 = p_1 = 1$; that is, the probability of the certain outcome is correctly interpreted as 1.

further details. Maximization of the simulated likelihood function is performed using the ml routine in STATA.[6]

6. **Estimation Results**

In the data, all money amounts are divided by 107, so that the expected value of all lotteries is 1.

Six sets of results are presented in Tables 6a and 6b. All sets of results are from maximisation of a log-likelihood function based on (A6) in Appendix B. We start off with the "homogeneous" model (Model 1), in which it is assumed that all individuals have the same risk aversion and complexity aversion. These are estimated respectively as +2.964 and +0.031, both significantly greater than zero, implying (overall) significant risk aversion (RA) and complexity aversion (CA). We then estimate the finite mixture model (Model 2) which leads to a major improvement statistically, but for which the results are dubious. Both RA and CA are estimated as very large, but from the mixing proportions, we see that a large proportion of subjects are irresponsive to risk and/or complexity. For example, the proportion who are complexity-neutral is 0.289 + 0.554 = 0.843. The problem with this model is that all subjects who respond to complexity are being "forced" to have the same CA, with the result that a very small proportion are identified as extremely complexity-averse, with the remainder being complexity-neutral. This leads us to Model 3, which is the finite mixture random effects model. Here, we notice firstly that the two heterogeneity parameters (η_1 and η_2) are both strongly positive, indicating that RA and CA both vary continuously between subjects who are responsive. Secondly, we note that the parameter ρ is significantly negative, indicating a negative association between RA and CA: subjects who are more risk-averse tend to be less complexity-averse. Thirdly, we notice that the proportion (π_1) of subjects who are of type 1 has fallen all the way to zero. This is a promising result, since it implies that there are *no* subjects in the sample who respond to *neither* risk nor complexity. The change in the estimate of this parameter between Models 2 and 3 is a direct result of the introduction of continuous heterogeneity in RA and CA. Models 4-6 exclude types 1 and 3 because of their apparent absence from the population.

(Insert Tables 6a and 6b about here, if possible facing each other)

Model 4 introduces the effect of experience (represented by position of task in sequence, τ) in two places: CA and the error variance are both assumed to depend on experience. The effect of experience on RA was found to be insignificant.[7] Experience does have a significantly negative effect on CA, with the estimated equation (from Model 4) being:

$$\hat{\theta}_2(\tau) = 0.224 - 0.006\tau \qquad (7)$$

(7) essentially implies that a typical (type 4, i.e. not complexity-neutral) subject is moderately averse to complexity at the start of the experiment, but becomes less complexity-averse in the course of the experiment, and becomes complexity-loving after 37 tasks (recall that there are a total of 54 tasks in the experiment). Model 4 also allows the computational error variance, which represents the behavioral noise in our models, to change with experience, in

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[6] The STATA code used for estimation is available from the authors on request.

[7] When τ is added as a determinant of risk aversion to Model 4, its asymptotic t-statistic is -0.40 and the p-value is 0.69.

accordance with (A3) in Appendix B. The significantly negative estimate of the parameter φ indicates that this error variance falls with experience, and this is consistent with an experience effect rather than a boredom effect. Another feature of model is that the correlation (ρ) between RA and CA is again negative, but not significantly different from zero. It appears that the significant value seen in Model 3 was the manifestation of a misspecification bias caused by neglecting the effect of experience.

Models 5 and 6 introduce some subject characteristics to the CA equation. These variables were found to be insignificant when also added to the RA equation.[8] We will return to the subject characteristics shortly. Model 6 introduces the reference-dependence parameter δ defined in (6). We see that the estimate of δ is positive and significant. We also see that the AICs clearly indicate that Model 6 is the best of the six models. However, the estimate of δ is small in magnitude at +0.020. The interpretation, in accordance with (6), is that subjects perceive probabilities as slightly different from the true probabilities, in a direction towards an equal probability for all outcomes in the lottery.

Returning to the subject characteristics, and focusing on the results of Model 6, males appear to be less complexity-averse than females, although this effect is not statistically significant. Age and "non-UK" both have positive and (in the first case) significant effects on complexity aversion. In the sample, 66% are female, 75% are "non-UK", and the mean of age is around 23 (see Table 3). We will therefore use Model 6 to obtain an equation similar to (7) for a 23-year-old, female, non-UK student. The equation is:

$$\hat{\theta}_2(\tau) = +0.423 - 0.007\tau \qquad (8)$$

(8) implies that, for this type of subject, CA reaches zero after 60 tasks (i.e. roughly by the end of the experiment).

