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Stability of risk preferences and the reflection effect of prospect theory

Manel Baucells · Antonio Villasís

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Abstract Are risk preferences stable over time? To address this question we elicit risk preferences from the same pool of subjects at two different moments in time. To interpret the results, we use a Fechner stochastic choice model in which the revealed preference of individuals is governed by some underlying preference, together with a random error. We take cumulative prospect theory as the underlying preference model (Kahneman and Tversky, Econometrica 47:263–292, 1979; Tversky and Kahneman, Journal of Risk and Uncertainty 5:297–323, 1992). We observe that the aggregate pattern of preferences is very similar in both sessions, and it matches the results reported in the literature. Most subjects are risk averse for gains, and risk seeking for losses. However, the subjects that jointly agree with the reflection effect of prospect theory are around 50%. The percentage of individuals that change their responses across sessions is quite high, 63%. Estimating the stochastic choice model we find that 72% of the subjects have an underlying preference which agrees with the reflection effect of prospect theory. The remaining 28% are mainly classified as risk averse for both gains and losses. The results reinforce the empirical validity of the reflection effect. Deviations from the reflection effect can be attributed to noise, as well as to the existence of a fraction of risk averse subjects.

Keywords Reflection effect · Risk preferences · Stability of preferences

This paper is part of the Ph.D. thesis of Antonio Villasís.

M. Baucells (✉)
IESE Business School, Barcelona, Spain
e-mail: mbaucells@iese.edu

A. Villasís
IDE Escuela de Dirección de Empresas, Quito, Ecuador
e-mail: avillacis@alumni.unav.es

1 Introduction

Are risk preferences stable over time? In a world of rational decision makers, and assuming no changes in the state of the world, risk preferences are supposed to be stable over time. More precisely, when asked the same question at sufficiently separated moments in time, we expect most subjects to provide the same answer. Stability of preferences need not be a desirable property in certain domains in which we might seek variety. For instance, changing preferences might be driven by fashion in a changing environment. Still, there might be a stable underlying preference for conformity/disconformity to the current fashion. We would like to think that risk preferences fall in this category of fundamental underlying preferences that define our personality and identity.

Stability of risk preferences is also an assumption made when we elicit preferences for subjects. In doing so, we believe we are learning something about that subject. In areas such as financial investment, risk insurance, and health decision, clients are often asked about their risk preferences. The recommendations the client receives hinge on the assumption that risk preferences are stable.

It has been argued (Grether and Plott 1979) that several non-normative factors induce subjects to change their preferences. These factors include the framing of problems (Tversky 1969), compatibility effects (Lichtenstein and Slovic 1971), and elicitation procedures (Hershey and Schoemaker 1985; Bostic et al. 1990). Berg et al. (2005) also find evidence of changes in risk preferences as a function of the auction mechanism employed. Therefore, it is well established that decisions are not neutral to the response mode used to express the preference, and are labile and sensitive to the way in which a problem is framed. Most research has focused on switches in preferences due to slight changes in the experimental conditions.

Few studies have directly addressed the study of possible changes in preferences when the subject is confronted with exactly the same decision at two separate moments in time. Experiments in which subjects face similar choices were indirectly treated by examining the test–retest reliability questions (Schoemaker and Hershey 1992; Camerer 1989; Hey and Orme 1994; Ballinger and Wilcox 1997; Loomes and Sugden 1998). These studies find that, in the short term (less than one week), between one quarter and one third of subjects express different responses when confronted twice with the same set of choices.

There are some studies measuring risk attitudes in different sessions. In a study of the risk attitudes of business executives, Wehrung et al. (1984) found a small positive correlation of 0.36 for personal risk measures over a one-year interval. Smidts (1997) measured the risk attitudes of 1000 Dutch Farmers, and found a 0.45 correlation in risk attitudes in a one-year interval. Harrison et al. (2005) and Andersen et al. (2008) have made the most direct attempts to study the stability of risk attitudes. Using a laboratory experiment and a sample of the Danish population, Harrison and colleagues find that preferences, in the gains domain, are quite stable over a 7-month and a 17-month time separation, respectively.

This paper adds one more piece of evidence in the elicitation of risk preferences in separate sessions. However, the novelty of our work is that we interpret the results in light of a stochastic choice model. According to the model, a constant stimulus may be perceived with certain error and does not always produce the same reaction. Hence, different answers to the same question are not incompatible with having some underlying stable risk preferences. Our data allow us to estimate the distribution of this underlying preference. Perhaps due to the influence of EU, previous evidence of stability of preferences was restricted to the gains domain. Our work is also novel in that we elicit risk preferences in both gains and losses. Hence, we can examine the prevalence of risk preference in accordance with the reflection effect of prospect theory (Kahneman and Tversky 1979).

To account for the instability of risk preferences over time, we use a stochastic choice model (SCM) in which the revealed preference of individuals is governed by some underlying preference, together with a random error. Our SCM is similar to what Becker et al. (1963) call the Fechner model and has been used in the context of theories of decision making under risk by Hey and Orme (1994). The SCM is easy to estimate, yielding parameters that provide a nice interpretation and insight. The SCM is capable of estimating the magnitude of the decision error, and the underlying pattern of preference.

We adopt a simple Fechner model with an homoscedastic error term. At its face value, such model may predict violations of elementary stochastic dominance, which are hardly observed empirically. However, the model is appropriate to interpret our data, which are generated from choices that are far from exhibiting stochastic dominance. Buschena and Zilberman (2000) compare homoscedastic and heteroscedastic error models. Blavatskyy (2006) and Blavatskyy (2007) introduce heteroscedastic error models that avoid violations of stochastic dominance.

