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HETEROGENEITY IN PREFERENCES TOWARDS

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Abstract
We analyze lottery-choice data in a way that separately estimates the effects of risk aversion and complexity aversion, and allows both both of these to vary between individuals, and also to change with experience. The data is from an experiment in which 80 subjects engage in a sequence of 54 choices between pairs of lotteries. The lotteries always have the same expected value, but they differ in terms of variance and the level of complexity. Complexity is represented by the number of different outcomes in the lottery, and is either 1 (sure win), 3 (simple), 6 (complex) or 27 (very complex). A finite mixture random effects model is estimated which assumes that a proportion of the population are complexity neutral, and we find that around 32% of the population are complexity neutral. In those subjects who do react to complexity, there is 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 complexity neutral by the end of the experiment. Around 23% of subjects appear complexity loving. Some of these findings are consistent with switching patterns seen in the choice data. Complexity aversion is found to increase with age, and is found to be higher for non-UK students than for UK students

JEL classification codes
C91, D03, D81
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complexity aversion, complexity preferences, risk preferences, mixture models, learning

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ABSTRACT

We analyze lottery-choice data in a way that separately estimates the effects of risk aversion and complexity aversion, and allows both both of these to vary between individuals, and also to change with experience. The data is from an experiment in which 80 subjects engage in a sequence of 54 choices between pairs of lotteries. The lotteries always have the same expected value, but they differ in terms of variance and the level of complexity. Complexity is represented by the number of different outcomes in the lottery, and is either 1 (sure win), 3 (simple), 6 (complex) or 27 (very complex). A finite mixture random effects model is estimated which assumes that a proportion of the population are complexity neutral, and we find that around 32% of the population are complexity neutral. In those subjects who do react to complexity, there is 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 complexity neutral by the end of the experiment. Around 23% of subjects appear complexity loving. Some of these findings are consistent with switching patterns seen in the choice data. Complexity aversion is found to increase with age, and is found to be higher for non-UK students than for UK students.

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1. Introduction

That complexity matters in economic decisions and other realms of human life is neither surprising nor new. Previous studies have mainly focused in 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 portfolios 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 is the phenomenon of complexity aversion 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 are 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 45% of the sample being complexity averse, 32% being complexity neutral and 23% complexity loving, but also with complexity averse subjects tending to converge to complexity neutrality with experience. We find that our preference distribution helps explain choice switches in our experiment.

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

2. 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 4) 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.

Table 1 – Sonsino et al.'s choice problems 11 and 12

Problem11

SW		
Outcome	*Probability*	*Return*
1	1	107

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

Problem12

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

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 to consider also the number of reversals in the opposite direction (i.e. from S3 in task 1 to C3 in task 2). If the number 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.

3. Experiment

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

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 face 27 tasks in which they are 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 are 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 are presented changes between the two phases. Also, the way in which individual lotteries are presented, in terms of the order of the outcomes, changes between the two phases.

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

4. Experimental Design

Our experimental design is built on the pair of tasks used by Sonsino et al. (2002), presented in table 1 in section 2. 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 Table 2 about here*.]

Table 2 shows the 18 lotteries we used other than the sure win SW of 107 points. Six lotteries are simple (S), 6 are complex (C), and 6 are very complex (VC). We derived the

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

[2] The instructions and questionnaire are provided in the Appendix.

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 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:

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

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" (VC) 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:

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

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:

$$VC_b = \left(vec(\mathbf{qp'});vec\left(0.9\,\mathbf{i}_9\mathbf{x}' + \mathbf{y}\mathbf{i_3}'\right)\right)$$

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 number of outcomes is 9 and 27. 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.

In our experiment we use 3 simple lotteries, S1, S2 and S3. 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).

For each of the nine lotteries described above, we also include a “safe” version, 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).

