The SGG risk elicitation task: Implementation and results[1]

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Abstract

We propose a simple task for the elicitation of risk attitudes, initially used in Sabater-Grande and Georgantzís (2002) [SGG], capturing two dimensions of individual decision making: subjects' average willingness to choose risky projects and their sensitivity towards variations in the return to risk. We report results from a large dataset obtained from the test and discuss regularities and the desirability of its bi-dimensionality when used to explain behaviour in other contexts.

Key words: Psychometric Tests, Decision-making; Lotteries; Risk aversion.

JEL: C91; D03; D81

[1] This is a longer version of a companion paper accepted for publication in *Psicothema*, under the title: "The lottery-panel task for bi-dimensional parameter-free elicitation of risk attitudes".

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1. Introduction

Testing for interdependence across different aspects of behavior requires jointly studying stated or observed attitudes which are informative on the corresponding individual attributes.[2] Beyond the question of what explains what in such studies, the search of associations among decisions in different tasks is a main motivator for experimentalists. A systematic rejection of such associations would confine experimental results to the specific setting in which they were obtained, undermining the practical relevance of our research outside the lab.

In order to produce reliable tests, psychologists invest a substantial amount of effort in (i) developing the task and proposing it to the scientific community, (ii) standardizing the format and applying it among large populations, (iii) generating result distributions by subject category, (iv) identifying successful tasks as reliable approximations of an idiosyncratic factor, and (v) identifying contexts in which behavior correlates with performance in a given task. This process is parallel and significantly synergic to the very important endeavor of producing correct theories on the measured aspect itself. However, metaphorically speaking, looking for appropriate tasks in the absence of a perfect theory is like the practice in medicine of establishing clinical protocols for the cure of a disease even before the disease is fully understood.

This paper is inspired by the surprising observation that the process with which the existing tests of risk attitudes in economic domains are chosen and used totally ignores stages (ii) and (iii) above, while (i), (iv) and (v) are rarely performed in an intentional and systematic way. Economists usually aim at testing theories, rather than at relating risk attitudes with behavior in other contexts. Even the need for external risk measurements is often not recognized by some economists[3], often explaining the effect of risk preferences on observed behavior by theoretically deriving the sufficient conditions for this effect to emerge, thus explaining fact Y by its sufficient (but not necessary) condition X.

The remaining part of the paper is structured as follows: Section 2 reviews economic theories of risky decision making and comments on some devices used to elicit risk attitudes as an external explanatory factor of behavior in other contexts. Section 3 reports results obtained from the application of the lottery-panel test by Sabater-Grande and Georgantzís (2002), SGG. Section 4 concludes. In a longer working paper, we provide more information on the design of the test, as well as instructions for subjects and the experimenter.[4]

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[2] For example, when studying the effects of psychometric intelligence on complex decisions, psychologists correlate scores in, say, Raven (1976)'s Advanced Progressive Matrices (APM), and performance in complex microworlds, like NEWFIRE or COLDSTORE. On this, Rigas, Carling and Brehmer (2002) note that performance in APM and each one of these complex tasks correlate because they provide different measurements of intelligence.

[3] Some famous examples of inferring risk attitudes without using an external risk elicitation task are Cox and Oaxaca (1996), inferring risk attitudes from bidding in private value auctions, Goeree, Holt and Palfrey (1999) whose data are from laboratory matching pennies games and Campo, Guerre, Perrigne and Vuong (2002) on real timber auctions.

[4] García-Gallego, Georgantzís, Jaramillo-Gutiérrez and Parravano (2010).

