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Abstract

We use a multiple price list (MPL) method to elicit attitudes to risky and ambiguous prospects. In particular we wish to investigate if there are differences in agent behaviour under uncertainty over gain amounts vis a vis uncertainty over loss amounts. On an aggregate level, we find that (i) in the domain of risk, subjects are risk averse over both gain and loss lotteries with the degree of risk aversion being lower for losses than gains, (ii) subjects are ambiguity averse over ambiguous prospects that involve gains, but that they are mildly ambiguity seeking over such prospects that involve loss and (iii) attitudes toward risk and ambiguity are positively correlated in the domain of gains and are independent of each other in the domain of losses. These behavioural observations are statically significant using both parametric as well as non-parametric tests. Further analysis shows that at an individual level, (a) in the domain of risk, there is a high incidence of a reflection effect across gains and losses though the subjects' behaviour is bimodal, that is, many are risk averse in gains and risk seeking in losses while many others are risk seeking in gains and risk averse in losses, while (b) in the domain of ambiguity, there is also a high incidence of a reflection effect although almost all such cases exhibit ambiguity aversion in gains and ambiguity seeking in losses.

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1. Introduction

A fundamental problem in decision theory is the study of decision making under ambiguity, where uncertainty regarding the occurrence of an event is immeasurable or only partially so. Camerer (1995) has defined ambiguity with respect to events as "…known to be missing information, or not knowing relevant information that could be known." Knight (1921) distinguished between measurable uncertainty or risk, which may be represented by precise odds or probabilities of occurrence, and immeasurable uncertainty which cannot find such representation. In situations of immeasurable uncertainty, where individuals are partly ignorant of the precise statistical frequencies of events that are relevant to their decisions, casual empiricism suggests that people tend to impute numerical probabilities related to their beliefs regarding the likelihood of particular outcomes (Ellsberg, 1961). Thus, ambiguity has been referred to as "…uncertainty about uncertainties…" (Einhorn and Hogarth, 1986)

The two important theories that have attempted to characterize decision making under uncertainty are often jointly referred to as the Savage-Bayes approach. This approach includes the Expected Utility Theory (von Neumann and Morgenstern, 1944) and the Subjective Expected Utility Theory (Savage, 1954). The most fundamental implication of the Savage-Bayes approach is what has been termed "probabilistic sophistication" which requires on the part of individuals to possess a complete and exhaustive list of all the possible states of the world along with a subjective assessment of "likelihoods" of uncertain events that can be represented by a unique and additive probability distribution. However, experimental evidence, since Ellsberg (1961) has demonstrated the inability of the SEU theory to describe behaviour under uncertainty. The essential problem with the Savage-Bayes approach is best seen through the following example which is adopted from Mukerji (1997). Consider two decision problems A and B each of which consists of two possible states of the world, θ and its negation $\sim\theta$. Suppose that in both the problems the available set of acts (an act is a function from the state space to the space of possible consequences) is identical and that in A as well as in B, the state θ is two times more likely than $\sim\theta$. The difference is that while in problem A, the decision maker is informed that the probability assessment above is based on a sample of size 3, the sample size used in problem B is 3 million. SEU theory would predict that the decision maker takes the same action in both the problems, while it would not be surprising to see a more "conservative" act in A than in B. Experimental evidence supports the latter claim. An important observation that emerges from Ellsberg (1961) and various other studies that investigate the `Ellsberg paradox' like Einhorn and Hogarth (1986), Fox and Tversky (1995), Becker and Brownson (1964) and Hogarth and Kunreuther (1985) is that decision making under uncertainty may be governed by individual attitudes to ambiguity and subjective ways in which decision makers infer probabilities in situations in which there is limited or no information regarding the underlying probability distributions.

There are two existing approaches to overcome the problem concerning SEU theory as stated above. The first one [Bewley (1986) and Gilboa and Schmeidler (1989)] deals with additive but non-unique priors. The second approach, pioneered by Gilboa (1987) and Schmeidler (1989), assumes that subjective probabilities exist and are unique, but they do not satisfy the usual mathematical properties of probability measures in the sense that they are non-additive. All existing axiomatizations of this non-additive expected utility start out with a preference relation on acts and then derive the representation of the expectation by use of some weaker version of Savage's Independence axiom. The most important contribution of this approach is to establish behavioural principles that imply preferences consistent with the maximization of Choquet (1955) expected utility with respect to non-additive priors. These approaches take a rather extreme stand on the way a DM evaluates uncertainty. In particular they essentially assume that whenever it is the case that some probability mass cannot be assigned with certainty across the available set of alternatives, the decision maker (DM henceforth) is assumed to assign it directly to the "worst possible" or the "best possible" alternative [see Marinacci 2000]. Consequently, these approaches do not readily help an experimenter to distinguish between three fundamental aspects of decision making under uncertainty, namely, attitude towards risk, attitude towards ambiguity and subjective beliefs which in turn reflect a DM's degrees of optimism/pessimism. Finally, it also fails in providing a clear picture about different degrees of ambiguity aversion that may exist.

A recent work by Klibanoff, Marinacci and Mukerji (2005) [KMM henceforth] is a much awaited and excellent attempt to address these issues concerning beliefs and attitudes. Our experiment is based on the theoretical foundations provided in this study and will be discussed in detail in section 2. By using the KMM assumptions, we ask the following question: Does our attitude towards ambiguity differ across domains of gains and losses? We perform within-subject comparisons of behaviour between gambles involving gains and those involving losses to answer this question. We also check for a possible reflection effect reported first by Kahneman and Tversky (1979) in the attitude towards risk across gains and losses. Finally, we investigate whether there is any correlation between risk and ambiguity attitudes. Existing experimental studies assume a utility function over money and then independently provide a theory of attitude towards ambiguity given this utility function without first gauging an agent’s attitude to risk. Our study provides a cleaner test of attitude to uncertainty by measuring both attitudes to risk and uncertainty in a within subjects design. Our results show the following: on an aggregate level (i) subjects are risk averse in both gains and losses, though they are more so in gains, (ii) subjects are ambiguity averse in the domain of gains but mildly ambiguity seeking in the domain of losses, and (iii) attitudes towards risk and ambiguity are positively correlated in the domain of gains but there is no such correlation at all in the domain of losses. Further analysis shows that at an individual level, (a) in the domain of risk, there is significant incidence of a “reflection effect” across gains and losses though the subjects’ behaviour is bimodal, that is, among the agents that display reflection, about 60 percent are risk averse in gains and risk seeking in losses while the remaining fraction are risk seeking in gains and risk averse in losses. (b) In the domain of ambiguity, there is a slightly higher incidence of a reflection effect than in risk albeit with a crucial difference: all such cases (barring a single subject) exhibit ambiguity aversion in gains and ambiguity seeking in losses.

The rest of the paper is structured as follows. In section 2, we describe the KMM model in a discrete choice environment. In section 3 we describe the design of the experiment. Section 4 relates the tasks with the KMM theory. Section 5 reports the results from the experiment and section 6 draws our conclusions.

2. Theories of Risk and Ambiguity

In this section we present the theoretical background on which this experimental exercise is built. As we shall see there are two aspects of attitude towards uncertainty, namely, risk and ambiguity, which are partly independent and partly interdependent. In order to understand the interdependence between the two traits, we begin first by focusing on the attitude towards risk in isolation.

2.1 Utility for money and attitude towards risk

Our experiment includes two tasks where subjects choose between binary lotteries of the form $\langle x,0;p\rangle$ where x and 0 are payoffs (in money) and $p \in [0,1]$ is the probability of receiving x (while 1 – p is the probability of receiving 0). We assume that DMs are expected utility maximizers. Moreover, we will assume, as has been done in many experimental works including that of Kahneman and Tversky (1979), that each DM has a Bernoulli utility function for money $u : R \to R$ which is domain specific and is given by

$$u(x) = \begin{cases} x^r & \text{whenever } x > 0, \\ 0 & \text{whenever } x = 0, \\ -(-x)^s & \text{whenever } x < 0. \end{cases} \quad (1)$$

Hence, facing a lottery $\langle x,0;p \rangle$, each DM evaluates this in terms of its expected utility value given by

$$EU(x,0,p) = pu(x). \quad (1)'$$

In this formulation there is no effect of loss aversion.[1] The utility function we assume is of the Constant Relative Risk Aversion (CRRA) form for a given domain and yields a domain specific Arrow-Pratt measure of risk aversion equal to $1-r$ if $x > 0$ and $1-s$ if $x < 0$. In particular,

1. If $r = s = 1$, then the DM is called *risk-neutral* in both the domains.
2. For the domain of gains, that is when $x > 0$, if $r > 1$, then the DM is risk-seeking while if $r < 1$, the DM is risk-averse. On the other hand, for the domain of losses, that is when $x < 0$, if $s > 1$, then the DM is risk-averse while if $s < 1$ then he is risk-seeking.

Kahneman and Tversky (1979) define *reflection effect* as the phenomenon where a DM exhibits risk aversion (seeking) in gains and risk seeking (aversion) in losses. We classify this effect into two cases: The first one is called the "exact risk-reflection effect", which roughly means the following: If for some DM it happens that $r = s < 1$, then this DM is exactly as risk-averse in gains as he is risk-seeking in losses; if for some DM it happens that $r = s > 1$, then this DM is exactly as risk-seeking in gains as he is risk-averse in losses [Kahneman and Tversky (1979) in their mostly unpaid experiments found that $s = r = 0.88$].[2] A weaker version of this exact effect is what we term as "weak risk-reflection effect" which occurs if and only if either (i) $s, r > 1$ or (ii) $s, r < 1$.