Based on Model 6, it seems that there exist subjects (around 33% of the population) who are complexity-neutral throughout, while the remaining 67% are (on average) complexity-averse, with complexity aversion falling fairly rapidly with experience, to the extent that they are (on average) almost complexity-neutral by the end of the experiment.

Although we already have an estimate of the proportion of the *population* who are complexity-neutral (33%), we can go further by classifying individual subjects on the basis of posterior estimation. Figure 2 shows a frequency histogram of the posterior probability of being type 2 (complexity-neutral), obtained using (A9) in Appendix B, following estimation of Model 6. We see that, although a large number of subjects appear very *unlikely* to be complexity-neutral, few have a very high posterior probability of being so. In order to be true to our estimate of 33% being complexity-neutral, it seems sensible to classify as complexity-neutral the 33% of subjects (26 out of 80) with the highest posterior probabilities of being so. The cut-off appears to be 0.51; 26 subjects (33%) have posterior probabilities of greater than 0.51, and we shall classify these 26 as complexity-neutral.

(*Insert Figure 2 about here.*)

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[8] When the three explanatory variables male, (age-18), and non_UK are all added to the risk-aversion equation in Model 5, the LogL rises very slightly to -2410.25, but the associated AIC is 4848.5, which is vastly inferior to Model 5.

Figure 3 shows posterior estimates of α and γ obtained from Model 6, using a formula such as (A10) in Appendix B. Observations on the horizontal axis are the 26 subjects whose posterior type probabilities indicate that they are of type 2 (CN), and hence with $\gamma = 0$. Based on the information displayed in Figure 3, Table 7 classifies subjects by risk and complexity preferences. In particular, we find that 17%, 33% and 50% of the subjects are complexity-loving, neutral and averse, respectively.

(*Insert Figure 3 and Table 7 about here.*)

7.   Conclusion

An understanding of complexity preferences is important both in assessing the relevance of theoretical models that assume complexity-averse populations, and in evaluating previous experimental evidence on the phenomenon.

Using lotteries that vary in terms of both complexity and variance, we have conducted a choice experiment, and then estimated a model which allows heterogeneity in both risk aversion and complexity aversion.

Both types of heterogeneity are seen to be important. The need for a finite mixture approach, with different types of subject, is clear, since the population seems to divide between subjects who respond to complexity, and those who are complexity-neutral. However, we have found that a model which only assumes a mixture of types, while far superior to the homogeneous model, gives misleading results, because of the failure to allow variation in complexity preferences. Our preferred model was one which contained both a finite mixture structure, and also continuous between-subject variation in both complexity aversion and risk aversion. For this model – the finite-mixture random-effects model - the results seemed much more plausible. Further useful extensions of the model included allowance for the effects of experience and subject characteristics, and also the introduction of a parameter capturing prospective reference theory, which allows for misperceptions of probabilities in the direction of equal probabilities for all outcomes.

The main findings are that around 33% of the population are complexity neutral. Of the 67% who respond to complexity, the typical subject displays a moderate level of complexity aversion, but in the course of the experiment, this complexity aversion falls all the way towards zero, implying complexity neutrality at the end of the experiment. These results are consistent with the results of simple non-parametric tests for complexity aversion reported in Section 4. There is also an effect of experience in reducing the variance of computational error. Both of the experience effects may be interpreted as forms of learning. These results have important implications in real life decisions. When decisions are infrequent[9] (such as buying a house, choosing a retirement plan or a health plan, choosing a tariff plan) and learning opportunities are scarce, decision makers are more likely to be complexity-averse. They might avoid making a decision altogether; they might stick with the default option (Iyengar and Lepper 2000, Thaler and Sunstein 2007); they might procrastinate; or they might choose a simple but worse option. In any of these cases, there are opportunites for policies to be designed to make the decision environment simpler and hence to 'nudge' individuals to better outcomes. However, when decisions are complex but made frequently, decision makers may become

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[9] Changing an energy tariff, a mobile phone tariff, or a bank account are decisions that can in principle be made frequently. However, in practice such decisions are typically seen to be quite infrequent (Sitzia et al. 2014). In addition, frequent changes in tariffs are likely to impede learning. Hence we expect complexity aversion to play an important role in these situations.

12

accustomed to the decision environment, hence becoming less complexity-averse, and reducing the need for policy interventions. We further conjecture that, if feedback on decisions were available (unlike in our experiment), one could expect a faster convergence towards complexity neutrality, better decisions, and therefore less need for policy intervention (Thaler and Sunstein, 2003). We leave this for future research.