2. Theories and tests of risk attitudes

An early explanation of why subjects do not evaluate risky choices by their mathematical expectation is attributed to the Expected Utility Theory (EUT) by von Neuman and Morgestern (1944). According to the theory, when comparing a lottery $L_1 = (p_{11}, x_{11}€; ... p_{1n}, x_{1n}€)$ with $L_2 = (p_{21}, x_{21}€; ... p_{2m}, x_{2m}€)$, where p_{ji} is the probability that the i th best outcome of lottery j occurs, yielding a reward of x_{ij} €, an agent whose utility is $U(x)$, with $U'(*) > 0$, will strongly prefer L_1 to L_2, as long as

(1) $$\sum_{i=1}^{n} p_{1i} \cdot U(x_{1i}) > \sum_{i=1}^{m} p_{2i} \cdot U(x_{2i}).$$

The preference for less risky projects is then explained by a negative second derivative of $U(x)$, implying a decreasing marginal utility from money, a condition often used as synonymous to *risk aversion*. Despite its survival as the main paradigm in economics as observed by Rabin and Thaler (2001), the EUT was proved to be an incorrect descriptive model since Allais' (1953) paradox, emerging when subjects are faced to alternative lottery pairs with same probability/reward ratios. According to (1), such lotteries should be ranked in the same way, whereas people systematically change their choice in favor of the certain payoff when this becomes part of the feasible set. Kahneman and Tversky (1979) proposed an alternative model, Prospect Theory (PT), assuming that people implicitly use non linear weights $w(p)$ to evaluate probabilities. Therefore, in our example, L_1 would be strongly preferred to L_2, if:

(2) $$\sum_{i=1}^{n} w(p_{1i}) \cdot U(x_{1i}) > \sum_{i=1}^{m} w(p_{2i}) \cdot U(x_{2i})$$

PT accommodates Allais' paradox, whereas it reduces to EUT for $w(p) = p$. Tversky and Kahneman (1992) assumed later a power utility function defined separately over gains and losses: $U(x) = x^a$ if $x > 0$, and $U(x) = -\lambda(-x)^b$ for $x < 0$. So a and b are risk aversion parameters, and λ is the coefficient of loss aversion. This new version, called Cumulative Prospect Theory (CPT), defines probability weighting over the cumulative probability distributions, offering an explanation of risk-loving behavior for payoffs below their reference point (losses), while exhibiting risk-averse behavior for rewards above their reference point (gains). The form of the probability weighting function proposed by Tversky and Kahneman (1992) has been widely used for both separable and cumulative versions of PT, and assumes weights $w(p) = p^{\gamma} / [p^{\gamma} + (1-p)^{\gamma}]^{1/\gamma}$. Therefore, in its simplest formulation, CPT explains risk attitudes using a minimum of four parameters, a, b, λ and γ. Our overview does not pretend to narrate the history of economic theories of decision making.[5] We simply want to stress the

[5] For example, we have intentionally omitted heuristics and other theories which cannot be used to propose tasks for the elicitation of risk attitudes. Also, for space reasons we omit the theory proposed by Birnbaum and Navarrete (1998) which can explain violations of stochastic dominance by introducing

fact that the evolution of these theories achieves the aim of accommodating phenomena which invalidated earlier theories by the use of more degrees of freedom.

Contrary to this evolution of theories towards more complete and complex descriptions of human behavior in risky environments, all tests currently used are fundamentally uni-dimensional, despite their creation in the post-PT era. This does not mean that all studies of behavior under uncertainty have ignored the multi-dimensional approach dictated by modern theories. In fact, a fruitful line of research has specifically designed and analyzed data obtaining parameters for utility and probability weighting functions.[6] However, in order to produce ready-to-use data, the elicitation of risk attitudes as an explanatory factor of behavior in another context should not depend on the parameterization or even the theory used.[7]

A measure of risk aversion is obtained in recent economic studies by the use of the Holt and Laury (2002) HL procedure. Although the task was not, initially, proposed as an external risk-related task to explain behavior in other contexts, it has served this purpose in several occasions.[8] Due to its uni-dimensionality, costlessly allowing a one-to-one mapping of choices on specific utility parameters, the test entails a possible loss of information due to under-specification of risk attitudes, which is also likely to reduce its power to explain behavior in other contexts. This is also true for the whole set of alternative procedures used by economists to elicit risk attitudes.[9] The task elicits one individual *datum* from each block of 10 binary choices, designed to obtain the switching point from a less risky to a more risky alternative. This causes a practical problem since some choices do not satisfy the "single-switching" condition. Posterior applications have opted for different solutions to this problem, leading to a variety of alternative implementations which, together with the plethora of designs aimed at

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a third component of risky decision making, namely the attention paid by subjects to the best outcomes among those feasible in a given lottery.