With these theoretical assumptions on risk attitudes, we now move on to the theory of ambiguity.

2.2 Ambiguity attitudes and the KMM theory

In our experimental setting, an ambiguous prospect is a tuple $\langle x,0;1,0 \rangle$ where the two payoff outcomes are again x and 0, but now there are two possible probability distributions on this binary payoff set $\{x,0\}$. The first one assigns probability 1 to outcome x while the second one assigns probability 1 to outcome 0. There is no other information provided in this environment. The obvious question that arises hence is how a DM evaluates this ambiguous prospect.

Choquet (1955) in his theory of capacities suggests that beliefs (or capacities) over events or outcomes can be exogenously modelled as non-additive probabilities P such that if the universal set of events is denoted by Θ, then $P(\phi) = 0, P(\Theta) = 1$ and for any two events E, F such that $E \subseteq F \subseteq \Theta$, we have $P(E) \leq P(F)$. Notice that this specification allows for sub-additivity which is helpful in order to rationalize why past experiments revealed that while betting on a colour, some subjects preferred urns with equal number of each colour to urns where the exact proportion was unknown although they were all indifferent between colours within each urn. Moreover, as Fishburn (1993) suggests, the ambiguity of a prospect can be assumed to be equal to the residual capacity that cannot be assigned to any non-universal event if the capacity is sub-additive. Given this capacity, Choquet takes a pessimistic approach to computing expectations. To

[1] With loss aversion we require to multiply the utility function in the domain of losses by a constant $\lambda > 1$. All our analysis can be done with this as well, but we abstract away from this aspect. Moreover, it is typically of use when the outcome space involves loss and gain at the same time – which is absent in our design.

[2] Our data shows absence of perfect reflection in risk.

see this, let $X = \{x_1, x_2, \ldots x_n\}$ be the set of outcomes in an ambiguous prospect of the type defined above such that $u(x_t) \geq u(x_{t+1})$. The Choquet expectation of *u* given *P* is

$$CEU\,(u \mid P) = u(x_n) + \sum_{t=1}^{n-1}[u(x_t) - u(x_{t+1})]P(\{x_1,\ldots,x_t\})\ ,$$

To understand how this operator works when n = 2, consider an ambiguous prospect with three possible probability distributions (.7, .3), (1/2, 1/2) and (.3, .7) on the set *X*. Then given a capacity *P*,

$$CEU(u \mid P) = u(x_2) + [u(x_1) - u(x_2)]P(x_1).$$

Several pioneering works exist that provide axiomatic foundations to preferences that lead to the use of this expectation operator by the weakening of Savage's Independence Axiom (see Schmeidler (1989) and Mukerji (1997)). The first problem of this approach is that the capacity is ad hoc, though it's possible sub-additivity captures the notion of ambiguity. A meaningful foundation to Choquet's capacities may be provided in environments, as in our case, where uncertainties are represented by sets of probability distributions by help of minimum probability guarantees. In the above example, a capacity with minimum probability foundation means that $P(x_1) = 0.3$ and hence,

$$\begin{aligned} CEU(u \mid P) &= u(x_2) + [u(x_1) - u(x_2)](0.3) \\ &= 0.3u(x_1) + 0.7u(x_2). \end{aligned}$$

It is easy to check that under this minimum probability guarantee, any uncertain prospect with multiple probability distributions would give rise to a convex capacity and result in ambiguity aversion under the above CEU decision rule. To understand a DM using this foundation to capacities, let us consider our ambiguous prospect $\langle x,0;1,0 \rangle$ and an over-conservative and cautious DM who thinks as follows:

"*The minimum probability guarantee of obtaining x is zero, and the minimum probability guarantee of obtaining 0 is zero as well. Hence, the total minimum probability guarantee that this prospect promises is 0 and since something is certain to occur, the probability of this something (which I don't know what) is 1 – (total minimum probability guarantee) = 1. Hence with probability 1 I have no idea what will occur.*"

If a DM thinks in such lines, then the ambiguity of our prospect, a la Fishburn (1993), is 1 (full) and if he is a Choquet expected utility maximizer, he would form an expected value of this ambiguous prospect, given his utility function for money *u*(.) as discussed above, equal to

$$CEU(x,0;1,0) = \begin{cases} 0 & \text{if } x \geq 0 \\ -(-x)^s & \text{if } x < 0. \end{cases}$$

Given the ambiguous urn we construct, it seems that there is no other reasonable way of forming capacities. As the reader perhaps realizes, the major problem with this approach is that it assumes the DM to be unrealistically pessimistic in evaluating our ambiguous prospect. The second problem with this approach is that if we discard the minimum probability guarantee foundation to capacities, then this theory boils down to the theory of non-additive beliefs, captured by ad hoc capacities along with the pessimistic expectation formation given the capacity. Unfortunately then the theory of attitude towards ambiguity somehow recedes to the background because (a) utility functions define attitude towards risk and (b) capacities define perception of the amount of ambiguity in the prospect, and neither define an attitude to ambiguity itself. Choquet's expectation operator is indeed a model of attitude towards ambiguity, but as highlighted above, it is too extreme.[3]

We believe that individuals think differently in face of ambiguity that is representable by multiple probability distributions, as in the case of Ellsberg urns. First, they look at the set of all possible

[3] One can define extreme optimism using the Choquet operator as well as explained in Marinacci (2000).

probability distributions [(1,0) and (0,1) in our case], and for each such distribution, they compute the expected utility given their attitude towards risk (as represented by *u*). They then assign an environmentally plausible probability of occurrence of each such distribution. We believe that in our experiment it would imply, as we shall see later, that subjects would assign equal (and additive) probabilities of 0.5 and 0.5 to the distributions (1,0) and (0,1) respectively. Once they do this, in their mind they ask what expected utility would they expect. KMM does exactly this and overcomes some of the drawbacks in CEU theory, and in some sense is a generalization of Choquet's extreme aversion attitude to, what KMM call, smooth ambiguity. For formal descriptions of these axioms, please refer to KMM. However, to get a first hand and informal understanding of this theory, consider a DM who is betting on a colour from an Ellsberg-type urn described above which contains 10 beads, which are either all red or all yellow. Suppose that the winning prize equals 100 and if you lose you get 0. This Ellsberg urn induces two probability distributions $\{(1,0),(0,1)\}$. Suppose that u:{0,100}→R is the utility function as described in section 2.1. KMM provides axioms (which are simple and reasonable) that allow us to represent the value of our ambiguous prospect by an operator which we denote as $KMM(x,0;1,0)$. The first requirement for the KMM representation is that the DM satisfies the expected utility hypothesis given *u* and the two probability distributions (1,0) and (0,1) on {0,100} in this betting exercise. The second requirement is as follows. Suppose the bet is not directly on the colour, but on the composition of the urn.[4] Hence, the DM is now asked to announce the exact composition and wins 100 if his prediction is correct. Let $\sigma_R \geq 0$ and $\sigma_Y \geq 0$ represent any subjective probability beliefs over the set {*R*: all red, *Y*: all yellow} with $\sigma_R + \sigma_Y = 1$. Denote $\sigma = (\sigma_R, \sigma_Y) \in \Delta$ as any such subjective belief – notice that these are additive probability beliefs. Suppose there is a utility function v:{0,100}→R (not necessarily different from *u*). The second requirement of the KMM representation is that the DM satisfies the subjective expected utility hypothesis given *v* and the set Δ of all subjective probability beliefs in this second-order betting exercise. The third requirement for the KMM representation is that preferences in the original betting exercise should be consistent with the preferences in this second order betting exercise. Given these three axioms, KMM show that the value of the above ambiguous prospect $\langle x,0;1,0 \rangle$ can be represented as an expected value of some function $\phi : R \to R$. To use this representation, we assume that this function takes the following domain-specific form:

$$\phi_i(z) = \begin{cases} z^a & \text{whenever } z > 0 \\ 0 & \text{whenever } z = 0 \\ -(-z)^b & \text{whenever } z < 0. \end{cases} \qquad (2)$$

Given this functional form, for a DM betting on red, we have

$$KMM(x,0;1,0) = \sigma_R \phi(EU(x,0;1) + \sigma_Y \phi(EU(x,0;0), \qquad (2)'$$

where the numbers in the parentheses are the expected utilities for each of the two distributions, given *u*, while the whole expression is an expected ϕ value of these expected utilities, given any belief σ and the function ϕ. In this representation, *u* characterizes the DM's attitude towards risk, ϕ characterizes the DM's attitude towards ambiguity, while the subjective belief σ characterizes his degree of optimism/pessimism and perception of ambiguity. Given two binary ambiguous prospects like ours, one is more ambiguous than the other, a la KMM, if the former generates a mean-preserving spread belief σ over the latter on the set of outcomes. In this sense, since in our design the non-ambiguous urn has a known distribution of (0.5,0.5), our ambiguous urn is indeed ambiguous a la KMM vis-à-vis the urn with known proportions. As KMM argues, this subjective belief in turn may be interpreted as a perception of ambiguity. As far as attitude towards

[4] In our design these two betting tasks are identical since whenever a DM is able to match the colour, he automatically also matches the composition.

ambiguity goes, the more concave is ϕ the more ambiguity averse the DM is. Since from (1)' we have

$$EU(x,0;1) = \begin{cases} x^r & x > 0 \\ -(-x)^s & x < 0, \end{cases}$$

and $EU(x,0;0) = 0$, if a DM bets on the colour red, the KMM value becomes

$$KMM(x,0;1,0) = \begin{cases} \sigma_R x^{ra} & x > 0 \\ -\sigma_Y (-x)^{sb} & x < 0. \end{cases} \quad (3)$$

As in the case of u and its respective attitude towards risk, and as explained in KMM, we can analogously define the domain-specific coefficient of ambiguity aversion as equal to $(1 - a)$ in the domain of gains and $(1 - b)$ in the domain of losses. As in the case of risk,

1. If $a = b = 1$, then the DM is called ambiguity-neutral in both the domains.
2. For the domain of gains, that is when $z > 0$, if $a > 1$, then the DM is ambiguity-seeking while if $a < 1$, then the DM is ambiguity-averse. On the other hand, for the domain of losses, that is when $z < 0$, if $b > 1$, then the DM is ambiguity-averse while if $b < 1$, then the DM is ambiguity-seeking.