We highlight the following findings: (1) The error term is smaller in gains than it is in losses. This finding is in agreement with previous research (Gonzalez et al. 2005; Lopes 1987) which argue that choices involving losses create more conflict and cognitive effort, and hence are less stable. (2) The most common underlying pattern of preference is given by the reflection effect of Prospect theory (risk averse for gains, risk seeking for losses). The proportion of individuals that agree with this pattern is significantly higher (72%) than the approximately 50% that has been found in the literature on single-session elicitation (see average results in Table 2). (3) The other common preference pattern (24%) is subjects who are risk averse on both domains, which is the preference pattern assumed in many economic models of insurance and portfolio investment.

The paper is organized as follows: Sect. 2 reviews the reflection effect of cumulative prospect theory and the empirical support found in the literature. Section 3 develops the SCM. In Sect. 4 we design an experiment to elicit basic risk attitudes in two sessions with the same subjects. The results allow us to estimate the proposed SCM model. We use our model in Sect. 5 to make predictions. Finally, discussion and conclusions are given in Sect. 6.

2 The reflection effect: theory and evidence

According to cumulative prospect theory (CPT), risk preferences are reference dependent, i.e., the carrier of value is not the consequences measured in absolute wealth, but the relative consequences of perceived gains and losses with respect to some reference point. CPT further stipulates the *reflection effect*: for event of moderate probability, subjects are risk averse for gains and risk seeking for losses. The reflection effect is captured by a value function that is concave for gains and convex for losses. Cumulative prospect theory also incorporates a probability weighting function that transforms given probabilities into decision weights.

A decision maker that follows the reflection effect of CPT will behave as risk averse for gains and risk seeking for losses of moderate to high probability. For gains and losses of low probability, the pattern is reversed due to the effect of the probability weighting function. In this paper, we will focus on risk attitudes for intermediate probabilities.

In comparing our results with existing literature, we may identify a response (say risk averse) with a claim on the curvature of the value function (concave). It is well known that a concave value function can coexist with risk seeking preferences, because of the influence of the probability weighting function. We use a method to elicit risk preferences that minimizes the distorting impact of probability weighting. It is under this proviso that in our discussion we identify risk preferences with the curvature of the value function.

We elicit risk preferences for gains and losses separately. We have not elicited risk preferences for mixed gambles. In the context of prospect theory, such elicitation could be used to study the stability of the parameter of loss aversion (an abrupt change of the slope of the value function at the reference point).

Throughout our classifications in the paper, A^+ denotes the subjects who exhibit risk aversion in the gains domain, N^+ those that exhibit risk neutrality in the gains domain, and S^+ those that exhibit a risk seeking attitude in the gains domain. For the losses domain, we use A^-, N^-, and S^-, to denote subjects in the corresponding categories, respectively.

The reflection effect of CPT is expected to hold for most decision makers. For intermediate probabilities, Tversky and Kahneman (1992) found 88% of subjects as being risk averse for gains and 87% of subjects as being risk seeking for losses. Results from other studies shown in Table 1 confirm the findings of Tversky and Kahneman, even though the percentages are not so strong.

The results of Table 1 are silent with respect to the joint pattern of preference in both domains. The modal pattern (74% risk averse for gains and 64% risk seeking for losses) does not tell us what fraction of subjects are *both* risk averse for gains and risk seeking for losses. Few subsequent studies took note of this criticism (Hershey and Schoemaker 1980) and reported joint preferences. We found four such studies, summarized in Table 2. Table 2 completes the picture of Table 1: While the risk averse–risk seeking pattern is the most prominent, the proportion of subjects that are simultaneously risk averse for gains and risk seeking for losses falls to 47%. This weakens the claim that the reflection effect holds for a great majority of people.

3 The stochastic choice model

Assume decision makers express their underlying preferences, but with error. Errors in reporting one's true preference tend to act against the modal preference. For instance, if the reflection effect is the modal preference, then random errors will decrease the

Table 1 The reflection effect in the literature

Study	Gains			Losses			
	A^+	N^+	S^+	A^-	N^-	S^-	n
Abdellaoui (2000)[a]	58	19	22	23	29	49	32
ABP[b]	71	4	25	8	23	69	48
Fennema and Van Assen (1998) CE[c]	83	0	17	5	5	91	64
Fishburn and Kochenberger (1979)	53	7	40	33	7	60	30
Laury and Holt (2005)[d]	71	9	20	41	6	53	66
Schoemaker (1990)	76	7	17	30	11	59	214
Tversky and Kahneman (1992)	88	2	10	6	7	87	25
Weighted average	74	7	20	24	11	64	481

Values are percentages

[a] Subjects classified with mixed preferences are excluded

[b] *ABP* Abdellaoui et al. (2007). Subjects classified as mixed are shown as linear

[c] CE Refers to the results of the certainty equivalence elicitation

[d] Only the results for gambles with intermediate probabilities were considered

Table 2 Joint risk attitudes in the gains and losses domain

Gain–losses domain	A^+A^-	A^+N^-	A^+S^-	N^+A^-	N^+N^-	N^+S^-	S^+A^-	S^+N^-	S^+S^-	n
Abdellaoui (2000)[a]	13	13	40	9	0	12	3	9	0	32
Schoemaker (1990)	22	6	48	1	4	2	7	1	9	214
ABP	2	15	54	0	2	2	6	6	13	48
L&H (2000)[b]	30	2	39	3	3	3	8	1	11	66
Weighted average	20	7	47	2	3	3	7	2	9	360

Values are percentages

[a] Subjects classified with mixed preferences are excluded

[b] *L&H* (2000) Laury and Holt (2005). Only the results for gambles with intermediate probabilities were considered

observed support for the reflection effect. To illustrate, consider that the true underlying preference of all subjects is given by the reflection effect. However, due to the random error component of the evaluation, any given individual has a 74% chance of revealing his true risk averse preference in the gains domain, and a 64% chance of revealing his true risk seeking preference in the losses domain (percentages are taken from Table 1). Further, assume that the random error is independent in both choices. Then, it follows that the chance of revealing a pattern fully consistent with the reflection effect is $74\%*64\% = 47\%$. This is precisely the response pattern shown in Table 2.