Complexity aversion also depends on subject characteristics such as age and nationality. It is very interesting that risk aversion, in contrast, does not appear to depend on either experience or subject characteristics.

We found some evidence of a negative association between risk aversion and complexity aversion, although the correlation parameter representing this association was estimated as positive but insignificant in our preferred model.

When we use posterior estimation to classify subjects, we find that around 17% of subjects are complexity-loving. This is an important finding, of which theorists who construct models on the assumption of complexity aversion should be aware. This is particularly important if the theoretical models are intended to represent the behavior of agents with repetition and learning opportunities.

In the presence of inexperienced agents, our results suggest that making a general assumption of complexity aversion may indeed be an adequate way of reflecting aggregate behavior, since the proportion of complexity-averse agents is likely to be larger than that of complexity-loving agents. That said, further research should be targeted at gaining a better understanding of complexity-loving preferences.

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Experimental Instructions

In the course of this experiment, over a number of periods you will be asked to choose between lotteries that pay returns in experimental points with given probabilities.

In the table below you see an example of a lottery of the kind a unit of which you can choose each period:

OUTCOME	PROBABILITY	RETURN
1	35%	50
2	15%	15
3	18%	80
4	22%	139
5	10%	10

Table 1: Example of Product

In this example, the lottery will give you the chance to earn the following returns at the end of the experiment: 50 points with a probability of 35% (Outcome 1); 15 points with a probability of 15% (Outcome 2); 80 points with a probability of 18% (Outcome 3); and so on.

If you see a lottery which provides a given return with a probability of 100%, this means that, if you choose this lottery, you will get that return for sure.

Earnings

At the end of the experiment the computer will randomly select one of the periods that will be used to determine your earnings. The computer will then randomly select one outcome of the lottery you have chosen in that period based on the probabilities. This outcome determines the return of that lottery and the points you have earned in the experiment. Every 10 points you own are converted into 1 pound, and so for example 80 points are worth 8 pounds.

Before starting to take decisions, we ask you to fill the enclosed questionnaire, with the only purpose of checking whether you have understood these instructions. Raise your hand when you have completed the questionnaire.

Questionnaire

1) Your earnings in the experiment are the sum of your earnings each period?

Yes _____   No _____

2) Consider the example lottery in Table 1. What is the probability of obtaining a return of 80?

_____

**PLEASE RAISE YOUR HAND WHEN YOU HAVE FINISHED.
THANK YOU FOR ANSWERING THE QUESTIONNAIRE**

APPENDIX B

Construction of log-likelihood function.

For a given subject (i), who is of type j, facing a given choice problem (t), we define:

$$\nabla U_{it,j}\left(\alpha_i,\gamma_i\right) = U_{i,j}\left(\mathbf{p_t},\mathbf{x_t}\right) - U_{i,j}\left(\mathbf{q_t},\mathbf{y_t}\right) \qquad \text{(A1)}$$

where the two terms on the right are defined according to one of (4a)-(4d), depending on the type of subject i.

Subject i (of type j) chooses lottery $\left(\mathbf{q_t},\mathbf{y_t}\right)$ over lottery $\left(\mathbf{p_t},\mathbf{x_t}\right)$ if the following inequality holds:

$$\nabla U_{it,j}\left(\alpha_i,\gamma_i\right) + \varepsilon_{it} < 0 \qquad \text{(A2)}$$

where ε_{it} is a stochastic term with distribution:

$$\varepsilon_{it} \sim N\left(0,\exp\left(\varphi\tau_{it}\right)\right) \qquad \text{(A3)}$$

The stochastic term ε may be interpreted as computational error, and its variance is assumed to depend on τ_{it}, which is the position of task t in subject i's sequence of tasks (τ=1,…,54). According to (A3), this variance is 1 at the start of the experiment—a normalization that is required for identification of the model. A negative sign of the parameter φ will indicate that the magnitude of errors tends to decrease as the experiment progresses (an experience effect), while a positive sign will indicate an increase in errors over the course of the experiment (a boredom effect).

We define the binary variable y_{it} as follows. y_{it} = +1 if subject i chooses $\left(\mathbf{q_t},\mathbf{y_t}\right)$ over $\left(\mathbf{p_t},\mathbf{x_t}\right)$; y_{it} = -1 if subject i chooses $\left(\mathbf{p_t},\mathbf{x_t}\right)$ over $\left(\mathbf{q_t},\mathbf{y_t}\right)$. By (A2) and (A3):

$$P\left(y_{it} = 1 \mid i \in j\right) = P\left[\nabla U_{it,j}\left(\alpha_i,\gamma_i\right) + \varepsilon_{it} < 0\right] = \Phi\left(-\frac{\nabla U_{it,j}\left(\alpha_i,\gamma_i\right)}{\sqrt{\exp\left(\varphi\tau_{it}\right)}}\right) \quad i = 1,\cdots,n \quad t = 1,\cdots,T$$

$$\text{(A4)}$$

Where "$i \in j$" denotes that subject i is of type j. Note that we are assuming that there are in total n subjects each facing T choice problems.