[6] Numerous studies have used experimental data to estimate the Tversky and Kahneman (1992) probability weighting function and other specifications like, for example, Goldstein and Einhorn's (1987) $w(p)= \lambda p^{\gamma}/[\lambda p^{\gamma}+(1-p)^{\gamma}]^{1/\gamma}$ and Prelec's (1998) two-parameter specification $w(p)=e^{-\lambda(-\ln p)^{\gamma}}$. Furthermore, the nonlinearity of responses to probabilities has even been confirmed at the level of neural responses by Hsu, Krajbich, Zhao and Camerer (2009), and, for aversive outcomes, by Berns, Capra, Chappelow, Moore and Noussair (2008), while it is rejected in a study of neural signals reflecting reward uncertainty reported by Schultz et al. (2008).

[7] Mapping choices on parameters of utility and probability weighting functions is further complicated by Harrison and Rutström's (2009) observation that we may even have to switch between theories in order to account for the heterogeneity observed.

[8] It has been used to explain behavior in strategic games (Goeree, Holt and Palfrey, 2003), agricultural economics (Lusk and Coble, 2005), risky settings outside the lab (Harrison, List and Towe, 2007), and setups relating risk attitudes and discounting (Andersen, Harrison, Lau and Rutström, 2008).

[9] A variety of alternatives to HL, adopted by Wakker and Deneffe (1996), Bleichrodt and Pinto (2000), Abdellaoui (2000) and Abdellaoui, Bleichrodt and Paraschiv (2007), use the trade-off method based on a series of binary choices between lotteries aiming at separating between attitudes toward consequences and attitudes toward probabilities. A second approach, adopted by Hey and Orme (1994), Camerer and Ho (1994), Carbone and Hey (2000) and Stott (2006) uses a large number of independent binary choices between lotteries to estimate risk attitudes. Both sets of procedures are specific to the EUT and are even more time-consuming and cognitively demanding for the subjects than the more frequently used HL procedure.

identifying other biases[10] of the set up, have created an –undesirable, for our purposes– plethora of non comparable datasets. Contrary to the problem of non comparability among small data sets, several studies[11] use hypothetical simple questions among large and even international samples, which however have not been used to explain behavior in other contexts.

A broadly used test among psychologists is Zukerman's (1978) Sensation Seeking Scale (SSS) with which our test exhibits some correlation[12]. The test is structured as a YES-NO questionnaire on attitudes towards risky activities under four subscales separating subject's riskiness in different domains, none of which is strictly speaking financial. The economic domain is used in the Iowa Gambling Task (IGT), introduced by Bechara, Damasio, Damasio and Anderson (1994). The task was originally aimed at measuring a subject's difficulty to identify the most profitable deck, from which he or she should, thereafter, extract all cards. Using the task as an external risk attitude elicitation device implies significant loss of control, because it mixes risk preferences with a subject's learning ability (a "slow" learner can be confused with a risk loving subject or one with low levels of loss aversion) and it does not fully account for different learning histories. For space reasons, we will not review other tests occasionally used to elicit risk attitudes as an explanatory factor of behavior in other contexts. Rather, we will risk a generalization. All existing tasks suffer from either lack of systematic replication in a stable format generating statistics with large comparable datasets, or they are insufficiently justified as measures of risk attitudes isolated from other parallel phenomena. Furthermore, they are all uni-dimensional.