Error models, or stochastic choice models, can take several forms: from the introduction of a noise term in the utility evaluation to random selection of preference orderings [for a summary, see Suppes et al. (1989)]. The combination of variable behavior and stable patterns of choices goes back to the idea of Fechner's psychophysical measurement of sensory error. The utility of a choice is computed using some underlying preference function plus an error term. This necessarily involves an assumption about the errors made by the subjects. Two such assumptions are a random error [e.g., Machina (1985); Sopher and Narramore (2000); Hey and Orme (1994)] or a "tremble" in the decision process [e.g.,Camerer and Ho (1994); Harless and Camerer (1994)]. Ballinger and Wilcox (1997) ran a test of both models and the data they collected rejects the tremble model but not the random error model. Here, we follow the random error approach.

We modify Fechnner's basic model to account for the choice between two prospects A and S, and include the option of being neutral between the two. The neutral option can be interpreted as either indifference between A and S, or, rather, lack of preference in either direction. The first interpretation assumes that decision makers have complete preferences, whereas the second interpretation assumes that decision makers may have incomplete preferences. As we cannot experimentally separate these two interpretations, we classify as risk neutral those subjects who choose the option "A and S are the same." In our experiments, A and S will be lotteries with the same expected value, and hence "neutral" is interpreted as "risk neutral."

Our SCM model has one error term ε and two parameters, Δ and $\theta > 0$. Δ is the underlying utility difference between the most and least preferred alternative, and θ is a utility threshold value to determine whether subjects can discriminate between the alternatives. The model operates as follows: Suppose a subject has a true risk preference type, say, A is preferred over S, and hence has an underlying utility gap in favor of A, denoted by Δ. However, the perceived utility U is

$$U = \Delta + \varepsilon, \tag{1}$$

The subject will choose indifference between A and S if $|U| \leq \theta$, will choose A if $U > \theta$, and will choose S if $U < -\theta$. We will also assume that errors are normally distributed, with zero mean. Without loss of generality, one can further assume a standard deviation of one, as the units of Δ can be properly defined relative to the error.

Therefore, Δ measures the utility of the preferred alternative relative to the size of the error. In this vein, Δ is similar to a *t*-value, as it measures utility in units of standard deviation. The higher the Δ, the higher the probability of selecting the alternative preferred according to one's own type. Hence, we propose Δ as a *measure of stability* of preferences.

We assume that subjects have underlying preferences corresponding to given types. We use lowercase letters a^+, n^+ s^+, a^-, n^-, and s^- to denote the three possible types for each domain. For instance, a^+ stands for risk averse for gains. Similarly, n^- stands for risk neutral for losses, and so on. $\tau^+ \in \{a^+, n^+, s^+\}$ denotes the gains type, $\tau^- \in \{a^-, n^-, s^-\}$ the losses type, and $\tau = (\tau^+, \tau^-)$ the full type. There are nine possible types, and $\tau = (a^+, s^-)$ corresponds to the *reflective type*. Accordingly, we introduce $p(\tau)$, which denotes the fraction of subjects of type τ.

The answer to the single choice question Q1 shown in Fig. 2 allows us to classify subject's responses as A^+, N^+, and S^+. Here, A^+ represents the less risky alternative (preferred by a^+ types) and S^+ the riskier alternative (preferred by s^+ types) in the sense of mean-preserving increase in risk. Similarly, the single choice question Q2 shown in Fig. 2 allow us to classify subject's responses as A^-, N^-, and S^-.

We will consider Δ^+, Δ^- and θ^+, θ^- as the domain specific values of Δ and θ, respectively. Δ^+, for instance, is the utility difference between the most and least preferred alternative in Q1. If one has in mind CPT as the decision model, then

$\Delta^+ = |V(A^+) - V(S^+)|$, where V is the evaluation function of CPT. Δ^+ could be obtained from any other decision model producing a numerical evaluation of alternative pairs. See Hey and Orme (1994) for a full characterization of other decision models. By definition, these four parameters are non-negative.

We will make the restrictive assumption that Δ and θ are constant across types. For instance, types a^+ and s^+ have the same utility difference between A^+ and S^+, namely, $+\Delta^+$ and $-\Delta^+$, respectively. This assumption is necessary to have a parsimonious model with few parameters that can be estimated. A pre-condition to justify this assumption is that both A^+ and S^+ have the same expected value.

Under these assumptions of the SCM, the following proposition yields the probabilities for different types of choosing among the three alternatives.

Proposition 1 *Let*

$$\beta_\tau^+ = \begin{cases} 1 & \text{if } \tau^+ = a^+ \\ 0 & \text{if } \tau^+ = n^+ \\ -1 & \text{if } \tau^+ = s^+ \end{cases} \quad \text{and} \quad \beta_\tau^- = \begin{cases} 1 & \text{if } \tau^- = a^- \\ 0 & \text{if } \tau^- = n^- \\ -1 & \text{if } \tau^- = s^- \end{cases}$$

then, in the gains domain, the probabilities of choosing A^+, N^+, or S^+ for different types are (Φ *stands for cdf of a standard normal distribution*)

$$\begin{aligned} P\left(A^+|\tau^+\right) &= 1 - \Phi(\theta^+ - \beta_\tau^+ \Delta^+) \\ P(N^+|\tau^+) &= \Phi(\theta^+ - \beta_\tau \Delta^+) - \Phi(-\theta^+ - \beta_\tau^+ \Delta^+) \\ P(S^+|\tau^+) &= \Phi(-\theta^+ - \beta_\tau^+ \Delta^+). \end{aligned} \tag{2}$$

Similarly, in the losses domain,

$$\begin{aligned} P\left(A^-|\tau^-\right) &= 1 - \Phi(\theta^- - \beta_\tau^- \Delta^-) \\ P(N^-|\tau^-) &= \Phi(\theta^- - \beta_\tau^- \Delta^-) - \Phi(-\theta^- - \beta_\tau^- \Delta^-) \\ P\left(S^-|\tau^-\right) &= \Phi(-\theta^- - \beta_\tau^- \Delta^-). \end{aligned} \tag{3}$$