As noted in (5) in the main text, we are assuming between-subject heterogeneity both in risk aversion (α) and in complexity aversion (γ), and their joint distribution will be assumed to be:

$$\begin{pmatrix} \alpha \\ \gamma \end{pmatrix} \sim N\left[\begin{pmatrix} \theta_1 \\ \theta_2 \end{pmatrix}, \begin{pmatrix} \eta_1^2 & \rho\eta_1\eta_2 \\ \rho\eta_1\eta_2 & \eta_2^2 \end{pmatrix}\right] \qquad \text{(A5)}$$

ρ is the correlation coefficient between risk aversion and complexity aversion.

The likelihood contribution associated with subject i is:

$$L_i = \int_\alpha \int_\gamma \sum_{j=1}^{4} \pi_j \prod_{t=1}^{T} \Phi\left(-y_{it} \times \frac{\nabla U_{it,j}(\alpha_i, \gamma_i)}{\sqrt{\exp(\varphi \tau_{it})}}\right) f(\alpha, \gamma; \theta_1, \eta_1, \theta_2, \eta_2, \rho) \, d\gamma \, d\alpha \qquad (A6)$$

where $f(\alpha, \gamma; \theta_1, \eta_1, \theta_2, \eta_2, \rho)$ is the joint density function of α and γ, and the parameters π_j, j=1…4 are mixing proportions, representing the proportion of the population who are of each type.

A further extension to the model allows risk aversion and complexity aversion to depend on experience within the experiment, and also on demographics. In Models 5 and 6, we assume that:

$$\theta_{1,it} = \theta_{10} + \theta_{11}\tau_{it}$$
$$\theta_{2,it} = \theta_{20} + \theta_{21}\tau_{it} + \theta_{22}male_i + \theta_{23}(age - 18)_i + \theta_{24}non\_uk_i$$

$$(A7)$$

where τ_{it} is, as in (A3), the position of task *t* in subject *i*'s sequence of tasks (τ=1,…,54). (A7) allows the means (over the population) of the coefficients of risk aversion and complexity aversion, to change with experience and demographics. For example, the mean of the coefficient of complexity aversion (for an 18-year-old, female, UK subject) is θ_{20} at the start of the sequence, and changes by an amount θ_{21} with each task undertaken.

A yet further extension allows misinterpretation of stated probabilities in accordance with Prospective Reference Theory. If the transformed probabilities defined in (6) are used in place of true probabilities, we may rewrite (A1) as:

$$\tilde{\nabla} U_{it,j}(\alpha_i, \gamma_i) = U_{i,j}(\tilde{\mathbf{p}}_\mathbf{t}, \mathbf{x}_\mathbf{t}) - U_{i,j}(\tilde{\mathbf{q}}_\mathbf{t}, \mathbf{y}_\mathbf{t}) \qquad (A8)$$

where $\tilde{\mathbf{p}}_\mathbf{t}$ and $\tilde{\mathbf{q}}_\mathbf{t}$ are vectors of transformed probabilities. Then the likelihood function is constructed using $\tilde{\nabla} U_{it,j}$ defined in (A8) in place of $\nabla U_{it,j}$ in (A6).

If Prospective Reference Theory were assumed, and specification (A7) were used, there would be a total of 15 parameters to estimate: θ_{10}, θ_{11}, η_1, θ_{20}, θ_{21}, θ_{22}, θ_{23}, θ_{24}, η_2, ρ, φ, δ, and three of the four mixing proportions: π_1, π_2, π_3. The models we in fact estimate contain somewhat fewer parameters since they are restricted versions of the general model.

Estimation is performed using the method of Maximum Simulated Likelihood (MSL) (Train 2003). This requires the use of two sets of Halton draws, which, when converted to normality, represent simulated realizations of the random parameters α and γ. Maximization of the simulated likelihood function is performed using the ml routine in STATA.[10]

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[10] The STATA code used for estimation is available from the authors on request.