5. Exploratory Data Analysis

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

There are 9 types of choice problem; these are defined in the second column of Table 3. 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 3 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 3 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

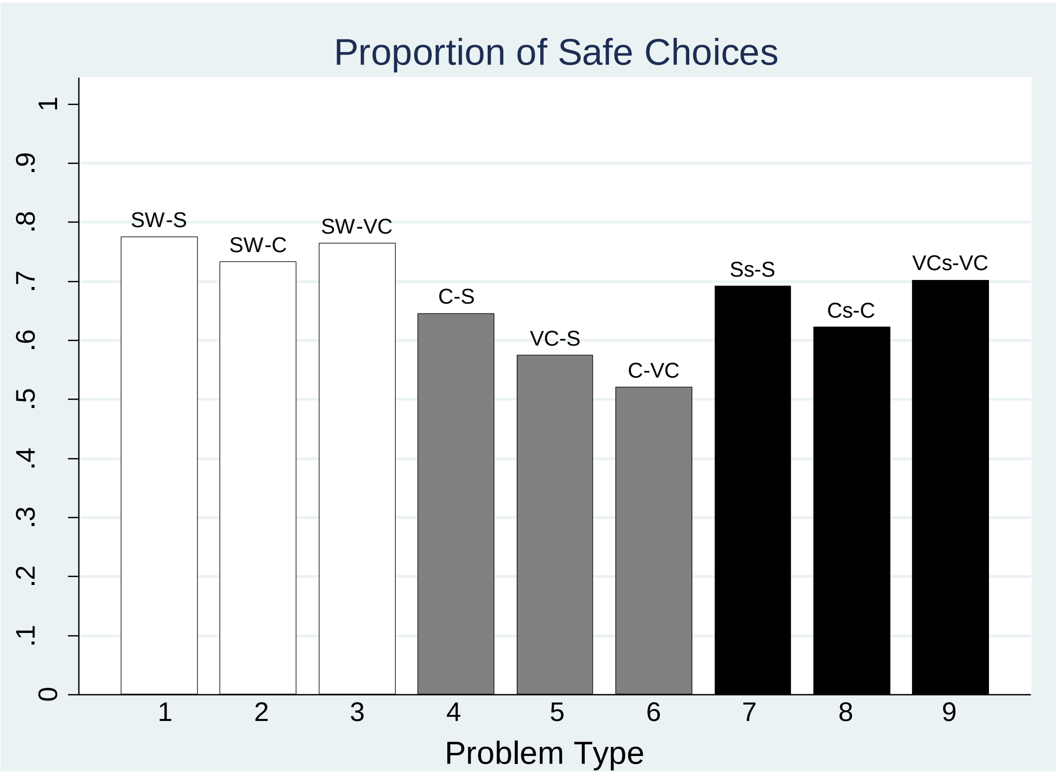
[3] Note that task types 1 and 5 have only 440 observations, while all other task types have 480. The reason for this difference is a minor programming bug that led to the loss of data on 40 of the 80 subjects’ choices on each of the two choice problems: VC3-S3 and SW-S3.

the sure win, black bars for tasks with lotteries of the same complexity level, and grey bars for the remaining tasks.

Table 3 – 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

Figure 1 – Proportions of Safe Choices



With respect to table 3 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. Hoever, 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 4.

pair a	*pair b*	*n*	*RR*	*RS*	*SR*	*SS*	*McNemar*	*Mcnemar*	*Conclude*
							$\chi^2(1)$	*p-value*	
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**

Table 4: Reversal patterns for selected task-pairs, and McNemar test results for complexity aversion. 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.

The first two columns of Table 4 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. If the number of SR reversals is significantly greater, there is evidence of complexity aversion. As with the example in Section 2, the the McNemar test (Siegel and Castellan, 1988) is used to formalise this comparison. The last three columns of Table 4 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.

6. A Finite Mixture Random Effects Model of Complexity Aversion

The model we develop here is similar in some ways to that of Sonsino et al. (2002). Let the two lotteries be defined as:

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

safer: $(\mathbf{q},\mathbf{x}) = (q_1 \cdots q_J, x_1 \cdots x_J)$

The two lotteries have expected values:

$$\begin{aligned} E(\mathbf{p},\mathbf{x}) &\equiv \mu_{(\mathbf{p},\mathbf{x})} = \sum_{j=1}^{J} p_j x_j \\ E(\mathbf{q},\mathbf{y}) &\equiv \mu_{(\mathbf{q},\mathbf{y})} = \sum_{j=1}^{J} q_j y_j \end{aligned} \qquad (1)$$

and variances:

$$\begin{aligned} V(\mathbf{p},\mathbf{x}) &\equiv \sigma_{(\mathbf{p},\mathbf{x})}{}^2 = \sum_{j=1}^{J} p_j \left(x_j - \mu_{(\mathbf{p},\mathbf{x})}\right)^2 \\ V(\mathbf{q},\mathbf{y}) &\equiv \sigma_{(\mathbf{q},\mathbf{y})}{}^2 = \sum_{j=1}^{J} q_j \left(y_j - \mu_{(\mathbf{q},\mathbf{y})}\right)^2 \end{aligned} \qquad (2)$$

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

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

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. Within this framework, we assume the existence of four "types". Indexing individuals by i, the four types are defined as follows:

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

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

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

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

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). $C(\mathbf{p,x})$ 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.

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

$$\nabla U_{it,j}\left(\alpha_i,\gamma_i\right)=U_{i,j}\left(\mathbf{p_t},\mathbf{x_t}\right)-U_{i,j}\left(\mathbf{q_t},\mathbf{y_t}\right) \tag{5}$$

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:

$$\nabla U_{it,j}\left(\alpha_i,\gamma_i\right)+\varepsilon_{it}<0 \tag{6}$$

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

$$\varepsilon_{it}\sim N\left(0,\exp\left(\varphi\tau_{it}\right)\right) \tag{7}$$

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 (7), 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 (a learning 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 (6) and (7):

$$P\left(y_{it}=1\,|\,i\in j\right)=P\left[\nabla U_{it,j}\left(\alpha_i,\gamma_i\right)+\varepsilon_{it}<0\right]=\Phi\left(-\frac{\nabla U_{it,j}\left(\alpha_i,\gamma_i\right)}{\sqrt{\exp\left(\varphi\tau_{it}\right)}}\right)\quad i=1,\cdots,n\quad t=1,\cdots,T \tag{8}$$

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 previously noted, 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:

$$\begin{pmatrix}\alpha\\ \gamma\end{pmatrix} \sim N\left[\begin{pmatrix}\theta_1\\ \theta_2\end{pmatrix}, \begin{pmatrix}\eta_1^2 & \rho\eta_1\eta_2\\ \rho\eta_1\eta_2 & \eta_2^2\end{pmatrix}\right] \tag{9}$$

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

The likelihood contribution associated with subject i is:

$$L_i = \int_\alpha \int_\gamma \sum_{j=1}^{4} \pi_j \prod_{t=1}^{T} \Phi\left(-y_{it} \times \frac{\nabla U_{it,j}(\alpha_i, \gamma_i)}{\sqrt{\exp(\varphi \tau_{it})}}\right) f(\alpha, \gamma; \theta_1, \eta_1, \theta_2, \eta_2, \rho)\, d\gamma\, d\alpha \tag{10}$$

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. We might, for example, assume that:

$$\begin{aligned}\theta_{1,it} &= \theta_{10} + \theta_{11}\tau_{it} + \theta_{12} male_i + \theta_{13}(age-18)_i + \theta_{14} non\_uk_i\\ \theta_{2,it} &= \theta_{20} + \theta_{21}\tau_{it} + \theta_{22} male_i + \theta_{23}(age-18)_i + \theta_{24} non\_uk_i\end{aligned} \tag{11}$$

where τ_{it} is, as in (7), the position of task *t* in subject *i*'s sequence of tasks (τ=1,…,54). (11) 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.

If specification (11) were used, there would be a total of 17 parameters to estimate: θ_{10}, θ_{11}, θ_{12}, θ_{13}, θ_{14}, η_1, θ_{20}, θ_{21}, θ_{22}, θ_{23}, θ_{24}, η_2 , ρ, φ, 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[4].