Proof Consider a type a^+ subject facing the choice between A^+, N^+, and S^+. As the most and least preferred alternatives are A^+ and S^+, respectively, the subject's *perceived utility* of A^+ over S^+ is given by $\Delta^+ + \varepsilon^+$. If $\varepsilon^+ \sim \mathcal{N}(0, 1)$, then the probability that a type a^+ chooses the prospect A^+ is

$$P(A^+|a^+) = P(\Delta^+ + \varepsilon^+ > \theta^+) = P(\varepsilon^+ > -\Delta^+ + \theta^+) = 1 - \Phi(\theta^+ - \Delta^+).$$

This probability corresponds to the light gray area $P(A^+|a^+)$in Fig. 1. The probability of being neutral between A^+ and S^+ is

$$P(N^+|a^+) = P(-\Delta^+ - \theta^+ \leq \varepsilon^+ \leq -\Delta^+ + \theta^+) = \Phi(\theta^+ - \Delta^+) - \Phi(-\theta^+ - \Delta^+),$$

as indicated in the blank area $P(N^+|a^+)$ in Fig. 1. Finally, the probability of choosing S^+ is

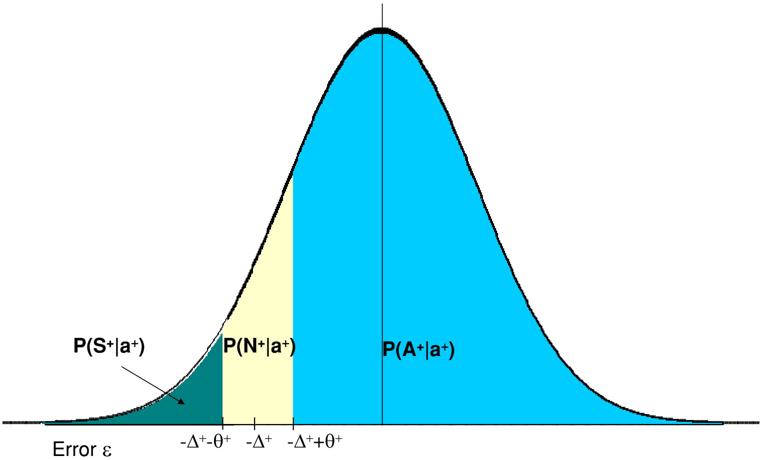

Fig. 1 Representations of the probabilities that a subject type a^+ choose a gamble A^+, S^+, or being indifferent between A^+ and S^+

$$P(S^+|a^+) = P(\Delta^+ + \varepsilon^+ < -\theta^+) = P(\varepsilon^+ < -\Delta^+ - \theta^+) = \Phi(-\theta^+ - \Delta^+),$$

as shown in the dark gray area $P(S^+|a^+)$ in Fig. 1. Given the definitions of β_τ^+ and β_τ^-, one can check that the perceived utility difference between the most and least preferred alternative is given by:

$$U_\tau^+ = \beta_\tau^+ \Delta_\tau^+ + \varepsilon^+ \quad \text{and} \quad U_\tau^- = \beta_\tau^- \Delta_\tau^- + \varepsilon^-. \tag{4}$$

Using this, and the assumption of normality, we can calculate, for each type, choice, and domain the 18 relevant probabilities. These probabilities are summarized in Eqs. 2 and 3. □

Let $R_t^+ \in \{A^+, N^+, S^+\}$ and $R_t^- \in \{A^-, N^-, S^-\}$ denote the response of a subject for the gains and losses choices in session t, $t = 1, 2$. Subjects make a total of four choices, two in each session. The probability of observing a particular answer pattern is given by:

$$\begin{aligned} P(R_2^+, R_2^-, R_1^+, R_1^-) &= \sum_\tau p(\tau) \times P(R_2^+, R_2^-, R_1^+, R_1^-|\tau) \\ &= \sum_\tau p(\tau) \times P(R_2^+, R_2^-|R_1^+, R_1^-, \tau) \times P(R_1^+, R_1^-|\tau) \end{aligned} \tag{5}$$

Taking the logarithm of (5) yields the loglikelihood of a given answer by a given subject. Assuming, as usual, that answers from different individuals are independent, we obtain the loglikelihood function of the entire sample as the sum of individual loglikelihoods. We denote this loglikelihood function by $L(\Delta^+, \Delta^-, \theta^+, \theta^-, p(\tau))$. The MLE estimations are the parameter values $\Delta^+, \Delta^-, \theta^+, \theta^-$, together with the probabilities $p(\tau)$, that maximize L.

If the time interval lapsed between sessions is long enough, it is safe to assuming that subjects did not remember their past choices, and that the random error term is independent across sessions. Formally, we assume *session independence*, i.e., both ε_1^+ and ε_1^- are independent of both ε_2^+ and ε_2^-.[1] Under normality, this is equivalent to assuming that the three pair correlations are zero.

We will also assume *domain independence*, i.e., ε^+ and ε^- are independent. Cohen et al. (1987) provide evidence supporting this assumption.[2] Assuming a zero correlation will yield a conservative estimate of the proportion of reflective types in the population.

Using both *session independence* and *domain independence* allow use to rewrite (5) as:

$$P(R_2^+, R_2^-, R_1^+, R_1^-) = \sum_{\tau} p(\tau) \times P(R_2^+|\tau) \times P(R_2^-|\tau) \times P(R_1^+|\tau) \times P(R_1^-|\tau), \tag{6}$$

which together with (2) and (3) will be the base model to estimate the parameters Δ^+, Δ^-, θ^+, and θ^-, and the probabilities $p(\tau)$.