One can now define reflection issues in exactly the same manner as in the case of risk and utility. As before, we classify this effect into two cases: The first one is called the "exact ambiguity-reflection effect", which roughly means the following: If for some DM it happens that $a = b < 1$, then this DM is exactly as ambiguity-averse in gains as he is ambiguity-seeking in losses; if for some DM it happens that $a = b > 1$, then this DM is exactly as ambiguity-seeking in gains as he is ambiguity-averse in losses. A weaker version of this exact effect is what we term as "weak ambiguity-reflection effect" which occurs if and only if either (i) $a, b > 1$ or (ii) $a, b < 1$.

3. Design of the Experiment

The subjects were 47 students at the Indian Institute of Management (IIM) in Ahmedabad, the premier Business School in India. Subjects as in Chakravarty et al (2005) were generally representative of the student population at IIM Ahmedabad in terms of family income levels (moderate to high, by average Indian standards), sex (predominantly male), ethnicity (predominantly Hindu) and undergraduate major (engineering and computer sciences). We employ an experimental procedure for risk aversion, called a multiple price list (MPL), previously used by Holt and Laury (2002) and Harrison, et al (2005) and modify it to recover not just attitudes to risk but also attitude to ambiguity.[5] In the risk tasks (Task A and Task B), each subject is presented with a choice between two lotteries while in the ambiguity tasks (Task C and Task D) they choose between a lottery and an ambiguous prospect. The exact decision sheets given to the subjects may be found in the appendix.

Tables 1 and 2 illustrate the basic payoff matrices presented to subjects for the risk tasks.

<Insert Table 1 about here> <Insert Table 2 about here>

[5] Recently, the MPL method has come under some criticism. Anderson et al (2005) find that it biases responses to the middle of the table (causing an overestimation of the coefficient of risk aversion). This type of 'embedding bias' has also been documented by Bosch-Domeneche and Silvestre (2005) where subjects tend to switch earlier from the safe to the risky lottery if some later choices in an MPL are removed. However Bosch and Silvestre (2005) assert that this is a quantitative effect (which may result in over estimation of the coefficient of risk aversion in Holt and Laury (2005a)) entailing no qualitative change in the structure of preferences. In our case we are primarily interested in within subject comparisons of attitude towards risk and ambiguity over the domains of gain and loss. For this purpose the MPL method serves us well.

The first row of task A shows that lottery A (denoted by option A) offered a 50/50 chance of receiving Rs. 40 (A_1) and Rs. 60 (A_2), whereas lottery B (denoted by option B) has a zero chance of a realization of Rs 100 (B_2) and a 100 % chance of a realization of Rs 0 (B_1). Thus the two lotteries have a relatively large difference in expected values, and in this case lottery A would always be chosen. As one proceeds down the matrix, the expected value of lottery B increases and becomes greater than the expected value of lottery A. A subject chooses A or B in each row, and one row is later selected at random for payout for that subject (using a 10 sided die). The logic behind this test for risk aversion is that only risk-loving subjects would take lottery B in the second row, and only risk-averse subjects would take lottery A in the last row. Assuming local non-satiation, the first row is simply a test that the subject understood the instructions, and has no relevance for risk aversion at all. Most subjects would be expected to switch from A to B on some row in the table, and this switch point can then be used to infer their risk attitude. A risk neutral subject should switch from choosing A to B when the expected value of each is about the same, so a risk-neutral subject would choose A for the first six rows and B thereafter. The loss task (Task B) depicted in table 2 has the same absolute value of the prizes as the gains task described above but the amounts are negative (except K_2 which is zero). In this case too, subjects would be asked to make ten decisions and one would be selected randomly. The subject's attitude to risk in both gain and loss domains can be calibrated within an interval using the point at which he switches from lottery A to lottery B in gains and from lottery J to lottery K in losses as described in the next section.

For the ambiguity tasks (shown in tables 3 and 4), the subjects are given a choice between a lottery with known probabilities and an ambiguous prospect in tasks C and D.[6]

<Insert Table 3 about here> (Insert Table 4 about here>

The lottery has prizes calibrated with one prize equal to 0 and the other changing from 140 to 20 (and -20 to -140 for the loss tasks). For the ambiguous choice, in both domains of gain and loss, the prizes remain fixed at 0 and 100 (-100 in the loss treatment). The value of the prizes of the lottery for decision 1 make the worth of the lottery, given by (1)', initially higher than that of the ambiguous prospect whose value is determined by (2)'. By the 10^{th} decision however, due to the decrease in one of the prizes of the lottery, the worth of the ambiguous prospect is higher than that of the lottery. A subject with a given smooth ambiguity attitude would typically start by choosing the lottery and cross over to the ambiguous prospect at some point on the table. The subjects make ten choices just like in the risk tasks and bets on a colour (green and blue for task C and red and yellow for Task D). After all tasks are complete, a 10 sided die is rolled once to determine the decision to be used for payment. As an example, for Task C, at the end of the entire experiment the subject draws from an urn P with 5 green beads and 5 blue beads (the non-ambiguous (0.5, 0.5) urn which they verify before the task) if he chose P in that decision. If he chose Q he draws from urn Q with either 10 green beads or 10 blue beads (the ambiguous Ellsberg type [(1,0) (0,1)] urn explained in greater detail in section 4). If the colour of the drawn bead matches with the colour he bet on, the subject gets the higher prize, if not he gets the lower prize amount. In task D over losses, the subject makes another bet on a colour (red or yellow) and takes part in a 10 decision lottery-gamble choice problem just like task C. After all tasks are complete the 10 sided die is rolled once for this task and now depending on the choice of X or Y in the decision number realized by the die-roll, the subject draws from an urn with 5 red and 5 yellow beads (the non-ambiguous [0.5, 0.5] urn which they verify before the task) or the an ambiguous (10 yellow beads or 10 red beads) urn.[7]

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[6] We conducted two sessions, one with gain tasks before loss tasks for both risk and ambiguity and the other with loss tasks before gain tasks. This is to control for order effects as reported for these types of MPL tasks by Harrison et al (2005). So task C and D (and indeed task A and B for risk) were different depending on the session. For the sake of simplicity we report the design as gain before loss.

[7] Notice that since the subjects themselves bet on a colour, the experimenters have no strategic interest to prefer one or the other colour in the ambiguous urn. Our instructions to the subjects very clearly mention

The subjects were told that the maximum each of them could earn from the entire experiment was Rs.500 (which is equivalent to USD 55 in terms of PPP). On average a subject earned Rs.275 for participating in a session. In the next section we explore the properties of the experimental tasks and the benchmarks that we would use to compare with the experimental data.

4. Properties of the Experimental Tasks

Keeping the above theoretical background in mind, in this section we describe some detailed features of the risk and ambiguity tasks used in the experiment and comment on the particular ambiguous urn that we construct. We begin with the risk tasks.

4.1 Risk Tasks and calibrated values of *r* and *s*

Table 5 summarizes the calibrated values of r and s from the two risk tasks presented to the subjects. In this calibration, the following methodology is used. Consider the risk task for the domain of gains (Task A) which is used to recover r. Let us suppose that an individual is indifferent between option A and B at some decision number where the probability of obtaining 100 in option B is p. Given (1)', it follows that at this decision number, we have

$$0.5(60^r + 40^r) = p100^r. \qquad (4)$$

We then solve for r by providing a numerical approximation to it. Notice now that if $r = 1$ then the DM would make the following decisions:

{1A, 2A, 3A, 4A, 5A, 6A or 6B, 7B, 8B, 9B, 10B}

We do not allow subjects to report indifferences. Given this, suppose we observe that a DM makes the following sequence of choices:

{1A, 2A, 3A, 4A, 5A, 6B, 7B, 8B, 9B, 10B}

To obtain this DM's interval for r we shall call decision number 6 his *risk flip-point* and obtain values of r assuming that he is indifferent between options A and B at decision numbers 5 and 6 using equation 4. From his indifference at 5, we will obtain $r = 1.33$ while from his indifference at 6, we will obtain $r = 1$. These values of r are the maximum and minimum values possible for an expected utility maximizer making the above choice. We will then assume that this DM's true value is the mean of these two numbers, that is we will assume that $r = (1 + 1.33)/2 = 1.17$.[8] Next observe that the sequence of lotteries is constructed in such a way that any expected utility maximizer must select 1A. Given this, observe now that any expected utility maximzer can have at most one flip point (that is the decision number at which he switches from option A to option B). The set of possible flip points is $\{2,3,4,5,6,7,8,9,10,11\}$ where the flip point 11 represents any DM who never chooses option B. As explained above, for each observed flip point g we will first calibrate the corresponding values for r once by assuming indifference at decision number g and next at decision number $g - 1$ and then take the average of the two calibrated values.[9] These calibrated intervals are reported in Table 5 along with the average value which we

this aspect of the design. Schneeweis (1973) identified some strategic motivations in the tasks of the original Ellsberg (1961) study on ambiguity aversion. Our tasks, by having two independent ambiguous mechanisms for the loss and gain tasks (i.e. two separate bets that apply to two separate sets of urns), achieve a complete separation of the tasks being performed by the subjects. Moreover since the subjects were shown that the contents of the ambiguous urns only after all decisions for all tasks had been performed, our design greatly minimises strategic incentives for subjects.