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:

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

$$P\left(i \in j \mid y_{i1} \cdots y_{iT}\right)=\frac{\hat{\pi}_j \int_\alpha \int_\gamma \prod_{t=1}^{T} \Phi\left(-y_{it} \times \nabla U_{it,j}(\alpha,\gamma)\right) f\left(\alpha,\gamma;\hat{\theta}_1,\hat{\eta}_1,\hat{\theta}_2,\hat{\eta}_2,\hat{\rho}\right) d\gamma d\alpha}{\hat{L}_i} \tag{12}$$

Where hats indicate MLEs, and $\hat{L}_i$ is the likelihood contribution for subject i as defined in (10), with parameters replaced by MLEs.

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

$$\hat{\alpha}_i = E\left(\alpha_i \mid y_{i1} \cdots y_{iT}\right)=\frac{\int_\alpha \int_\gamma \alpha \prod_{t=1}^{T} \Phi\left(-y_{it} \times \nabla U_{it,4}(\alpha,\gamma)\right) f\left(\alpha,\gamma;\hat{\theta}_1,\hat{\eta}_1,\hat{\theta}_2,\hat{\eta}_2\right) d\gamma d\alpha}{\int_\alpha \int_\gamma \prod_{t=1}^{T} \Phi\left(-y_{it} \times \nabla U_{it,4}(\alpha,\gamma)\right) f\left(\alpha,\gamma;\hat{\theta}_1,\hat{\eta}_1,\hat{\theta}_2,\hat{\eta}_2\right) d\gamma d\alpha} \tag{13}$$

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 (13).

7. Results from the Finite Mixture Random Effects Model

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

Five sets of results are presented in Table 5. All sets of results are from maximisation of a log-likelihood function based on (10). 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 identifed 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.

Table 5. Maximum Likelihood Estimates of Model (10) and restricted versions thereof.

	Model 1	***Model 2***	***Model 3***	***Model 4***	***Model 5***
θ_{10} risk av.	2.964(0.153)	5.595(0.243)	3.930(0.532)	3.138(0.406)	3.289(0.396)
θ_{11} experience					
η_1			3.521(0.349)	2.495(0.336)	2.871(0.303)
θ_{20} complex. av.	0.031(0.015)	0.714(0.076)	0.095(0.077)	0.224(0.069)	0.003(0.088)
θ_{21} experience				-0.006(0001)	-0.006(0.001)
θ_{22} male					-0.096(0.081)
θ_{23} (age-18)					0.029(0.044)
θ_{24} non-UK					0.154(0.087)
η_2			0.509(0.065)	0.349(0.052)	0.291(0.042)
ρ			-0.333(0.127)	-0.112(0.195)	-0.143(0.107)
φ				-0.008(0.002)	-0.008(0.002)
π_1 RN + CN		0.289(0.050)	0.000(0.060)		
π_2 CN only		0.554(0.060)	0.496(0.120)	0.356(0.118)	0.323(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)	0.644(0.118)	0.677(0.120)
n	80	80	80	80	80
T (mean of)	53	53	53	53	53
k	2	5	8	8	11
LogL	-2668.98	-2465.09	-2429.03	-2418.39	-2410.45
AIC=-2(LogL-k)	5341.96	4940.18	4874.06	4852.78	4842.90

Notes. 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. 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. Asymptotic s.e.s in parentheses. *k* is the number of (estimated) parameters. AIC is Akaike's Information Criterion (preferred model has *lowest* AIC).

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[5]. Experience does have a significantly negative effect on CA, with the estimated equation (from Model 4) being:

$$\hat{\theta}_2(\tau) = 0.224 - 0.006\tau \qquad (14)$$

(14) 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 accordance with eq. (7). The significantly negative estimate of the parameter φ indicates that this error variance falls with experience, and this is consistent with a

[5] 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.

“learning effect” rather than a “boredom effect”. Another feature of model (4) 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.

Finally, model 5 introduces some subject characteristics to the CA equation. These variables were found to be insignificant when also added to the RA equation[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 significant effects on complexity aversion. In the sample, 66% are female, 75% are “non-uk”, and the mean of age is around 23. We will therefore use model 5 to obtain an equation similar to (14) for a 23-year-old, female, non-UK student. The equation is:

$$\hat{\theta}_2(\tau) = +0.302 - 0.006\tau \qquad (15)$$

(15) implies that, for this type of subject, CA reaches zero after 50 tasks (i.e. roughly by the end of the experiment).