4 Experimental estimation of the SCM

4.1 Design

Our experimental design consisted of two sessions separated by a time interval of three months. In each session, we measured the risk preferences in the domains of gains and of losses separately. With the aim of estimating the proportions of different types in an environment with error, we purposely chose a design that maximized instability in responses. To do so, we used a single choice question in each domain. Having used a battery of questions to estimate risk preferences would have reduced the noise due to cancelation of errors. Furthermore, within-session errors could be positively correlated by induced arbitrary coherence (Ariely et al. 2003). Each choice had two prospects with the same expected values, and one of them being riskier in the sense of second-order stochastic dominance. It was clear, but not immediately obvious, to determine which prospect was less risky. Figure 2 contains the two questions of the experimental design (Q1 for gains, Q2 for losses). For each question, subjects had three possible

[1] Introducing positive correlation between ε_1^+ and ε_2^+, and between ε_1^- and ε_2^-, would allow us to model the notion of arbitrary coherence (Ariely et al. 2003). The idea is that the response noise is higher in the first choice, and lower later on. One explanation is that subjects try to be coherent with their first answer, even though this answer may be in itself unstable due to noise. Positive correlation between errors of similar or identical questions in different sessions would be appropriate if the time interval between sessions were short. In fact, we estimated a specification of the SCM that included positive correlation as follows: $\varepsilon_2 = \rho\varepsilon_1 + \sqrt{1-\rho^2}e_2$, where ε_1 and e_2 are iid $N(0, 1)$. However, the correlation was not significant, and the results did not differ from the specification with *session independence*.

[2] The natural way to relax this assumption is to introduce positive correlation between the errors ε^+ and ε^-. This increases the probability of choosing the same response in both domains, say, A^+ and A^-, even though the true type might be reflective.

Q1- Which of these two lotteries A or S would you prefer?
Quantities are in euros.

A

x	p
€ 0	10%
€ 1,000	40%
€ 2,000	40%
€ 3,000	10%

S

x	p
€ 0	50%
€ 3,000	50%

Question 1

○ A is preferred ○ A and S are the same ○ S is preferred

Q2- Which of these two lotteries S or A would you prefer?
You have no option other than S or A.
Quantities are in euros.

S

x	p
-€ 3,000	50%
€ 0	50%

A

x	p
-€ 3,000	10%
-€ 2,000	40%
-€ 1,000	40%
€ 0	10%

Question 2

○ S is preferred ○ S and A are the same ○ A is preferred

Fig. 2 Questionnaire of the experimental session

responses: A, N (neutral or indifferent), or S. In the experiment, the two prospects were labeled F and G, respectively, to avoid the label influencing the choice.

Q2 is basically the same as Q1, but with the signs reversed. Notice that the best and worst outcomes in A and S are the same. With this specification we seek to minimize the distorting effect of the non-linear probability weighting function for extreme probabilities. Hence, the answer to Q1 and Q2 provide both the risk attitude of the subject, and the curvature-sign of the value function (see Baucells and Villasís (2008) for evidence and discussion of this so-called equal tails method to elicit the value function). Of course, using the same outcomes (in terms of absolute value) in Q1 and Q2 carries the risk that subjects may believe the questions are linked leading to arbitrary coherence. This may have deflated support for the S-shaped utility function.[3]

[3] It is possible to argue that our stimuli entail a bias toward s-shaped utility. For gains, A offers three gains and S only one. It is well known from the psychological literature that alternatives that offer more positive outcomes are more attractive, regardless of the probabilities. Hence, our design favored A for gains. A symmetric argument then entails that for losses S will be more attractive than A because it has less negative outcomes.

Table 3 Comparison of the results of Session 1 and Session 2, the average of both sessions, and the average values found in the literature (Table 2)

Gain–losses domain	A^+A^-	A^+N^-	A^+S^-	N^+A^-	N^+N^-	N^+S^-	S^+A^-	S^+N^-	S^+S^-	n
Session 1	26	0	40	2	18	3	4	0	7	141
Session 2	25	2	53	0	6	1	10	0	3	141
Avg. Session 1 & 2	26	1	46	1	12	2	7	0	5	282
Avg. Table 2	20	7	47	2	3	3	7	2	9	360

Values are percentages

Ultimately, the assurance that our elicitation method is not biased is provided by the fact that the proportion of subjects having the same risk attitude in both gains and losses in our sample is similar to that obtained in the literature (see Table 2).

The subjects were 141 MBA students from IESE Business School (Barcelona) representing more than 30 different countries. In the first session, Q1 and Q2 were part of a larger questionnaire on biases in decision making. The first questionnaire was distributed at the beginning of the MBA program, and students seemed highly motivated to respond. A total of 210 students completed this first questionnaire. The second questionnaire consisted exclusively on responding to Q1 and Q2. After three months, it is safe to assume that most students did not remember their previous answers. Students were explicitly told not to retrieve electronically the answer they gave in session one, or, in case they remembered, to try to match the same answer. The order of questions was the same in both cases, Q1 followed by Q2. In total, 141 subjects completed the questionnaire in both sessions. Both questionnaires were distributed and collected via e-mail. Given the difficulties of using real incentives in the losses domain, we decided to carry out the experiment with hypothetical payoffs. Camerer and Hogarth (1999) find small differences between using real vs. hypothetical incentives, except for less risk seeking individuals when using real incentives.

4.2 Results

Table 3 exhibits the aggregate risk preferences separated for each session, the average over the two sessions (third line), and the weighted average results from Table 2 (last line). The reflection effect pattern A^+S^- is the most frequent in both sessions, and, as in Table 2, it is slightly below 50%.

We now compare our results to those obtained in the literature to see if they are similar. To do so, we perform a χ^2 test. Table 4 (nine categories) shows that Session 1 is significantly different from Session 2. However, the average of Sessions 1 and 2 is not significantly different from the average in Table 2. Session 1 is also different from the average of Table 2. Session 1 is different from the other data mostly because of the high number of risk neutral answers. Indeed, if we reconstruct Table 3 by evenly splitting the neutral responses between A and S, then the χ^2 test (Table 4, four categories) shows that Session 1 is not significantly different from Session 2, and the average from the other results. In summary, we find proportion of neutral responses that is larger than expected in Session 1. However, the average of Sessions 1 and 2 is in line with previous results.