[8] Notice that from a DM's revealed preference over the lotteries (and gambles, see next section) the best we can do is estimate the range in which the parameters r, s, a and b may lie. We have chosen the mean of value in this range to proxy for this interval. A way in which it is possible to precisely estimate the value of the parameter within these intervals is by using a binary choice model and DM specific covariates (see Anderson et al (2005) and Chakravarty et al (2005). Our study is concerned more with studying ordinally the differences in risk and ambiguity attitudes over gains and losses rather than estimating precise values for the parameters that engender these differences in attitude, so we do not attempt to estimate these parameters.

[9] For the case when $g = 2$, we will assume that the upper bound for r is $+\infty$ while for $g = 11$, we will assume that the lower bound for r is $-\infty$. For DMs that exhibit these extreme behaviours we assume that

then use as a proxy for the true value of *r*. The same procedure is used on the risk task for the domain of losses in order to recover *s*. This task is constructed by multiplying the payoffs of the gains task by (-1).

<Insert Table 5 about here>

DMs representing the following pairs of flip-points (*g*,*l*) exhibit perfect risk-reflection effect:

{(2,11), (3,10), (4,9), (5,8), (6, 7), (7,6), (8,5), (9,4), (10, 3), (11, 2)}.

On the other hand, a DM with a flip-point pair (8, 3) or (7, 3) or (2, 8) would exhibit a weak risk-reflection effect. Absence of reflection would mean that the DM has a flip-point pair like (4, 4) or (8, 9) etc.

4.2 Ambiguity Tasks and calibrated values of *a* and *b*

In this section we begin by describing the ambiguous urn used in the experiment and then report the calibrations for gains and losses.

4.2.1 The Ellsberg-type urn

To the best of our knowledge, all existing experiments on ambiguity (see Einhorn and Hogarth (1986), Ellsberg (1961), Halevy (2005)), paid or not, employ a single binary betting decision problem as follows. Subjects are presented with two urns, say 1 and 2. Urn 1 contains 100 beads out of which exactly 50 are of one colour while the remaining 50 are of another colour. Urn 2 contains 100 beads comprising the two colours but the subjects are not told anything more. Urn 2 is typically referred to as the Ellsberg urn, which induces 101 possible distributions of colours, viz.

{(0,100), (1,99), …., (99,1), (100,0)}.

Subjects are asked to bet on a colour and obtain 100 if they win and otherwise get zero.

The ambiguous urn we constructed contained 10 beads. Hence, if we used the same method as above, it would have induced 11 possible distributions of colours, viz.,

{(0,10), (1,9), …., (9,1), (10,0)}.

Instead, we told the subjects that all the 10 beads in the ambiguous urn were either of one colour, or of another. This information reduces the above set of possible distributions to two, viz., {(0,10), (10,0)}. We call our urn the *Ellsberg-type urn*. There are two reasons behind our choice. First, given our non-ambiguous urn that contained exactly 5 beads of each colour (and hence generating the probability distribution of (0.5,0.5) over the two prizes), by KMM theory, our Ellsberg-type urn is at least as ambiguous than the standard one since any subjective belief regarding the chance of winning and losing in our case is at least as big a mean-preserving spread from (0.5,0.5) as in the case with the standard urn.[10] Second, and as shall be clear from our method of calibrating the values of *a* and *b*, reducing the set of possible distributions from 11 to 2 not only makes the calculations significantly simpler but also enables us to produce a series of payoffs in our marginal price list task such that choice remains invariant to attitude towards risk. This, as a result, helps one observe the choice and immediately infer the values of *a* and *b*.

4.2.2 Ambiguity Tasks

Our experiment is the first attempt to use the MPL method to elicit ambiguity attitudes. The main reason behind the use this method is that since our aim is to elicit different degrees of this attitude,

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their *r* is equal to the lower (upper) value of the interval as we cannot compute an average. This is a conservative assumption but one that does not fundamentally change any of the results as the proportion of tasks exhibiting these behaviours is less than 0.5% of our sample.

[10] As mentioned before, if one applies the definition of ambiguity in terms of the amount of probability mass over and above the sum of lower probabilities, then the typical Ellsberg urn is exactly as ambiguous as our urn.

the standard single binary betting decision problem method is not sufficient. Given the way we construct the urn and the discussion in Section 2, in what follows we will assume that subjects held subjective beliefs of $\sigma = (0.5, 0.5)$ over the composition of the Ellsberg-type urn.

The calibration method used to recover the ambiguity parameters *a* and *b* is identical to the one used for the risk tasks. Let us begin by looking at the ambiguity task for the domain of gains (Task C) that is used to recover *a*.[11] Let us suppose that an individual is indifferent between option P and Q at some decision number where winning the bet yields a payoff of *x* in option P. Given (1)' and (3), it follows that at this decision number, we have

$$0.5x^r = 0.5(100)^{ra}.$$

Solving for *a,* we have $a = \dfrac{\ln x}{\ln 100}$ and so the value of *a* is independent of *r*. Next observe that if *a* = 1, then the DM would make the following decisions:

$$\{1P, 2P, 3P, 4P, 5P \text{ or } 5Q, 6Q, 7Q, 8Q, 9Q, 10Q\}.$$

As we do not allow subjects to declare indifferences, suppose a DM makes the following choice:

$$\{1P, 2P, 3P, 4P, 5P, 6Q, 7Q, 8Q, 9Q, 10Q\}.$$

Call decision 6 his *ambiguity flip-point.* As in the case of the risk tasks, we first assume that this DM is indifferent between options P and Q at decision number 6 by which we obtain *a* = 0.9771 and then assume indifference between options P and Q at decision number 5 to obtain *a* = 1. We then take the average of these two extremes and assume that any DM with a flip point 6 in the gains task has *a* = 0.988. Next observe that the sequence of decisions in this task is constructed in such a way that for every DM following KMM theory, if at some decision he chooses option P, then he must choose option P for all previous decisions and if at some decision he chooses option Q then he must continue choosing option Q for all subsequent decisions. Hence no DM following the KMM theory can have more than 1 flip point (that is the decision at which he switches – if at all – from option P to option Q).[12] Finally observe that the smaller is this flip point (that is earlier the DM switches from option P to option Q), the higher is the value of *a*. The set of possible ambiguity flip points is

$$\{1,2,3,4,5,6,7,8,9,10,11\}$$

where 1 represents a DM who never chooses option P while 11 represents the one who never chooses option Q. For a DM with flip point 1, the upper bound for *a* is assumed to be $+\infty$ while for the flip point 11, the lower bound for *a* is assumed to be $-\infty$.[13] Nothing in the above analysis changes when we move to the domain of losses. The ambiguity task for the domain of losses (Task D) is constructed by first multiplying the payoffs in the gains task by (-1) and then inverting the order in which the decisions arrive. The inversion is done in order to anchor the DMs into ambiguity aversion. The letters P and Q are replaced by X and Y respectively to minimize any anchor on letters. The range and the average values of *a* and *b* are calibrated for every calibrated value of *r* and *s* and are summarized in Table 6. The ambiguity tasks are constructed in such a way that the calibrated values of *a* and *b* do not depend upon the calibrated values of *r* and *s*. Hence the following table does not require us to report *r* and *s*.

[11] We anchor our subjects such that the first choice they have to make is biased towards the choice of an unambiguous bet. We do this because as our aim is to find relative difference in attitudes, we want to make sure that all anchoring, if any, are in the same direction. In the risk tasks, all subjects were anchored towards risk aversion as well.

[12] This property of at most one flip point is however not necessarily restricted to only those DMs following KMM theory. But every DM following the KMM theory must satisfy this property in our tasks.

[13] As with the risk tasks (see footnote 9), we will assume that people displaying these extreme amounts of ambiguity aversion or ambiguity seeking have *a* and *b* equal to the higher or lower bounds of the infinite interval. Again as with the risk tasks we have a very small fraction of our subjects behaving in this way and so the bias that arises from this conservative assumption is miniscule.

<Insert Table 6 about here>

DMs with the following flip point pairs (*G*,*L*) exhibit exact ambiguity-reflection effects:

{(1,11), (2,10), (3,9), (4,8), (5,7), (7,5), (8,4), (9,3), (10,2), (11,1)}.