3. The SGG lottery-panel test

The SGG lottery-panel task was originally used to study risk preferences parallel to cooperation/competition in prisoner's dilemma games. Riskier subjects were found to be more cooperative. The task consists of four different panels, like those in Figure 1, every one of which contains ten different lotteries. In each lottery, subjects can win a payoff (x) with a probability (p) and otherwise nothing.

FIGURE 1 HERE

Subjects choose (marking the preferred lottery as in the example of Figure 1) one of the ten lotteries from each panel. In the implementation of the task with real money, only one of these four panels, selected randomly at the end of the session, is used to determine a subject's

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[10] See, for example, the work by Bosch-Domènech and Silvestre (2006) on the embedding bias induced by the fact that subjects tend to change their switching point when some extreme alternatives of binary choice are removed.
[11] See Wang, Rieger and Hens (2010) and Weber and Hsee (1998, 1999).
[12] This is based on small sample reported in Georgantzís, Genius, García-Gallego and Sabater-Grande (2003) in which only results from the first panel of the SGG test exhibited a weak correlation (-0.248) with SSS on the expected direction: more sensation seeking, riskier choices.

earnings in the experiment. The range of winning probabilities in all panels is the same (from 1 to 0.1 in steps of 0.1). The payoff associated to each lottery's winning probability is constructed using the rule:

$$E(L_{ij}) = p_{ij} \cdot x_{ij} = c_j + (1 - p_{ij}) \cdot t_j \Rightarrow x_{ij} = {c_j + (1 - p_{ij}) \cdot t_j} \Big/ {p_{ij}} . \tag{3}$$

$E(L_{ij})$ is the expected value of lottery L_{ij}, where $i \in \{1,2,...,10\}$ designates one of the 10 lotteries offered in panel $j \in \{1,2,3,4\}$. The parameter c_j is a constant amount of money which is fixed for this dataset to 1€. The parameter $t_j \in \{0.1,1,5,10\}$ is a panel-specific risk premium, which generates an increase in the lotteries' expected values as we move from safer to riskier options within the same panel. All the panels begin with a sure amount of 1€, which is increased as winning probabilities are decreased, resulting in increments of expected values as we move from left to right within each panel. These increments are larger as we move from panel 1 to panel 4. This structure implies that more risk-averse subjects choose lotteries closer to the left of a panel.[13] All risk neutral and risk loving subjects should choose the lotteries at the far right extreme of the panels.

Considering the fact that with 4 choices the researcher obtains 4 different observations (as opposed to 10 choices for 1 observation in HL) per individual subject, we can easily see that the test parsimoniously produces a panel rather than a single column of data. By definition, this corresponds to a multi-dimensional description of individual attitudes towards risk.

3.1 A large dataset

Since its first implementation, the SGG test has been used in several occasions producing various small experimental datasets.[14] Here, we report results from a large dataset[15] (N=785) obtained under comparable conditions, paying special attention to the bi-dimensional nature of decision making and its implications for the explanation of behavior in other contexts.

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[13] In terms of EUT, García-Gallego, Georgantzís, Navarro-Martínez and Sabater-Grande (forth.) observe that a subject with constant relative risk aversion (CRRA), as implied in the utility function $U(x) = \frac{x^{1-r}}{1-r}$ makes choices which associate higher risk aversion parameters *r* to safer choices in each panel. Furthermore, for a given risk aversion parameter, weakly monotonic transitions towards riskier choices are predicted as we move from panel 1 to panel 4.

[14] Brañas-Garza, Guillén and López del Paso (2008) have shown that choices in the test do not correlate with subjects' mathematical skills. García-Gallego, Georgantzis, Martínez Navarro and Sabater-Grande (2010) warn us that repeated implementation without any intermediate treatment generates regression to the mean phenomena. Implementation by Brañas-Garza, Georgantzís and Guillén (2007) in a gambler anonymous session among pathological gamblers and their spouses captures an unprecedented risk-averse behavior by the latter. Earlier, Georgantzís et al. (2003) had studied the effect on choices of knowing expected utility theory and hypothetical vs. real monetary rewards.