Table 4 χ^2 test for Session 1 and Session 2, the average of both sessions, and the average values of Table 2

Comparison	Nine categories		Four categories	
	χ^2	p-value	χ^2	p-value
Session 1 vs. Session 2	17.02	**0.02**	4.80	0.09
Avg. Session 1&2 vs. Avg. Table 2	14.53	0.07	0.89	0.64
Session 1 vs. Avg. Table 2	22.39	**0.00**	1.16	0.56
Session 2 vs. Avg. Table 2	13.2	0.11	3.28	0.19

Significant differences are in bold

Table 5 Risk attitudes across domains (the reflective answers A^+S^- are in bold)

1st\2nd	$A_2^+A_2^-$	$A_2^+N_2^-$	$A_2^+S_2^-$	$N_2^+A_2^-$	$N_2^+N_2^-$	$N_2^+S_2^-$	$S_2^+A_2^-$	$S_2^+N_2^-$	$S_2^+S_2^-$	Total
$A_1^+A_1^-$	11	1	**10**		1		4			**26**
$A_1^+N_1^-$										**0**
$A_1^+S_1^-$	**7**		**24**		**5**		**2**		**1**	**40**
$N_1^+A_1^-$			**1**				1			**2**
$N_1^+N_1^-$	4		**11**			1	1		1	**18**
$N_1^+S_1^-$	1		**1**						1	**3**
$S_1^+A_1^-$			**3**				1			**4**
$S_1^+N_1^-$										**0**
$S_1^+S_1^-$	2	1	**3**				1			**7**
Total	**25**	**2**	**53**	**0**	**6**	**1**	**10**	**0**	**3**	**100**

Values are percentages ($n = 141$)

To get a rough estimate of stability of preferences, we calculate the correlation between responses by assigning the numerical values $A = 1$, $N = 0$, $S = -1$. The correlation between the 282 responses to the same question in the two sessions is $\rho = 0.322$ (p-value $= 0.00$). The correlation for the 141 gains domain questions is $\rho^+ = 0.064$ (p-value $= 0.44$), and for the 141 losses domain questions is $\rho^- = 0.204$ (p-value $= 0.02$). While these coefficients are in line with the values reported in the literature, the three estimates are very different.[4]

Besides correlation, another simple measure of stability could be the proportion of subjects who give identical answers in both sessions. This can be seen in the diagonal of Table 5, which provides the full distribution of responses in both sessions (notice that the row total and the column total agree with Table 3). The subjects in the diagonal are 37%, which is far from the 100% in a world with completely stable preferences. In the gains 3×3 sub-matrix obtained by collapsing the responses from the losses domain, the diagonal represents 56% of the population. Similarly, in the 3×3 matrix corresponding to the losses domain the diagonal represents 48%.

[4] It might be surprising that the overall correlation is higher than the correlations for gains and losses, separately. In the gains domain, the most frequent answer is (1, 1), followed by (0, 1), (1, 0), (−1, 1), and (1, −1), and not many (0, 0) or (−1, −1). This produces low correlation. Something similar occurs in the losses domain. When we combine the data, we have many (1, 1) and (−1, −1) that yield a high correlation.

Table 6 Results of the stochastic choice model

Specification	MLE	Δ^+	Δ^-	θ^+	θ^-	LRT	p-value
(a) Parameters							
(1) $\Delta^+, \Delta^-, \theta^+, \theta^-$	−483.8	0.98	0.67	0.29	0.21		
(2) $\Delta^+ = \Delta^-, \theta^+ = \theta^-$	−485.4	0.92		0.25		3.36	0.19
(3) $\theta^+ = \theta^-$	−485.0	0.95	0.71	0.25		2.49	0.11
(4) $\Delta^+ = \Delta^-$	−484.4	0.95		0.29	0.209	1.21	0.27

Specification	a^+a^-	a^+n^-	a^+s^-	n^+a^-	n^+n^-	n^+s^-	s^+a^-	s^+n^-	s^+s^-
(b) Probability of types									
(1) $\Delta^+, \Delta^-, \theta^+, \theta^-$	0.24	–	0.72	0.01	–	–	0.03	–	–
(2) $\Delta^+ = \Delta^-, \theta^+ = \theta^-$	0.14	0.32	0.51	–	–	–	0.03	–	–
(3) $\theta^+ = \theta^-$	0.25	–	0.72	0.01	–	–	0.03	–	–
(4) $\Delta^+ = \Delta^-$	0.10	0.41	0.45	–	–	–	0.03	–	–

Both correlation and diagonal counting are imperfect measures of stability. They can give divergent results, as in our case where the gains domain is more stable than the losses domain when measured by the diagonal counting, but the losses domain is more stable than the gains domain when measured by correlation. Of course, diagonal counting is highly dependent on the number of categories. In any case, both measures indicate high instability of preferences, as the answers in the first session are a poor predictor of the answers in the second session.

4.3 Estimation of the SCM parameters

The values in Table 5 are the inputs to estimate the parameters of the stochastic choice model given in Eqs. 2, 3, and 6. In the basic specification of the model, we estimate the probabilities $p(\tau)$ and the four parameters Δ^+, Δ^-, θ^+, and θ^- with no additional constraints. This will be called Specification 1.

The results of the MLE are given in Table 6a and b, first corresponding row. We observe that Δ^+ is higher than Δ^-. Recall that Δ is a measure of strength of preference relative to the error term, and as such it measures stability of preferences. Hence, preferences in the gains domain are more stable than in the losses domain. Still, one has to keep in mind that the restricted model ($\Delta^+ = \Delta^-$) cannot be rejected, so that the difference between Δ^+ and Δ^- is statistically not large.