On the other hand, a DM with a flip-point pair (10,3) or (3,8) or (8,1) exhibit a weak ambiguity-reflection effect. Absence of reflection would mean that the DM has a flip point pair like (10,10) or (2,3) etc.

5. Results

This section reports results from the two sessions, one with 24 participants (with the gain tasks before the loss tasks) and the other with 23 participants (with the loss tasks before the gain tasks). In all case however, risk tasks were performed first. Each participant made 40 paired decisions (20 decisions for the risk tasks and 20 for the ambiguity tasks), giving us a total of 1880 binary decisions. We pool the observations as qualitatively similar behaviour is observed over both sessions. This section is divided into four subsections: the first deals with our findings from the risk tasks, the second deals with our findings from the ambiguity tasks, the third deals with the relationship between risk and ambiguity attitudes, and the fourth takes a closer look at the incidence of reflection effects.

5.1 Risk

From the risk tasks over gains, we find that subjects are risk averse with an average coefficient of risk aversion r given as 0.86.[14] The average value of r obtained from Chakravarty et al. (2005) from a similar cohort at IIM Ahmedabad was 0.42. The higher degree of risk aversion in the latter study could be due to the prizes being about 10 times higher in that study. The coefficient of risk aversion over losses, s averages 1.16. Thus the subjects were risk averse over losses too but significantly less so than over gains. We thus get a result that is qualitatively similar to Holt and Laury (2005b) who find that subjects are on average risk averse over gains and approximately risk neutral over losses. The average number of safe choices per subject in gains is 6.25 and the average for losses is 5.74. These averages are different using both a parametric two-sided paired t-test (p-value 0.03) and a non-parametric two-sided Wilcoxon test (p-value 0.008).[15] Figure 1 plots the average proportion of safe choices (the proportion of lottery A in task A and the proportion of lottery J in task B) for each of the 10 decision. Note that the average safe choices for gains are always at or above the average for losses. The utility function u(x) has been plotted in figure 2. Notice that in the aggregate there is very little evidence of a "reflection effect" as posited by Kahneman and Tversky (1979).

<Insert Fig.1 about here> <Insert Fig.2 about here>

5.2 Ambiguity

For the paired lottery-ambiguous prospect tasks we find the average KMM coefficient of ambiguity aversion a over gains to be equal to 0.94. Interestingly the average value of the coefficient b over losses recovered from our sample is 0.99. *Thus our sample is on average ambiguity averse over gains and mildly ambiguity seeking over losses.*[16] The plot of the KMM

[14] As mentioned in a footnote in section 4.1, our calibrated r is the midpoint of a range that it could assume the observed preference pattern over the uncertain choices. This average is thus an "average of the averages."

[15] We have used a general power function for utility. It may be interesting to use other forms of utility and ambiguity value functions such as exponential forms. These may be explored in future research on this topic.

[16] Mention must be made here that the expected values of the lotteries in these tasks are small and since we use the CRRA-type measure for ambiguity, very small changes in these calibrated values would mean a

value function $\phi(x)$ (figure 2) shows a weak reflection. The number of non-ambiguous choices made per decision in gains and losses are given respectively in figures 3 and 4. From the graphs it appears that the proportion of non-ambiguous responses is smaller in losses than in gains.

<Insert Fig.3 about here> <Insert Fig.4 about here>

However, one has to be careful when interpreting these two graphs. Notice that as the switch points are different in gains and losses, comparing the number of non-ambiguous choices (in a manner analogous to what we did in risk) may not reveal a significant difference in behaviour where there *may actually be* a significant difference. For example, a switch at decision 5 is mildly ambiguity seeking in gains but considerably ambiguity seeking in losses where the neutral switch point is 7. Thus we compare the within subjects number of safe choices in gains and losses corrected by the respective switch point. Define the Ambiguity Preference Scores S_G = (6- *Observed Switch Point*) for gains and S_L = (7- *Observed Switch Point*) for losses, where $S_G \in \{-5, -4, -3, -2, -1, 0, 1, 2, 3, 4, 5\}$ and $S_L \in \{-4, -3, -2, -1, 0, 1, 2, 3, 4, 5, 6\}$.[17] Depicting these Ambiguity Preference scores in figure 5 for each of our 47 subjects, we see that the score is significantly higher on average over losses than over gains.

<Insert Fig. 5 about here>

Comparing the within subject paired scores reveals that these series are significantly different using both a two-sided parametric t-test (p value 0.0000) and a non-parametric Wilcoxon test (p value 0.0000). Thus the behaviour over gains and losses is significantly different with respect to ambiguity and displays a clear reflection effect (more on this in the next section).

We also compare the distribution of choices between the ambiguous and non-ambiguous prospects at the neutral point (decision 5 for gains and 6 for losses) where the same prize amounts (0 and 100 for gains and -100 and 0 for losses) result from losing or winning the bet, when drawing from either the non-ambiguous (0.5, 0.5) urn or the ambiguous [(1,0) (0,1)] urn. We find that at this point 36 subjects out of 47 (77 percent) chose the non-ambiguous urn in the gain task, and this dropped to 22 out of 47 (44 percent) in the loss task. Einhorn and Hogarth's (1986) unpaid and single binary betting survey experiments of the Ellsberg problem finds the same qualitative effect with a larger fraction of the cohort choosing the non-ambiguous urn in the domain of gains than in the domain of losses. The studies are not strictly comparable though as our Ellsberg type urn is different from their [(100,0), (99,1),…,(1,99), (0, 100)] urn.

5.3 Risk-ambiguity connection

Given that we have within subject measurements over risk attitudes and ambiguity attitudes, a logical question to ask is if they are at all related. We find that the Pearson product moment correlation between the risk and ambiguity attitudes over gains is Cor(r,a) = 0.28. This correlation is significant using a two-sided t-test at the 5% level (p value 0.04). *This implies that risk aversion is positively associated with ambiguity aversion in the domain of gains*. However there is no corresponding significant correlation between s and b, indicating that in the domain of losses risk and ambiguity attitudes are independent. This in our opinion is a striking effect of the domain of gains vis a vis losses.

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relatively large change in actual attitudes. Hence, while reporting a and b we chose to do so up to 4 decimal points.

[17] For a person who does not switch from the non-ambiguous to the ambiguous prospect for all 10 decisions, we assume that his "switch point" is 11 and this gives a score of -5 for gains and -4 for losses.

5.4 More on Reflection Effects

We finally take a closer look at the incidence of reflection across gains and losses for risk and ambiguity. As defined before, there are the following categories of DMs who exhibit reflection effects (either perfect or weak) in risk and ambiguity:

1. Risk averse in gains and risk seeking in losses with $r < 1$ and $s < 1$. Call this type of DM as *R1*.
2. Risk seeking in gains and risk averse in losses with $r > 1$ and $s > 1$. Call this type of DM as *R2*.
3. Ambiguity averse in gains and ambiguity seeking in losses with $a < 1$ and $b < 1$. Call this type of DM as *A1*.
4. Ambiguity seeking in gains and ambiguity averse in losses with $a > 1$ and $b > 1$. Call this type of DM as *A2*.

Our data with a total of 47 subjects reveals the following:

a. 9 subjects are of type *R1* which is 19% of the population.
b. 6 subjects are of type *R2* which is 13% of the population.
c. 15 subjects are of type *A1* which is 32% of the population.
d. Only 1 subject is of type *A2*.

These observations lead us to make the following remarks:

Remark 1: The reflection effect in risk is significantly prevalent (close to 32%) in the population though it is *bi-modal* in nature. This means that within those who exhibited a reflection effect, many (60%) were risk averse in gains and risk seeking in losses while the remaining 40% of them were risk seeking in gains and risk averse in losses.

Remark 2: The reflection effect in ambiguity is equally prevalent (close to 35%). However there is a crucial difference: within those who exhibited a reflection effect, *almost all* (barring just one subject) were ambiguity averse in gains and ambiguity seeking in losses.

Figures 6 and 7 categorize subject behaviour over domains of gain and loss and illustrate the reflection effects noted above. Notice that the most common attitude for both our risky as well as ambiguous choice problems is aversion with approximately 44 percent displaying aversion over both domains. The co-existence of significant proportions of agents displaying behaviour consistent with EUT (averse in both domains) and Prospect Theory (averse in gains and seeking in losses) in the same sample is documented for risky choices in Harrison and Rutstrom (2005).

<Insert Fig.6 about here> <Insert Fig.7 about here>

6. Concluding Remarks

This paper presents the results of a multiple price list experiment in order to compare preferences towards risk and ambiguity across gains and losses. The payoffs were intermediate in scale and the chances of winning bets in ambiguous environments were high. We found that the subjects were risk averse in gains and losses, though less so in losses. This result is in line with the findings in Holt and Laury (2005b) and we do not observe risk seeking behaviour in losses at the aggregate as claimed by Kahneman and Tversky (1979). However, at a micro level our data shows that subjects indeed had a reflection effect, though this behaviour was found to be bimodal in risk tasks. Many were risk averse in gains and risk seeking in losses but at the same time many others were risk seeking in gains and risk averse in losses. Hence the direction of the reflection effect in risk remains largely ambiguous, and this leads to its absence at an aggregate level. When we move to ambiguous prospects, we start observing some consistent reflection effect where many subjects are ambiguity averse in gains and ambiguity seeking in losses while the reverse is largely absent. In general we found that aversion was the most popular trait. Finally, we also observe that the attitudes towards risk and ambiguity are positively correlated in the domain of gains and there is no such dependence in the domain of losses.