Note further that the AICs clearly indicate that Model 5 is the best of the five models. Based on this model, it seems that there exist subjects (around 32% of the population) who are complexity neutral throughout, while the remaining 68% are (on average) complexity averse, with complexity aversion falling fairly rapidly with experience, to the extent that they are (on average) complexity-neutral by the end of the experiment.

Although we already have an estimate of the proportion of the *population* who are complexity neutral (32%), 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 (12), following estimation of model 5. 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 32% being complexity neutral, it seems sensible to classify as “complexity-neutral” the 32% of subjects (26 out of 80) with the highest posterior probabilities of being so. The cut-off appears to be 0.45; 26 (32%) subjects have posterior probabilities of greater than 0.45, and we shall classify these 26 as complexity-neutral.

Figure 3 shows posterior estimates of α and γ obtained, using a formula such as (13), from Model 5. 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 6 classifies subjects by risk and complexity preferences. In particular, we find that 23%, 32% and 45% of the subjects are complexity loving, neutral and averse, respectively.

(*Insert Figure 2 and Table 6 about here*.)

[6] 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).

8. 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.

Sonsino et al. (2002) made a very useful contribution towards this understanding. We have attempted to build on this contribution in a number of ways. Using a similar design to theirs, we have conducted a choice experiment, and then estimated a model which allows two types of 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 extensions of the model included allowance for the effects of experience and subject characteristics.

The main findings are that around 32% of the population are complexity neutral. Of the 68% 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 5. There is also an effect of experience in reducing the variance of computational error. Both of the “experience” effects may be interpreted as a form of learning.

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 insignificant in our preferred model.

When we use posterior estimation to classify subjects, we find that around 28% 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.

APPENDIX

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

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 2. Lotteries Employed in the Experiment

	S1		**S2**		**S3**		**S1$_s$**		**S2$_s$**		**S3$_s$**	
Outcome	Probability	Return	Probability	Return	Probability	Return	Probability	Return	Probability	Return	Probability	Return
1	0.5	57	0.5	50	0.4	80	0.5	75	0.5	68	0.4	95
2	0.2	112	0.2	113	0.3	100	0.2	112	0.2	113	0.3	100
3	0.3	187	0.3	198	0.3	150	0.3	157	0.3	168	0.3	130

	C1		C2		C3		$C1_s$		$C2_s$		$C3_s$	
Outcome	Probability	Return	Probability	Return	Probability	Return	Probability	Return	Probability	Return	Probability	Return
1	0.25	57	0.25	50	0.16	80	0.25	75	0.25	68	0.16	95
2	0.2	84.5	0.2	81.5	0.24	90	0.2	93.5	0.2	90.5	0.24	97.5
3	0.04	112	0.04	113	0.09	100	0.04	112	0.04	113	0.09	100
4	0.3	122	0.3	124	0.24	115	0.3	116	0.3	118	0.24	112.5
5	0.12	149.5	0.12	155.5	0.18	125	0.12	134.5	0.12	140.5	0.18	115
6	0.09	187	0.09	198	0.09	150	0.09	157	0.09	168	0.09	130