[15] Between 2003 and 2008, at the *Laboratori d'Economia Experimental* (Universitat Jaume I, Castellón-Spain).

Figure 2 depicts the frequency of choices when all data from all panels are pooled together. Given the variation in prizes and payment methods, this image corresponds to what could be seen as a randomized experiment over the probability space. The peak on the certain payoff captures a certainty effect. A peak on the other extreme (*p=0.1*) as well as a valley on *p=0.9* are both compatible with over-(under-) weighting of small (large) probabilities predicted in PT. Strong attraction of choices towards the "center" (*p=0.5*) may be the result of subjects' familiarity with the *p=½* probability or simply because of an embedding bias similar to that reported by Bosch-Domènech and Silvestre (2006) on HL. No matter what causes this attraction to the center, this property favors close-to-normal distributions of the resulting variable, making it appropriate for simple OLS regressions.

FIGURE 2 HERE

In Figure 3 we present the same dataset broken down by panel, gender and reward method (hypothetical, N=384; real money, N=401). Males are less risk-averse than females. However, males and females behave in more different ways when playing hypothetical lotteries than real ones. Actually, with real rewards, mean choice varies significantly across genders only in panel 3 and 4 (2.7 and 3.9 percentage points at 5% and 1% confidence level, respectively). Responsiveness to risk-premium increases, captured by choice variation across panels, is similar for males and females. Specifically, when faced with hypothetical payoffs, both males and females make less risk-averse choices, the higher the reward, while, counterintuitively[16], when playing with real payoffs, riskier choices are observed in panels with lower risk-returns.

FIGURE 3 HERE

We have argued that it should be a main concern for experimentalists and decision theorists whether a subject's decision under one condition meaningfully relates to behavior under another condition.

FIGURE 4 HERE

Figures 4 and 5 present an aspect of behavior which is missed by other tests. Each graph presents the joint density of individual choices across panel pairs. Each color represents a percentage, i.e. the proportion of subjects whose choice combinations in each panel pair correspond to that specific chart label. Higher risk aversion in one panel predicts a higher risk aversion in another and, at the same time, reactions to the variation of risk returns across different panels seem to be rather moderate.

FIGURE 5 HERE

[16] Although Fiegenbaum and Thomas (1998) have already explained the negative correlation between firm-level risk taking and risk-return, using Prospect Theory and firm specific target profits.

As expected, reactions are more visible across more “distant panels”, showing that a bigger shock is necessary to guarantee a change of choices. This within-subject pattern reproduces in a more reliable way what we have already observed, namely, that the use of real rewards makes subjects to switch to safer options in the presence of higher returns to risk.

3.2 Principal Component Analysis

It is clear that multidimensional descriptions of risk attitudes require obtaining more than one choice per individual. This is done by the SGG test through the use of the four panels. However we have not shown yet that, first, the additional information obtained significantly improves the description of behavior and, second, that this improvement leads to a higher power of our task to explain behavior in other contexts.

We use Principal Component Analysis (PCA) to construct two synthetic variables (the first two components) capturing 85% of subjects’ choice variance. These variables have the following advantages: (1) they are subject to economic interpretation and, (2) since they are by construction orthogonal among each other, they can be used as explanatory variables of the same model. Intuitively, the first component can be interpreted as an arithmetic mean of choices across the four panels given that the loads of each panel in this component are similar and of the same sign. The second component involves a juxtaposition of panels 1 and 2 on one hand and 3 and 4 on the other, which can intuitively be seen as a measure of sensitivity to risk-premium variations. As observed in Table 1, the component is loaded more by the extreme panel 1 (negatively) and 4 (positively) than by choice differences across the adjacent panels, 2 and 3. Intuitively, the first component is increasing in the average probability of the lottery chosen in the four panels and can be seen as a standard measure of risk aversion. The second component can be seen as a measure of a subject’s sensitivity to variations in the return to risk in the “counterintuitive” direction of lower risk taking in the presence of higher returns to risk. While this confirms our comments on Figures 4 and 5, it provides a formal motivation for the use of bi-dimensional descriptions of risk attitudes, summarized as individual choice averages and choice variability across contexts (panels).