Having estimated the model, posterior type probabilities can be obtained, and also posterior subject-specific estimates of risk aversion and complexity aversion. To obtain the posterior type probabilities, we use a version of Bayes' rule:

$$P\left(i \in j \mid y_{i1} \cdots y_{iT}\right) = \frac{\hat{\pi}_j \displaystyle\int_\alpha \int_\gamma \prod_{t=1}^{T} \Phi\left(-y_{it} \times \frac{\nabla U_{it,j}\left(\alpha,\gamma\right)}{\sqrt{\exp\left(\varphi\tau_{it}\right)}}\right) f\left(\alpha,\gamma;\hat{\theta}_1,\hat{\eta}_1,\hat{\theta}_2,\hat{\eta}_2,\hat{\rho}\right) d\gamma d\alpha}{\hat{L}_i} \qquad \text{(A9)}$$

Where hats indicate MLEs, and $\hat{L}_i$ is the likelihood contribution for subject i as defined in (A6), with parameters replaced by MLEs.

To obtain the posterior subject-specific estimates of risk aversion, we use:

$$\hat{\alpha}_i = E\left(\alpha_i \mid y_{i1} \cdots y_{iT}\right) = \frac{\displaystyle\int_\alpha \int_\gamma \alpha \prod_{t=1}^{T} \Phi\left(-y_{it} \times \frac{\nabla U_{it,4}\left(\alpha,\gamma\right)}{\sqrt{\exp\left(\varphi\tau_{it}\right)}}\right) f\left(\alpha,\gamma;\hat{\theta}_1,\hat{\eta}_1,\hat{\theta}_2,\hat{\eta}_2\right) d\gamma d\alpha}{\displaystyle\int_\alpha \int_\gamma \prod_{t=1}^{T} \Phi\left(-y_{it} \times \frac{\nabla U_{it,4}\left(\alpha,\gamma\right)}{\sqrt{\exp\left(\varphi\tau_{it}\right)}}\right) f\left(\alpha,\gamma;\hat{\theta}_1,\hat{\eta}_1,\hat{\theta}_2,\hat{\eta}_2\right) d\gamma d\alpha} \qquad \text{(A10)}$$

Note that we are conditioning on the subject being of type 4 (responsive to both variance and complexity) when computing their posterior risk aversion. Posterior subject-specific estimates of complexity aversion, denoted $\hat{\gamma}_i$, are computed using a formula similar to (A10).

Table 1 – Sonsino et al. Binary Choices

Choice 1

SW		
Outcome	*Probability*	*Return*
1	1	107

S3		
Outcome	*Probability*	*Return*
1	0.4	80
2	0.3	100
3	0.3	150

Choice 2

C3		
Return	*Probability*	*Return*
1	0.16	80
2	0.24	90
3	0.09	100
4	0.24	115
5	0.18	125
6	0.09	150

S3		
Outcome	*Probability*	*Return*
1	0.4	80
2	0.3	100
3	0.3	150

Table 2a. Lotteries Employed in the Experiment

Outcome	S1 Probability	Return	S2 Probability	Return	S3 Probability	Return
1	0.5	57	0.5	50	0.4	80
2	0.2	112	0.2	113	0.3	100
3	0.3	187	0.3	198	0.3	150

Outcome	C1 Probability	Return	C2 Probability	Return	C3 Probability	Return
1	0.25	57	0.25	50	0.16	80
2	0.2	84.5	0.2	81.5	0.24	90
3	0.04	112	0.04	113	0.09	100
4	0.3	122	0.3	124	0.24	115
5	0.12	149.5	0.12	155.5	0.18	125
6	0.09	187	0.09	198	0.09	150

Outcome	VC1 Probability	Return	VC2 Probability	Return	VC3 Probability	Return
1	0.125	57	0.125	50	0.064	80
2	0.05	58.65	0.05	51.89	0.048	80.6
3	0.05	60.85	0.05	54.41	0.048	81.4
4	0.075	60.9	0.075	54.44	0.036	82
5	0.02	62.5	0.02	56.3	0.048	82.1
6	0.03	64.75	0.03	58.85	0.036	83.5
7	0.075	66.1	0.075	60.36	0.048	84.9
8	0.03	67.75	0.03	62.25	0.036	85.5
9	0.045	70	0.045	64.8	0.036	87
10	0.05	106.5	0.05	106.7	0.048	98
11	0.02	108.15	0.02	108.59	0.036	98.6
12	0.02	110.35	0.02	111.11	0.036	99.4
13	0.03	110.4	0.03	111.14	0.027	100
14	0.008	112	0.008	113	0.036	100.1
15	0.012	114.25	0.012	115.55	0.027	101.5
16	0.03	115.6	0.03	117.06	0.036	102.9
17	0.012	117.25	0.012	118.95	0.027	103.5
18	0.018	119.5	0.018	121.5	0.027	105
19	0.075	174	0.075	183.2	0.048	143
20	0.03	175.65	0.03	185.09	0.036	143.6
21	0.03	177.85	0.03	187.61	0.036	144.4
22	0.045	177.9	0.045	187.64	0.027	145
23	0.012	179.5	0.012	189.5	0.036	145.1
24	0.018	181.75	0.018	192.05	0.027	146.5
25	0.045	183.1	0.045	193.56	0.036	147.9
26	0.018	184.75	0.018	195.45	0.027	148.5
27	0.027	187	0.027	198	0.027	150