Lopes (1987) offers an explanation for higher instability in the losses domain. She proposes a system in which the driving factors of risk attitudes are security and aspiration. For our experiment, the A^- alternative is attractive because it offers a lower loss value (aspiration), but is disliked because it is almost certain (security). The S^- alternative is attractive because it offers a higher probability of zero losses (security), but is disliked because of the higher probabilities of losing more money (aspiration). This inverse ordering of security and aspiration causes a conflict in losses.

Under the interpretation that N corresponds to undecided subjects with incomplete preferences, θ is a measure of incompleteness of preferences. Hence, at higher

Table 7 Test of preference types

Hypothesis	MLE	Δ^+	Δ^-	θ^+	θ^-	LRT	p-value		
(a) Parameters									
(5) $a^+a^- = 0$	−485.0	0.99	0.88	0.29	0.19	2.54	0.11		
(6) $a^+s^- = 0$	−494.3	1.00	1.10	0.29	0.17	21.01	0.00		
(7) $s^+a^- = 0$	−484.1	1.00	0.66	0.29	0.21	0.66	0.42		
(8) $n^+a^- = 0$	−483.8	0.97	0.67	0.29	0.21	0.02	0.87		
Hypothesis	a^+a^-	a^+n^-	a^+s^-	n^+a^-	n^+n^-	n^+s^-	s^+a^-	s^+n^-	s^+s^-
(b) Probability of types									
(5) $a^+a^- = 0$	–	0.54	0.40	0.03	–	–	0.03	–	–
(6) $a^+s^- = 0$	–	0.92	–	–	–	0.06	0.02	–	–
(7) $s^+a^- = 0$	0.20	–	0.72	0.08	–	–	–	–	–
(8) $n^+a^- = 0$	0.25	–	0.72	–	–	–	0.03	–	–

θ, higher will be the probability that a subject will be unable to express preference between A and S in either domain. Following this interpretation, our data suggest that subjects have preferences that are more incomplete in gains than in losses domain.

Regarding the distribution of types (see Table 6b, line 1), we find that four types have strictly positive probability, and only two of those have a probability above 5%. The highest probability corresponds to the reflective type a^+s^-, with a value of 72%. The second most frequent type is the risk averse, a^+a^-, with a fraction of 24%.

In Specification 2, we imposed the restrictions $\Delta^+ = \Delta^-$ and $\theta^+ = \theta^-$. The likelihood ratio test (LRT) does not reject the hypothesis that the parameters in the restricted model (Specification 2) are different from the parameters in the unrestricted model (Specification 1). Hence, we cannot reject the joint hypothesis that the two parameters Δ and θ are constant across domains. Considering the restrictions separately, $\theta^+ = \theta^-$ in Specification 3 and $\Delta^+ = \Delta^-$ in Specification 4 yield similar results: For all the three constrained specifications, the LRT rejects the hypothesis of domain differences. In all cases, the type a^+s^- remains the most common. When we force $\Delta^+ = \Delta^-$ (Specifications 2 and 4), a new type that is averse for gains and neutral for losses (a^+n^-) appears. Accordingly, the probabilities of the reflective and averse types decrease.

Consider the four non-zero types identified in Specification 1. We test the hypothesis that the probability of those types equals zero. Each corresponding line of Table 7a and b reports the results of these constraints, imposed one at a time. The last column of Table 7a shows that the reflective type a^+s^- stands as the only one necessary to explain the behavior of the subjects in the experiment. When the a^+a^- type is forced to zero, the neighboring type a^+n^- becomes the dominant preference type.

Three considerations follow from the results of this section: (1) The propensity of subjects to be risk seeking for losses is not as strong as the propensity to be risk averse for gains; (2) if restrictions are imposed ($\Delta^+ = \Delta^-$), then there is certain evidence in favor of risk neutral preferences for the losses domain; and (3)

Table 8 Probability of obtaining an answer (row) given a preference type (column) in the gains domain (left) and the losses domain (right)

$P(R^+\|\tau^+)$	a^+	n^+	s^+
A^+	**75**	39	10
N^+	14	**23**	14
S^+	10	39	**75**
Total	100	100	100
$P(R^-\|\tau^-)$	a^-	n^-	s^-
S^-	**68**	42	19
N^-	13	**16**	13
A^-	19	42	**68**
Total	100	100	100

In bold the cells where the preference type match the reported risk preference

Specification 1 of the SCM recovers the original proportion of reflective types observed in Table 1.

5 Using our estimates to make predictions

In this subsection we use the estimates from the Specification 1 of the SCM to make predictions. The first prediction is the probability that a subject that belongs to a specific preference type would report a certain risk preference (A, N, or S). We simply apply Eqs. 2 and 3 using the results of Specification 1. Table 8 shows the probabilities for the gains and losses domains, separately. The table is symmetric because we have assumed that Δ is the same for all types. Note in Table 8 that there is greater stability in the gains domain, consistent with a higher value of Δ^+ over Δ^-. Also, for a risk neutral type, the low values of both θ^+ and θ^- make it more likely that he would report, in both domains, an answer that is different from his true preference (A or S).

The second prediction is the probability of belonging to a certain preference type given some reported answer(s). We apply the Bayes rule using our estimates of $p(\tau)$. For example, the probability that a subject belongs to a certain type after completing Session 1 is given by:

$$P(\tau^+, \tau^-|R_1^+, R_1^-) = \frac{P(R_1^+, R_1^-|\tau^+, \tau^-) \times p(\tau)}{P(R_1^+, R_1^-)} \tag{7}$$

The estimation of the posterior probabilities of types given the possible answers in Session 1 is given in Table 9. In each column, we indicate in bold the type that is most likely, given the answer. Remarkably, the reflective type is always the most likely, except when subjects report risk aversion in losses. In such a case, the best guess is that the subject belongs to the $\mathbf{a}^+\mathbf{a}^-$ type. In conclusion, the most likely a posteriori types are either $\mathbf{a}^+\mathbf{a}^-$ or $\mathbf{a}^+\mathbf{s}^-$. No other types are more likely, regardless of the responses of the subjects.