	VC1		VC2		VC3		$VC1_s$		$VC2_s$		$VC3_s$	
Outcome	Probability	Return	Probability	Return	Probability	Return	Probability	Return	Probability	Return	Probability	Return
1	0.125	57	0.125	50	0.064	80	0.125	75	0.125	68	0.064	95
2	0.05	58.65	0.05	51.89	0.048	80.6	0.05	76.11	0.05	69.35	0.048	95.15
3	0.05	60.85	0.05	54.41	0.048	81.4	0.075	77.46	0.075	71	0.048	95.35
4	0.075	60.9	0.075	54.44	0.036	82	0.05	77.59	0.05	71.15	0.036	95.5
5	0.02	62.5	0.02	56.3	0.048	82.1	0.02	78.7	0.02	72.5	0.048	96.05
6	0.03	64.75	0.03	58.85	0.036	83.5	0.03	80.05	0.03	74.15	0.036	96.4
7	0.075	66.1	0.075	60.36	0.048	84.9	0.075	80.74	0.075	75	0.048	97.45
8	0.03	67.75	0.03	62.25	0.036	85.5	0.03	81.85	0.03	76.35	0.036	97.6
9	0.045	70	0.045	64.8	0.036	87	0.045	83.2	0.045	78	0.036	98.5
10	0.05	106.5	0.05	106.7	0.048	98	0.05	108.3	0.05	108.5	0.048	99.5
11	0.02	108.15	0.02	108.59	0.036	98.6	0.02	109.41	0.02	109.85	0.036	99.65
12	0.02	110.35	0.02	111.11	0.036	99.4	0.03	110.76	0.03	111.5	0.036	99.85
13	0.03	110.4	0.03	111.14	0.027	100	0.02	110.89	0.02	111.65	0.027	100
14	0.008	112	0.008	113	0.036	100.1	0.008	112	0.008	113	0.036	100.55
15	0.012	114.25	0.012	115.55	0.027	101.5	0.012	113.35	0.012	114.65	0.027	100.9
16	0.03	115.6	0.03	117.06	0.036	102.9	0.03	114.04	0.03	115.5	0.036	101.95
17	0.012	117.25	0.012	118.95	0.027	103.5	0.012	115.15	0.012	116.85	0.027	102.1
18	0.018	119.5	0.018	121.5	0.027	105	0.018	116.5	0.018	118.5	0.027	103
19	0.075	174	0.075	183.2	0.048	143	0.075	148.8	0.075	158	0.048	126.5
20	0.03	175.65	0.03	185.09	0.036	143.6	0.03	149.91	0.03	159.35	0.036	126.65
21	0.03	177.85	0.03	187.61	0.036	144.4	0.045	151.26	0.045	161	0.036	126.85
22	0.045	177.9	0.045	187.64	0.027	145	0.03	151.39	0.03	161.15	0.027	127
23	0.012	179.5	0.012	189.5	0.036	145.1	0.012	152.5	0.012	162.5	0.036	127.55

24	0.018	181.75	0.018	192.05	0.027	146.5	0.018	153.85	0.018	164.15	0.027	127.9
25	0.045	183.1	0.045	193.56	0.036	147.9	0.045	154.54	0.045	165	0.036	128.95
26	0.018	184.75	0.018	195.45	0.027	148.5	0.018	155.65	0.018	166.35	0.027	129.1
27	0.027	187	0.027	198	0.027	150	0.027	157	0.027	168	0.027	130

Table 3 – 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 4: Reversal patterns for selected task-pairs, and McNemar test results for complexity aversion.

pair a	*pair b*	*n*	*RR*	*RS*	*SR*	*SS*	*McNemar*	*Mcnemar*	*Conclude*
							$\chi^2(1)$	*p-value*	
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 5. Maximum Likelihood Estimates of Model (10) and restricted versions thereof.

	Model 1	*Model 2*	*Model 3*	*Model 4*	*Model 5*
θ_{10} risk av.	2.964(0.153)	5.595(0.243)	3.930(0.532)	3.138(0.406)	3.289(0.396)
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θ_{21} experience				-0.006(0001)	-0.006(0.001)
θ_{22} male					-0.096(0.081)
θ_{23} (age-18)					0.029(0.044)
θ_{24} non-UK					0.154(0.087)
η_2			0.509(0.065)	0.349(0.052)	0.291(0.042)
ρ			-0.333(0.127)	-0.112(0.195)	-0.143(0.107)
φ				-0.008(0.002)	-0.008(0.002)
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π_3 RN only		0.088(0.030)	0.026(0.070)		
π_4 neither	1	0.069(0.030)	0.479(0.120)	0.644(0.118)	0.677(0.120)
n	80	80	80	80	80
T (mean of)	53	53	53	53	53
k	2	5	8	8	11
LogL	-2668.98	-2465.09	-2429.03	-2418.39	-2410.45
AIC=-2(LogL-k)	5341.96	4940.18	4874.06	4852.78	4842.90

Notes. 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. 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. 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 6. Preferences Distribution Classification of the 80 Subjects

	Complexity loving	Complexity neutral	Complexity averse
Risk loving	2	1	7
Risk averse	16	25	29

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 5.