Table 2b. Lotteries Employed in the Experiment (continued)

Outcome	$S1_S$ Probability	Return	$S2_S$ Probability	Return	$S3_S$ Probability	Return
1	0.5	75	0.5	68	0.4	95
2	0.2	112	0.2	113	0.3	100
3	0.3	157	0.3	168	0.3	130

Outcome	$C1_S$ Probability	Return	$C2_S$ Probability	Return	$C3_S$ Probability	Return
1	0.25	75	0.25	68	0.16	95
2	0.2	93.5	0.2	90.5	0.24	97.5
3	0.04	112	0.04	113	0.09	100
4	0.3	116	0.3	118	0.24	112.5
5	0.12	134.5	0.12	140.5	0.18	115
6	0.09	157	0.09	168	0.09	130

Outcome	$VC1_S$ Probability	Return	$VC2_S$ Probability	Return	$VC3_S$ Probability	Return
1	0.125	75	0.125	68	0.064	95
2	0.05	76.11	0.05	69.35	0.048	95.15
3	0.075	77.46	0.075	71	0.048	95.35
4	0.05	77.59	0.05	71.15	0.036	95.5
5	0.02	78.7	0.02	72.5	0.048	96.05
6	0.03	80.05	0.03	74.15	0.036	96.4
7	0.075	80.74	0.075	75	0.048	97.45
8	0.03	81.85	0.03	76.35	0.036	97.6
9	0.045	83.2	0.045	78	0.036	98.5
10	0.05	108.3	0.05	108.5	0.048	99.5
11	0.02	109.41	0.02	109.85	0.036	99.65
12	0.03	110.76	0.03	111.5	0.036	99.85
13	0.02	110.89	0.02	111.65	0.027	100
14	0.008	112	0.008	113	0.036	100.55
15	0.012	113.35	0.012	114.65	0.027	100.9
16	0.03	114.04	0.03	115.5	0.036	101.95
17	0.012	115.15	0.012	116.85	0.027	102.1
18	0.018	116.5	0.018	118.5	0.027	103
19	0.075	148.8	0.075	158	0.048	126.5
20	0.03	149.91	0.03	159.35	0.036	126.65
21	0.045	151.26	0.045	161	0.036	126.85
22	0.03	151.39	0.03	161.15	0.027	127
23	0.012	152.5	0.012	162.5	0.036	127.55
24	0.018	153.85	0.018	164.15	0.027	127.9
25	0.045	154.54	0.045	165	0.036	128.95
26	0.018	155.65	0.018	166.35	0.027	129.1
27	0.027	157	0.027	168	0.027	130

Table 3 – Demographic Composition of the Sample

Gender	Country					
	UK	China	Hong Kong	Other	Unknown	Sample
Female	40%	83%	50%	72%	100%	66%
Male	60%	17%	50%	28%	0%	34%
Sample	25%	37%	10%	25%	3%	100%

	N	mean	s.d	min	max
Age	80	22.63	2.88	18	34

Table 4 – Proportions of Safe Choices

Problem type	Lotteries	Number of decisions	Proportion of Safe choices
1	SW-S	440	0.78
2	SW-C	480	0.73
3	SW-VC	480	0.76
4	C-S	480	0.65
5	VC-S	440	0.58
6	C-VC	480	0.52
7	S_s-S	480	0.69
8	C_s-C	480	0.62
9	VC_s-VC	480	0.70