Table 9 Probabilities of types (row) given the answers (column)

$P(\tau^+\tau^-\|R^+R^-)$	$\mathbf{A^+A^-}$	$\mathbf{A^+N^-}$	$\mathbf{A^+S^-}$	$\mathbf{N^+A^-}$	$\mathbf{N^+N^-}$	$\mathbf{N^+S^-}$	$\mathbf{S^+A^-}$	$\mathbf{S^+N^-}$	$\mathbf{S^+S^-}$
$\mathbf{a^+a^-}$	**52**	24	8	**48**	23	8	**34**	18	7
$\mathbf{a^+s^-}$	45	**75**	**91**	42	**72**	**90**	29	**59**	**84**
$\mathbf{s^+a^-}$	1	0	0	6	3	1	31	18	7
$\mathbf{n^+a^-}$	1	1	0	4	2	1	7	4	2
Total	100	100	100	100	100	100	100	100	100
Proportion in the experiment	25	1	47	1	12	2	7	0	5

Not all answers are equally discriminatory. For example, if we observe an answer $\mathbf{A^+S^-}$, we can say with a 91% probability that the subject belongs to the type $\mathbf{a^+s^-}$. In general, the answer having the most discriminatory power is exhibiting risk seeking preference for losses. Given the answers A^+S^-, N^+S^-, or S^+S^- a subject has a posterior probability of 91%, 90%, or 84%, respectively, of belonging to the a^+s^- type.

After observing S^+A^-, an answer consistent with type s^+a^-, one is left with a high level of ambiguity about the true type. From Table 9 we see that the probability that a subject with the answer S^+A^- belongs to the type s^+a^- is roughly the same (31%) as the probability of belonging to types a$^+a^-$ (34%) and a^+s^- (29%).

In summary, the assessment of preferences for losses provides the most information about the individual's true risk preferences (for gains, everybody would be classified as risk averse).

6 Discussion and conclusion

Few studies have focused on the stability of preferences by asking the same subjects the same questions at two separate moments in time. In doing so, we learn that behind a stable statistical pattern from session to session, there is a lot of instability in individual preferences. We have analyzed the results in light of a stochastic choice model.

When cumulative prospect theory was initially presented, it was claimed that the reflection effect holds for a vast majority (more than 70% of the subject). These percentages were the reported results for gains and losses separately. Subsequent studies showed that the fraction of subjects that exhibit the reflection effect jointly in gains and losses is around 50%. We also observe these joint percentages, but also observe that 63% of all subjects change their risk preferences from session to session. Using a SCM to study the stability of preferences, we learn that the fraction of subjects whose true preferences agree with the reflection effect is around 72%, thus giving support to the original estimates.

The estimation of the SCM also detects a significant fraction of subjects (24%) that do not exhibit the reflection effect. These subjects are risk averse for both gains and losses. This is important to interpret aggregated results. In decision under risk it is common to report a representative value function that is calculated using the average or median value of certainty equivalents. In doing so, one implicitly assumes that all subjects have the same value function, and the average or median calculation reduces the noise and estimates this common value function. The value functions usually obtained are clearly concave for gains. For losses, however, the value function is convex, but less than for gains (Abdellaoui 2000). Our empirical findings of two prevalent types successfully explains this pattern. The clear concavity for gains is obtained because both a^+s^- and a^+a^- types possess a concave value function. For losses, the reduced convexity is the result of combining 72% of a^+s^- having a convex value function with 24% of a^+a^- having a concave value function.

The existence of two types has important implications in the area of elicitation of risk preferences. For instance, in measuring the value function, rather than taking a grand average of a “representative value function,” our results suggest to first classify subjects as either reflective or averse, and then calculate two separate representative value functions.

An alternative framework to a stochastic choice model is that of a random preference model (Loomes and Sugden 1995). Under this interpretation, the choices we observe do not reflect some underlying stable preference together with an error. Instead, decision makers possess multiple underlying preferences and a probability distribution describing the frequency with which any of them will be expressed. The frequencies of our data would directly estimate this probability distribution. This provides a “quantum prospect theory” interpretation of the data. Accordingly, at the moment preferences are elicited, any given individual has a 74% chance of appearing as risk averse, and a 64% chance of appearing as risk seeking (see Table 1). If sufficient time has passed, then a subsequent elicitation is an independent draw with same probabilities of 74% and 64%, respectively. Hence, we always observe a population percentage that is stable, but the individuals behind each answer change from session to session. Moreover, it follows that information about previous preferences of a given individual is not informative about future preferences of that individual, except for their statistical value to describe aggregate choice.

In contrast, under the interpretation of the stochastic choice model, preferences elicited in one session are predictive of future preferences, because they allow us to update the probability that this subject belongs to a given type.

Slovic (1995) suggests that preferences are often constructed—not merely revealed—in the elicitation process. The proposed SCM does not provide an answer to the issue of preferences being preexistent to the decision process or built in the moment of the decision. For instance, the preference type could correspond to a individual-specific tendency to construct preferences in a given way, and the random error to deviations from this tendency. Nevertheless, the model is most consistent with an interpretation where types reflect one’s true underlying preference, and the error accounts for imperfections in observing this true preference. However, the existence of true types is an assumption, and our model estimates the proportion of types based on this assumption.

Our results show that the correlation coefficients and the diagonal counting could be ambiguous measures of stability. We propose to measure stability with the parameter Δ, which is a standardized measure of the strength of preference relative to the error.

We propose that elicitation methods should be viewed within a sampling framework. Subjects may belong to different preference types, and elicitation methods are a sample with error from the true type. After the elicitation, we have an updated probability of the subject belonging to different preference types. If more knowledge about preferences is required, additional independent elicitation sessions should be carried out to obtain more informative posterior probabilities of the true preference type. Running elicitation procedures in separate sessions may help ensure independence of the responses and errors. Elicitation methods that include multiple questions in which subjects rethink each question from afresh (as opposed to responding in coherence with previous question) may lead to a better assessment of underlying preferences.

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