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Option A					Option B			
A_1	$P(A_1)$	A_2	$P(A_2)$		B_1	$P(B_1)$	B_2	$P(B_2)$
40	**0.5**	**60**	**0.5**		0	1	100	0
40	**0.5**	**60**	**0.5**		0	0.9	100	0.1
40	**0.5**	**60**	**0.5**		0	0.8	100	0.2
40	**0.5**	**60**	**0.5**		0	0.7	100	0.3
40	**0.5**	**60**	**0.5**		0	0.6	100	0.4
40	**0.5**	**60**	**0.5**		0	0.5	100	0.5
40	0.5	60	0.5		**0**	**0.4**	**100**	**0.6**
40	0.5	60	0.5		**0**	**0.3**	**100**	**0.7**
40	0.5	60	0.5		**0**	**0.2**	**100**	**0.8**
40	0.5	60	0.5		**0**	**0.1**	**100**	**0.9**

Table 1: Task A (lotteries with gains where the bold case indicates the preferred option of a risk neutral DM)

Option J					Option K			
J_1	$P(J_1)$	J_2	$P(J_2)$		K_1	$P(K_1)$	K_2	$P(K_2)$
-60	**0.5**	**-40**	**0.5**		-100	1	0	0
-60	**0.5**	**-40**	**0.5**		-100	0.9	0	0.1
-60	**0.5**	**-40**	**0.5**		-100	0.8	0	0.2
-60	**0.5**	**-40**	**0.5**		-100	0.7	0	0.3
-60	**0.5**	**-40**	**0.5**		-100	0.6	0	0.4
-60	**0.5**	**-40**	**0.5**		-100	0.5	0	0.5
-60	0.5	-40	0.5		**-100**	**0.4**	**0**	**0.6**
-60	0.5	-40	0.5		**-100**	**0.3**	**0**	**0.7**
-60	0.5	-40	0.5		**-100**	**0.2**	**0**	**0.8**
-60	0.5	-40	0.5		**-100**	**0.1**	**0**	**0.9**

Table 2: Task B (lotteries with losses where the bold case indicates the preferred option of a risk neutral DM)

Option P (draw from non-ambiguous [0.5, 0.5] urn P)			**Option Q (draw from ambiguous [(0,1) (1,0)]urn Q)**	
Colour doesn't match	Colour match		Colour doesn't match	Colour match
0	**140**		0	100
0	**130**		0	100
0	**120**		0	100
0	**110**		0	100
0	**100**		0	100
0	90		**0**	**100**
0	80		**0**	**100**
0	70		**0**	**100**
0	40		**0**	**100**
0	20		**0**	**100**

Table 3: Task C (lotteries and ambiguous prospects with gains where the bold case indicates the preferred option of an ambiguity neutral DM, independent of his attitude towards risk)

Option P (draw from non-ambiguous [0.5, 0.5] urn P)			**Option Q (draw from ambiguous [(0,1) (1,0)]urn Q)**	
Colour doesn't match	Colour match		Colour doesn't match	Colour match
0	**-20**		0	-100
0	**-40**		0	-100
0	**-70**		0	-100
0	**-80**		0	-100
0	**-90**		0	-100
0	**-100**		0	-100
0	-110		**0**	**-100**
0	-120		**0**	**-100**
0	-130		**0**	**-100**
0	-140		**0**	**-100**

Table 4: Task D (lotteries and ambiguous prospects with losses where the bold case indicates the preferred option of an ambiguity neutral DM, independent of his attitude towards risk)

Risk Task in Gains		**Risk Task in Losses**	
Risk Flip point	Bounds for *r* {*Max r, Min r*} *Average r*	Risk Flip point	Bounds for *s* {*Max s, Min s*} *Average s*
2	{3.56, +∞ } -	2	{-∞ , 0.15} -
3	{2.42, 3.56} *2.99*	3	{0.15, 0.32} *0.23*
4	{1.78, 2.42} *2.1*	4	{0.32, 0.51} *0.42*
5	{1.33, 1.78} *1.55*	5	{0.51, 0.73} *0.62*
6	{1, 1.33} *1.17*	6	{0.73, 1} *0.87*
7	{0.73, 1} *0.87*	7	{1, 1.33} *1.17*
8	{0.51, 0.73} *0.62*	8	{1.33, 1.78} *1.55*
9	{0.32, 0.51} *0.42*	9	{1.78, 2.42} *2.1*
10	{0.15, 0.32} *0.23*	10	{2.42, 3.56} *2.99*
11	{-∞ , 0.15} -	11	{3.56, +∞ } -

Table 5: Calibrated values of *r* and *s* at different risk flip-points

Ambiguity task in Gains		Ambiguity task in Losses	
Ambiguity Flip point: *G*	*Bounds for a* {*Max a, Min a*} Average *a*	Ambiguity Flip point: *L*	*Bounds for b* {*Max b, Min b*} Average *b*
1	{1.0731, +∞ } -	1	{ -∞ , 0.6505} -
2	{1.0570, 1.0731} 1.065	2	{ 0.6505, 0.8010} 0.726
3	{1.0396, 1.0570} 1.048	3	{0.8010, 0.9226} 0.862
4	{1.0207, 1.0396} 1.03	4	{0.9226, 0.9515} 0.937
5	{1, 1.0207} 1.01	5	{0.9515, 0.9771} 0.964
6	{0.9771, 1} 0.988	6	{0.9771, 1} 0.988
7	{0.9515, 0.9771} 0.964	7	{1, 1.0207} 1.01
8	{0.9226, 0.9515} 0.937	8	{1.0207, 1.0396} 1.03
9	{0.8010, 0.9226} 0.862	9	{1.0396, 1.0570} 1.048
10	{0.6505, 0.8010} 0.726	10	{1.0570, 1.0731} 1.065
11	{-∞ , 0.6505} -	11	{1.0731, +∞ } -