Table 5: Reversal patterns for selected task-pairs, and McNemar test results for complexity aversion

pair a	pair b	n	RR	RS	SR	SS	McNemar $\chi^2(1)$	McNemar p-value	Conclude
Phase 1									
SW-VC1	VC1 -S1	80	4	7	22	47	7.75	0.005	CA**
SW-S1	C1-S1	80	8	7	14	51	2.33	0.126	
SW-VC2	VC2-S2	80	5	11	27	37	6.73	0.009	CA**
SW-S2	C2-S2	80	10	6	14	50	3.2	0.073	
SW-VC3	VC3 −S3	40	4	7	17	12	4.17	0.041	CA*
SW-S3	C3-S3	40	7	5	17	11	6.55	0.011	CA*
Phase 2									
SW-VC1	VC1-S1	80	5	11	28	36	7.41	0.006	CA**
SW-S1	C1-S1	80	6	9	15	50	1.5	0.220	
SW-VC2	VC2-S2	80	5	15	26	34	2.95	0.085	
SW-S2	C2-S2	80	9	11	19	41	2.13	0.144	
SW-VC3	VC3-S3	80	13	10	31	26	10.75	0.001	CA**
SW-S3	C3-S3	80	12	9	25	34	7.52	0.006	CA**

Notes: In final column, an empty cell indicates no evidence of complexity aversion or complexity lovingness; CA* indicates evidence of complexity aversion; CA** indicates strong evidence.

Table 6a. Maximum Likelihood Estimates of Finite Mixture Random Effects Models.

	Model 1	*Model 2*	*Model 3*
θ_{10} risk av.	2.964**(0.153)	5.595**(0.243)	3.930**(0.532)
η_1			3.521**(0.349)
θ_{20} complex. av.	0.031*(0.015)	0.714**(0.076)	0.095(0.077)
θ_{21} experience			
θ_{22} male			
θ_{23} (age-18)			
θ_{24} non-UK			
η_2			0.509**(0.065)
ρ			-0.333**(0.127)
φ			
δ			
π_1 RN + CN		0.289**(0.050)	0.000(0.060)
π_2 CN only		0.554**(0.060)	0.496**(0.120)
π_3 RN only		0.088**(0.030)	0.026(0.070)
π_4 neither	1	0.069*(0.030)	0.479**(0.120)
n	80	80	80
T (mean of)	53	53	53
k	2	5	8
LogL	-2668.98	-2465.09	-2429.03
AIC=-2(LogL-k)	5341.96	4940.18	4874.06

Notes: Asymptotic standard errors in parentheses. * indicates significance (p<0.05); ** indicates strong significance (p<0.01). Model 1 (homogeneous) assumes all subjects have same RA and CA. Model 2 (finite mixture) assumes four different types; Model 3 (finite mixture random effects) assumes 4 types and continuous variation in both RA and CA. Asymptotic s.e.s in parentheses. *k* is the number of (estimated) parameters. AIC is Akaike's Information Criterion (preferred model has *lowest* AIC).

Table 6b. Maximum Likelihood Estimates of Finite Mixture Random Effects Models (continued).

	Model 4	*Model 5*	*Model 6*
θ_{10} risk av.	3.138**(0.406)	3.289**(0.396)	2.388**(0.320)
η_1	2.495**(0.336)	2.871**(0.303)	2.174**(0.252)
θ_{20} complex. av.	0.224**(0.069)	0.003(0.088)	0.104(0.090)
θ_{21} experience	-0.006**(0001)	-0.006**(0.001)	-0.007**(0.001)
θ_{22} male		-0.096(0.081)	-0.096(0.102)
θ_{23} (age-18)		0.029*(0.014)	0.037*(0.017)
θ_{24} non-UK		0.154*(0.087)	0.134(0.107)
η_2	0.349**(0.052)	0.291**(0.042)	0.321**(0.051)
ρ	-0.112(0.195)	-0.143(0.107)	0.128(0.092)
φ	-0.008**(0.002)	-0.008**(0.002)	-0.009**(0.003)
δ			0.020**(0.003)
π_1 RN + CN			
π_2 CN only	0.356**(0.118)	0.323**(0.120)	0.325**(0.100)
π_3 RN only			
π_4 neither	0.644**(0.118)	0.677**(0.120)	0.675**(0.100)
n	80	80	80
T (mean of)	53	53	53
k	8	11	12
LogL	-2418.39	-2410.45	-2362.35
AIC=-2(LogL-k)	4852.78	4842.90	4748.7

Notes: Asymptotic standard errors in parentheses. * indicates significance ($p < 0.05$); ** indicates strong significance ($p < 0.01$). Model 4 (finite mixture random effects with experience) assumes 2 types, and allows for effect of experience in CA and error variance. Model 5 (finite mixture random effects with experience and subject characteristics) allows CA to depend on subject characteristics as well as experience. Model 6 assumes Prospective Reference Theory in place of EUT. Asymptotic s.e.s in parentheses. *k* is the number of (estimated) parameters. AIC is Akaike's Information Criterion (preferred model has *lowest* AIC).