TABLE 1 HERE

FIGURE 6 HERE

Using these two components we reconsider gender and hypothetical/real reward effects. It can be seen on Figure 6 that gender differences are specific to the first component, while they diminish or even vanish in the second component. Therefore, males are less risk averse than females but both genders are similar in terms of their sensitivity to variations in the return to risk. Regarding differences between hypothetical and real rewards, both components are relevant. According to the first component, subjects make safer choices in hypothetical lotteries, while, according to the second component they switch more across panels with real rewards, but opposite to the expected pattern of riskier choices for higher risk-returns.

3.3 Using the SGG test to explain behavior: An example.

García-Gallego, Georgantzís, Pereira and Pernías-Cerrillo (2005) conducted experiments on pricing where firms have some captive clients and they also compete for informed consumers using price comparisons on the Internet. During 50 periods, subjects face the dilemma of setting high prices to benefit from captive clients or lower prices to compete for informed consumers too. Parallel to the main experiment controlling for more and less competitive markets and complete or incomplete price indexing (Treatments T1-T4), the SGG risk elicitation task was implemented with hypothetical rewards.

Following the estimates on Table 2 and abstracting from the specifics of the main experiment,[17] we see that risk attitudes provide significant explanatory power for the pricing behavior observed. In fact, both first and second principal components are necessary to identify the effect of risk attitudes on pricing behavior. On one hand, the first component capturing safe choices is associated to more competitive pricing. That is, more risk-averse subjects set lower prices in order to avoid the risk of not having the lowest price indexed by the engine. On the other hand, the second principal component is also associated with lower pricing. This means that subjects, recognizing the increased profitability of riskier choices across panels, also realize that setting higher prices guarantees profits which do not depend on the excessive randomness of the search process.

TABLE 2 HERE

4. Conclusions

We have discussed the properties of risk attitudes as captured by the SGG elicitation task. The danger of using unidimensional descriptions of risk attitudes goes beyond the incompatibility with modern economic theories like PT, CPT etc., all of which call for tests with multiple degrees of freedom. Faithfull to this prescription, the contribution of this paper is an empirically and endogenously determined bi-dimensional specification of risk attitudes, sufficient to describe behavior under uncertainty and necessary to explain behavior in other contexts.

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[17] Apart from the expected effect of firm number on prices, the model identifies a decreasing time trend and adoption of higher prices when the firm has not managed to be the cheapest on Internet in the last period.

APPENDIX

A1: Instructions

In this experiment you can earn a certain amount of money which depends on your decisions and luck.

Decision (please mark with an X in one of the empty cells of each panel):

In this task we ask you to choose **one** of the ten alternatives **of each panel**. Each alternative is a lottery defined as a combination of the **probability** of winning and of the **amount** (in euros) you will earn if the favorable result occurs. **If the favorable result does not occur, you get nothing.** In the case of choosing the probability 1 (with payoff equal to 1€), this choice implies that you will be paid 1€ for sure.

Your earnings:

How much are you going to earn in this experiment is going to be determined in two steps:

- Step 1: **A 4-sided die is tossed.** The number: 1, 2, 3 ó 4, determines the panel in which your decision will be taken into account in step 2.
- Step 2: **A 10-sided die is tossed. Note that:** The 10 side numbers are: 0, 1, 2, 3, 4,…, 8 or 9. The number shown by the die determines the upper limit of winning numbers. If, for example, the die shows an 8, all numbers except 9 win. Thus, everyone gets the prize that corresponds to the chosen lottery, **except** for those ones that played the 10% lottery (i.e. they chose the option 0.1)[18]. The ones that play the 20% lottery need at least an 8. The ones choosing 0,3 (30%) need at least a 7 to win. And so on and so forth.