Table 6: Calibrated values of *a* and *b* at different ambiguity flip points

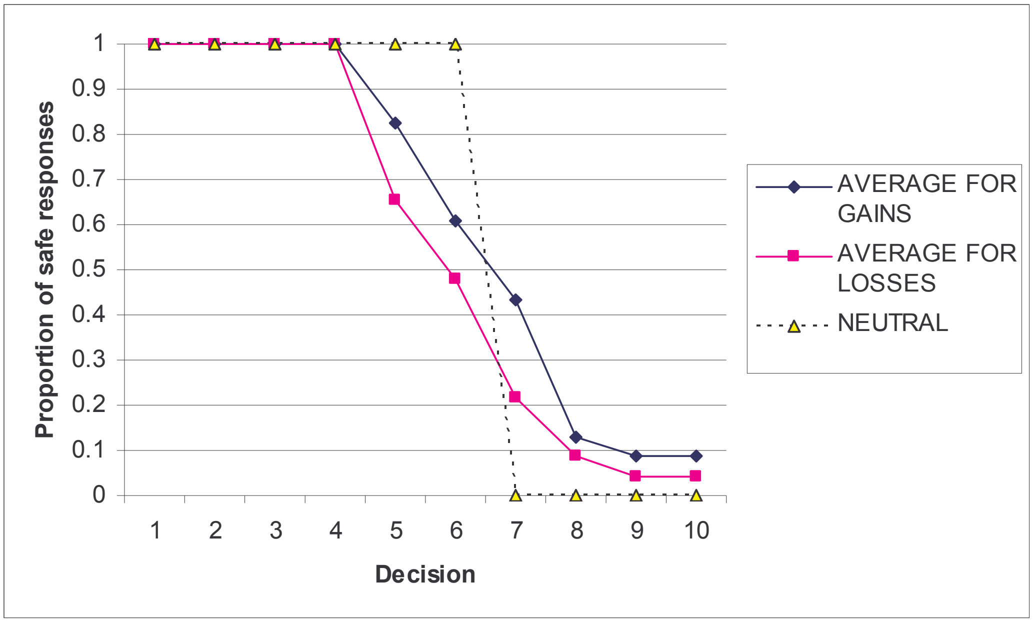

Figure 1: Proportion of safe responses in risk tasks

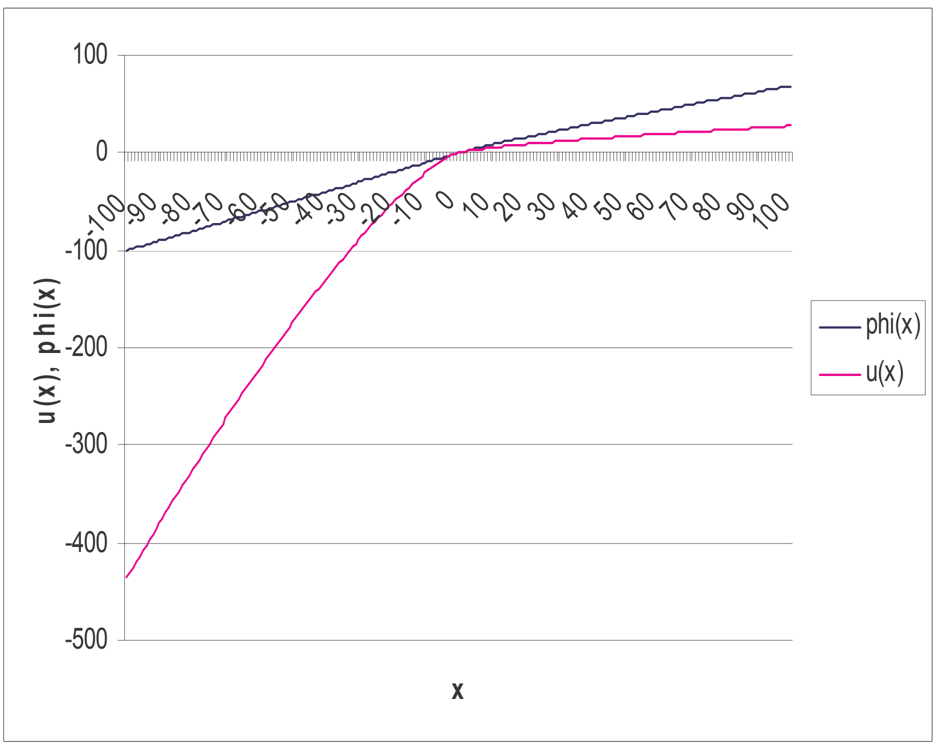

Figure 2: Calibrated utility and KMM value functions

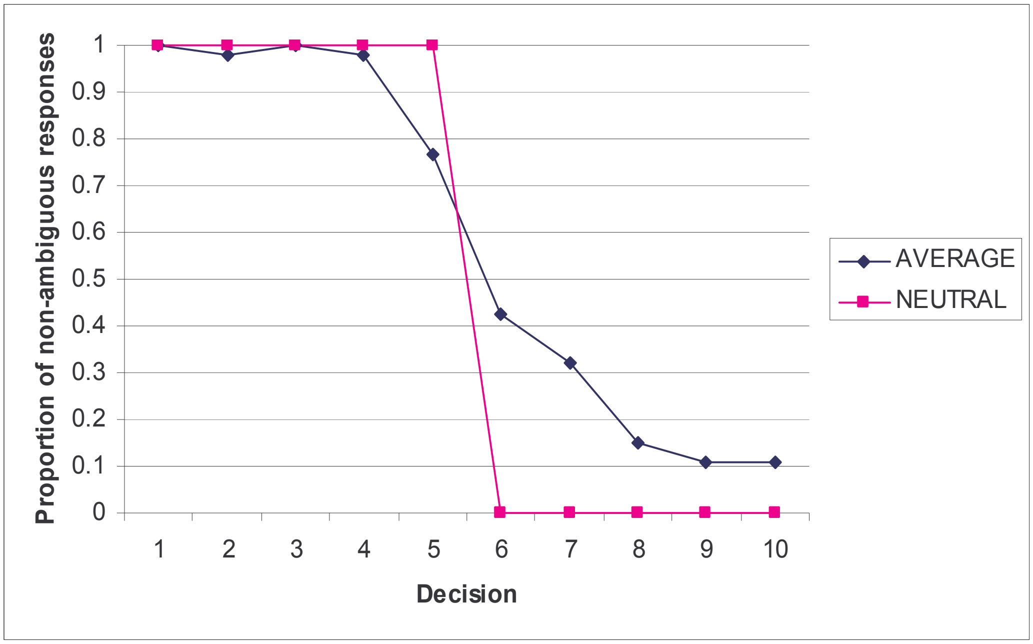

Figure 3: Proportion of non-ambiguous responses in gains

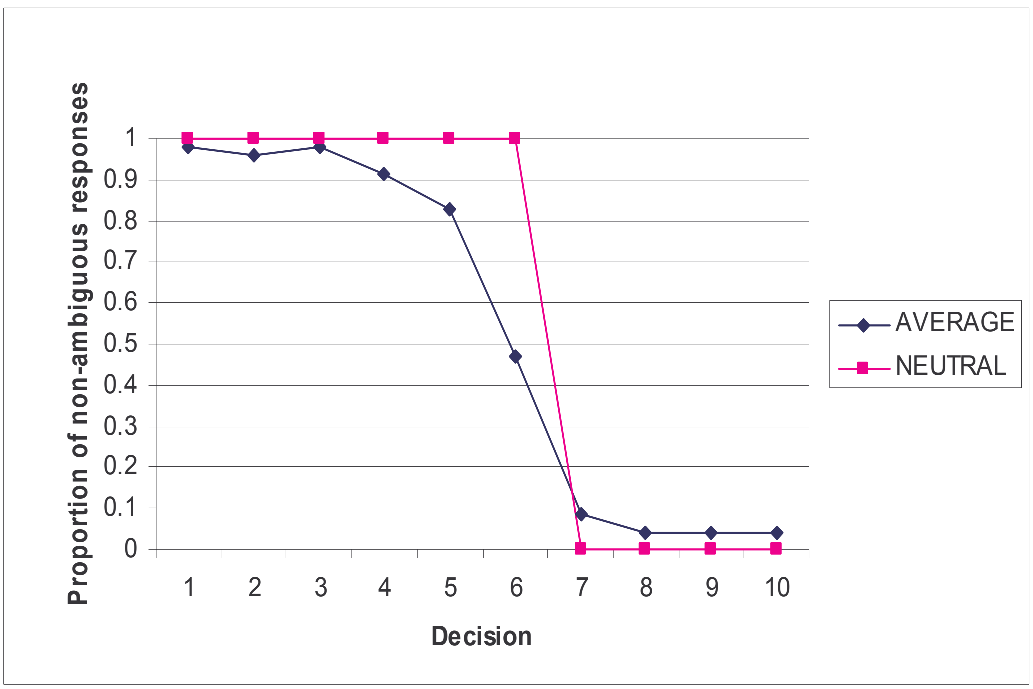

Figure 4: Proportion of non-ambiguous responses in losses

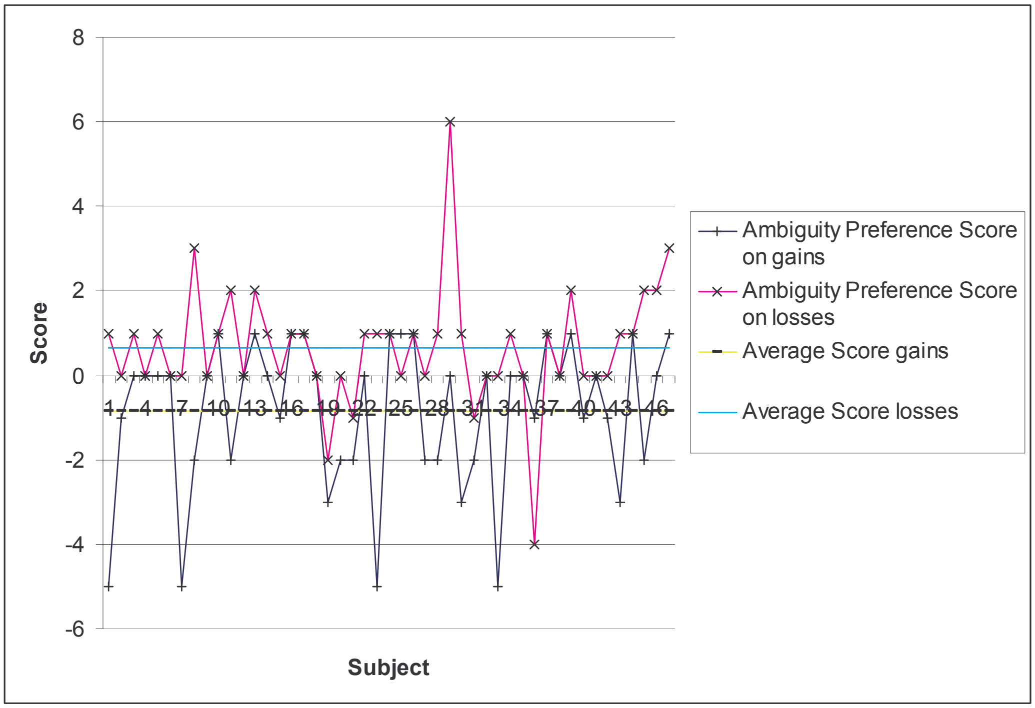

Figure 5: Ambiguity preference scores

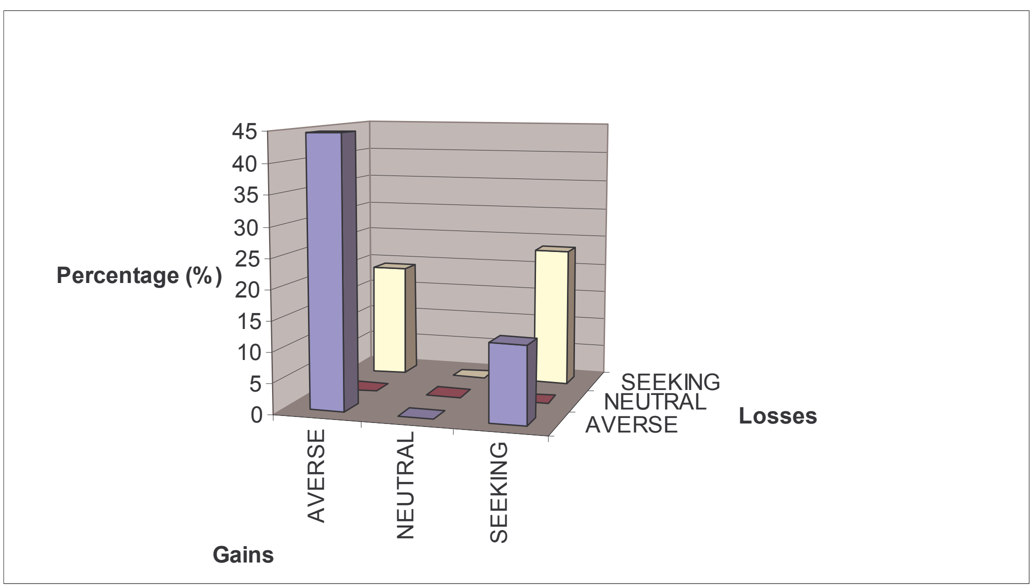

Figure 6: Categorizing Behaviour under Risk

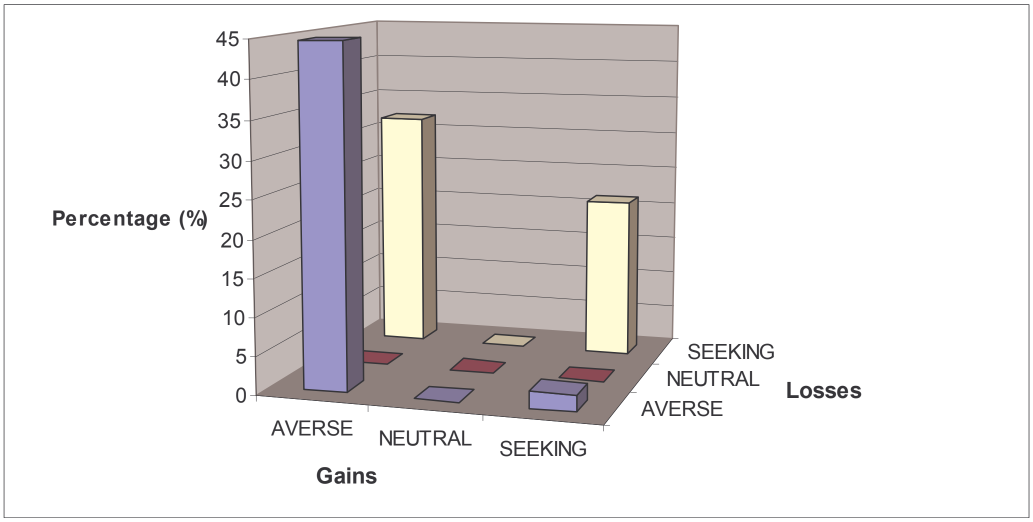

Figure 7: Categorizing Behaviour under Ambiguity

APPENDIX - DECISION SHEETS GIVEN TO SUBJECTS

Decision Sheet A

Your ID number once again: _____________

Decision	Option A	Option B	Your Choice (Circle A or B)
1	Die Roll 1-5: Rs 40 Die Roll 6-10: Rs 60	Die Roll 1-10: Rs. 0	A B
2	Die Roll 1-5: Rs 40 Die Roll 6-10: Rs 60	Die Roll 1-9: Rs 0 Die Roll 10: Rs 100	A B
3	Die Roll 1-5: Rs 40 Die Roll 6-10: Rs 60	Die Roll 1-8: Rs 0 Die Roll 9-10: Rs 100	A B
4	Die Roll 1-5: Rs 40 Die Roll 6-10: Rs 60	Die Roll 1-7: Rs 0 Die Roll 8-10: Rs 100	A B
5	Die Roll 1-5: Rs 40 Die Roll 6-10: Rs 60	Die Roll 1-6: Rs 0 Die Roll 7-10: Rs 100	A B
6	Die Roll 1-5: Rs 40 Die Roll 6-10: Rs 60	Die Roll 1-5: Rs 0 Die Roll 6-10: Rs 100	A B
7	Die Roll 1-5: Rs 40 Die Roll 6-10: Rs 60	Die Roll 1-4: Rs 0 Die Roll 5-10: Rs 100	A B
8	Die Roll 1-5: Rs 40 Die Roll 6-10: Rs 60	Die Roll 1-3: Rs 0 Die Roll 4-10: Rs 100	A B
9	Die Roll 1-5: Rs 40 Die Roll 6-10: Rs 60	Die Roll 1-2: Rs 0 Die Roll 3-10: Rs 100	A B
10	Die Roll 1-5: Rs 40 Die Roll 6-10: Rs 60	Die Roll 1: Rs 0 Die Roll 2-10: Rs 100	A B

Decision Row Chosen by first throw of the die: _____

Throw of the die to determine payment: _____

Your Earnings: ____

Decision Sheet B

Your ID number once again: ______________

Decision	Option J	Option K	Your Choice (Circle J or K)
1	Die Roll 1-5: -Rs 60 Die Roll 6-10: -Rs 40	Die Roll 1-10: -Rs 100	J K
2	Die Roll 1-5: -Rs 60 Die Roll 6-10: -Rs 40	Die Roll 1-9: -Rs 100 Die Roll 10: Rs 0	J K
3	Die Roll 1-5: -Rs 60 Die Roll 6-10: -Rs 40	Die Roll 1-8: -Rs 100 Die Roll 9-10: Rs 0	J K
4	Die Roll 1-5: -Rs 60 Die Roll 6-10: -Rs 40	Die Roll 1-7: -Rs 100 Die Roll 8-10: Rs 0	J K
5	Die Roll 1-5: -Rs 60 Die Roll 6-10: -Rs 40	Die Roll 1-6: -Rs 100 Die Roll 7-10: Rs 0	J K
6	Die Roll 1-5: -Rs 60 Die Roll 6-10: -Rs 40	Die Roll 1-5: -Rs 100 Die Roll 6-10: Rs 0	J K