Table 7. Preferences Distribution Classification of the 80 Subjects

	Complexity-loving	Complexity-neutral	Complexity-averse
Risk-loving	3	1	6
Risk-averse	11	25	34

Notes: each cell contains the number of subjects falling into each category on the basis of their posterior estimates of RA and CA obtained following estimation of model 6 in Table 6b.
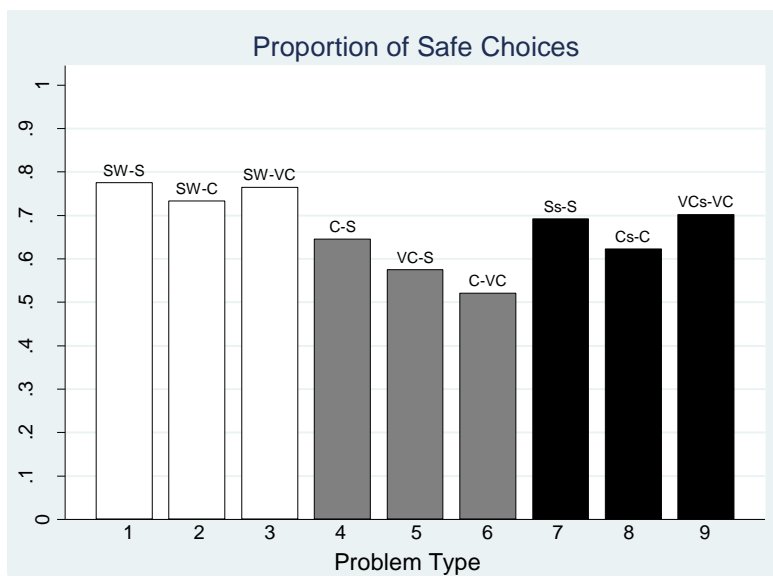
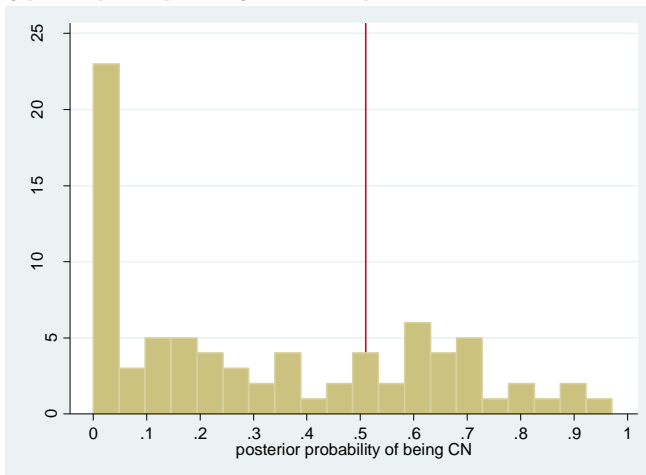**Figure 1 – Proportions of Safe Choices**

Figure 2: A frequency histogram of the 80 subjects' posterior probabilities of being type 2 (complexity-neutral) based on Model 6 in Table 6b

Notes: A vertical line is drawn at 0.51. 33% of the sample (26 subjects) are to the right of this, and on this basis they are classified as complexity neutral.

Figure 3: Posterior Estimates of α and γ based on Model 6 in Table 6b
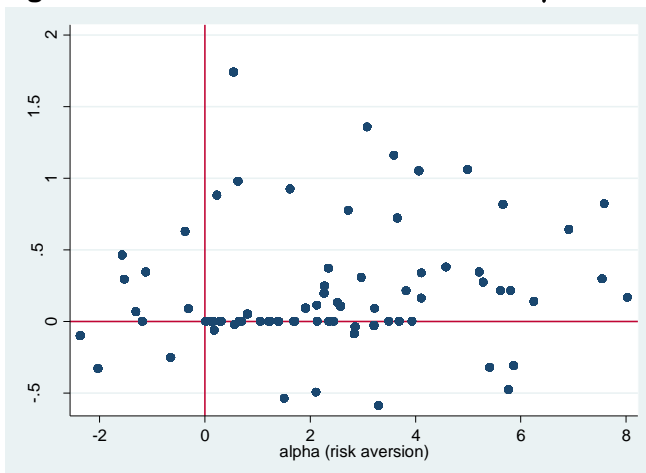
Notes: Observations on the horizontal axis are subjects whose posterior probabilities indicate that they are complexity-neutral.