Figure 1 – Proportions of Safe Choices

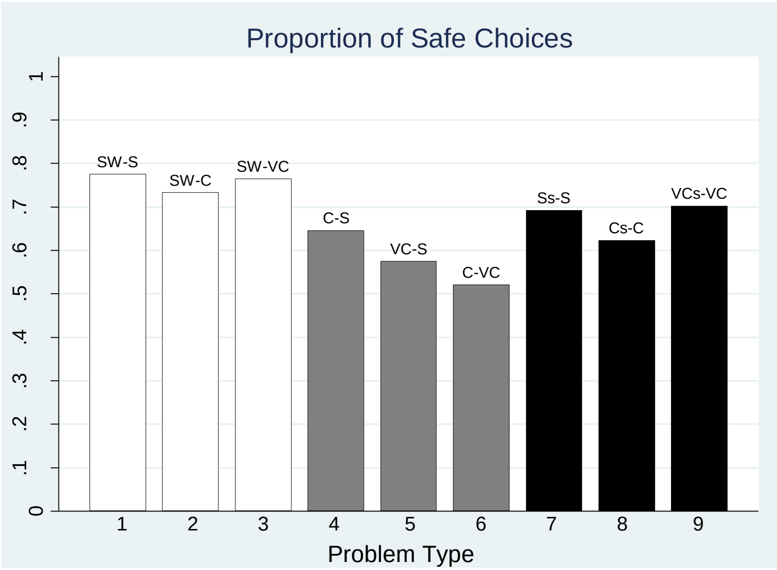


Figure 2: A frequency histogram of the 80 subjects' posterior probabilities of being type 2 (complexity neutral) based on model 5 in table 5

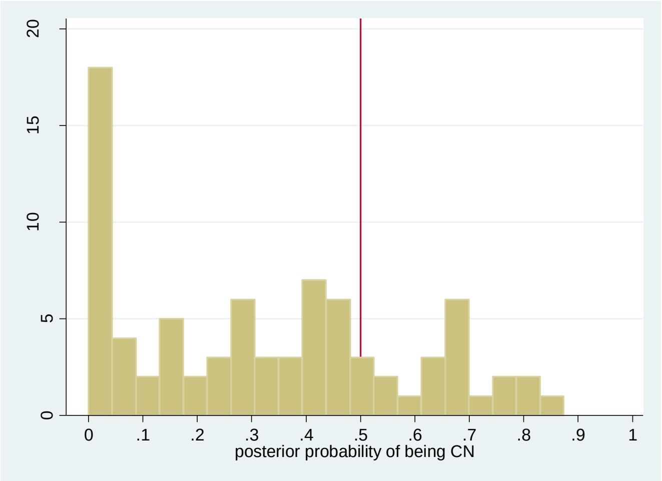
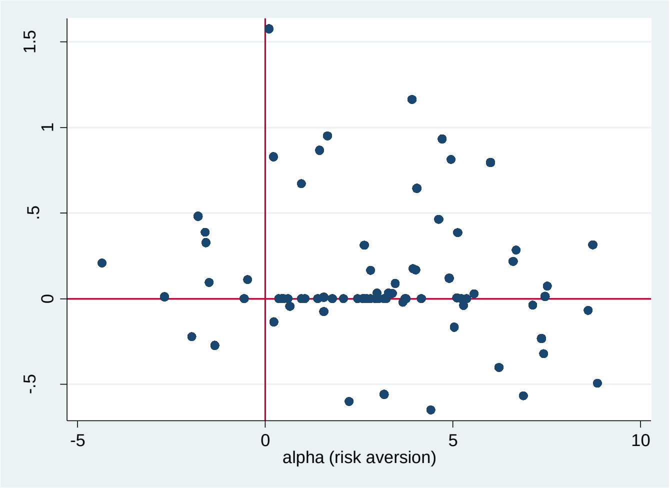


Figure 3: Posterior Estimates of α and γ based on Model 5 in Table 5



Notes: Observations on the horizontal axis are subjects whose posterior probabilities indicate that they are type 2 (complexity neutral).

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