7	Die Roll 1-5: -Rs 60 Die Roll 6-10: -Rs 40	Die Roll 1-4: -Rs 100 Die Roll 5-10: Rs 0	J K
8	Die Roll 1-5: -Rs 60 Die Roll 6-10: -Rs 40	Die Roll 1-3: -Rs 100 Die Roll 4-10: Rs 0	J K
9	Die Roll 1-5: -Rs 60 Die Roll 6-10: -Rs 40	Die Roll 1-2: -Rs 100 Die Roll 3-10: Rs 0	J K
10	Die Roll 1-5: -Rs 60 Die Roll 6-10: -Rs 40	Die Roll 1: -Rs 100 Die Roll 2-10: Rs 0	J K

Decision Row Chosen by first throw of the die: _____

Throw of the die to determine payment: _____

Your Earnings: ____

Decision Sheet C

Your choice of colour to bet on (circle your choice)	**GREEN**	**BLUE**

Your ID number once again: ____________

	Option P: Urn **P**			Option Q: Urn **Q**		Your Choice (Circle P or Q)
	If you pick the colour ***you did not choose*** above	If you pick the colour ***you chose*** above		If you pick the colour ***you did not choose*** above	If you pick the colour ***you chose*** above	
1	Rs 0	Rs 140		Rs 0	Rs 100	P Q
2	Rs 0	Rs 130		Rs 0	Rs 100	P Q
3	Rs 0	Rs 120		Rs 0	Rs 100	P Q
4	Rs 0	Rs 110		Rs 0	Rs 100	P Q
5	Rs 0	Rs 100		Rs 0	Rs 100	P Q
6	Rs 0	Rs 90		Rs 0	Rs 100	P Q
7	Rs 0	Rs 80		Rs 0	Rs 100	P Q
8	Rs 0	Rs 70		Rs 0	Rs 100	P Q
9	Rs 0	Rs 40		Rs 0	Rs 100	P Q
10	Rs 0	Rs 20		Rs 0	Rs 100	P Q
	Remember!! In urn P, the distribution of beads is: 5 GREEN - 5 BLUE			**Remember!!** In urn Q, the possible distributions of beads are: 10 GREEN - 0 BLUE or 0 GREEN - 10 BLUE		

Decision Row Chosen by throw of the die: _____

Outcome of the random rule: _____

Your Earnings: ____

Decision Sheet D

Your choice of colour to bet on (circle your choice)	**RED**	**YELLOW**

Your ID number once again: ____________

	Option X: Urn **X**			Option Y: Urn **Y**		Your Choice (Circle X or Y)
	If you pick the colour ***you chose*** above	If you pick the colour ***you did not choose*** above		If you pick the colour ***you chose*** above	If you pick the colour ***you did not choose*** above	
1	Rs 0	- Rs 20		Rs 0	-Rs 100	X Y
2	Rs 0	- Rs 40		Rs 0	-Rs 100	X Y
3	Rs 0	- Rs 70		Rs 0	-Rs 100	X Y
4	Rs 0	- Rs 80		Rs 0	-Rs 100	X Y
5	Rs 0	- Rs 90		Rs 0	-Rs 100	X Y
6	Rs 0	- Rs 100		Rs 0	-Rs 100	X Y
7	Rs 0	- Rs 110		Rs 0	-Rs 100	X Y
8	Rs 0	- Rs 120		Rs 0	-Rs 100	X Y
9	Rs 0	- Rs 130		Rs 0	-Rs 100	X Y
10	Rs 0	- Rs 140		Rs 0	-Rs 100	X Y
	Remember!! In urn X, the distribution of beads is: 5 RED - 5 YELLOW			**Remember!!** In urn Y, the possible distributions of beads are: 10 RED - 0 YELLOW or 0 RED - 10 YELLOW		

Decision Row Chosen by throw of the die: _____

Outcome of the random rule: _____

Your Earnings: ____