EXAMPLE: How much would you get if…?

If, in panel 1, you choose, **for example**, the lottery whose winning probability is 0.7, you will get the corresponding prize unless the sides with numbers 0, 1 or 2 are shown by the 10-sided die. That is, you win if one of the highest seven numbers is shown by the die (9, 8, 7, 6, 5, 4 or 3). Following the same reasoning, if you choose the lottery with winning probability 0,5 (50%), you get the corresponding prize as far as one the 5 highest numbers (9, 8, 7, 6 or 5) is shown by the 10-sided die, while you get nothing in case the die shows numbers 0, 1, 2, 3 or 4.

[18] Those win only in the case the die shows a 9.

Observe the following 4 panels and take your decision. Remember that you must choose one option for each panel.

Panel 1

Prob.	**1**	**0,9**	**0,8**	**0,7**	**0,6**	**0,5**	**0,4**	**0,3**	**0,2**	**0,1**
€	1,00	1,10	1,30	1,50	1,70	2,10	2,70	3,60	5,40	10,90
Choice										

Panel 2

Prob.	**1**	**0,9**	**0,8**	**0,7**	**0,6**	**0,5**	**0,4**	**0,3**	**0,2**	**0,1**
€	1,00	1,20	1,50	1,90	2,30	3,00	4,00	5,70	9,00	19,00
Choice										

Panel 3

Prob.	**1**	**0,9**	**0,8**	**0,7**	**0,6**	**0,5**	**0,4**	**0,3**	**0,2**	**0,1**
€	1,00	1,70	2,50	3,60	5,00	7,00	10,00	15,00	25,00	55,00
Choice										

Panel 4

Prob.	**1**	**0,9**	**0,8**	**0,7**	**0,6**	**0,5**	**0,4**	**0,3**	**0,2**	**0,1**
€	1,00	2,20	3,80	5,70	8,30	12,00	17,50	26,70	45,00	100,00
Choice										

A2: Figures

Panel 1

Prob.	1	0,9	0,8	0,7	0,6	0,5	0,4	0,3	0,2	0,1
Euros	1,00	1,10	1,30	1,50	1,70	2,10	2,70	3,60	5,40	10,90
Choice			X							

Panel 2

Prob.	1	0,9	0,8	0,7	0,6	0,5	0,4	0,3	0,2	0,1
Euros	1,00	1,20	1,50	1,90	2,30	3,00	4,00	5,70	9,00	19,00
Choice				X						

Panel 3

Prob.	1	0,9	0,8	0,7	0,6	0,5	0,4	0,3	0,2	0,1
Euros	1,00	1,70	2,50	3,60	5,00	7,00	10,00	15,00	25,00	55,00
Choice								X		

Panel 4

Prob.	1	0,9	0,8	0,7	0,6	0,5	0,4	0,3	0,2	0,1
Euros	1,00	2,20	3,80	5,70	8,30	12,00	17,50	26,70	45,00	100,00
Choice									X	

Figure 1. *The SGG lottery-panel test and example of subject choices.*

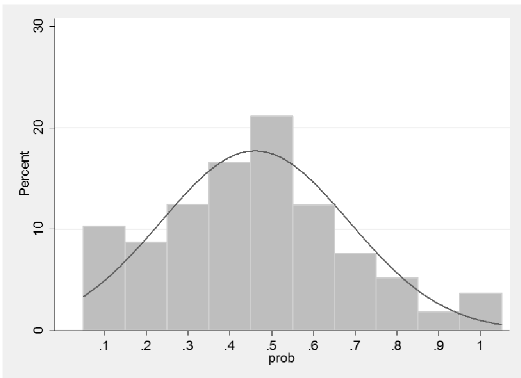

Figure 2. *Histogram of subjects' pooled probability choices across all panels and implementation conditions.*

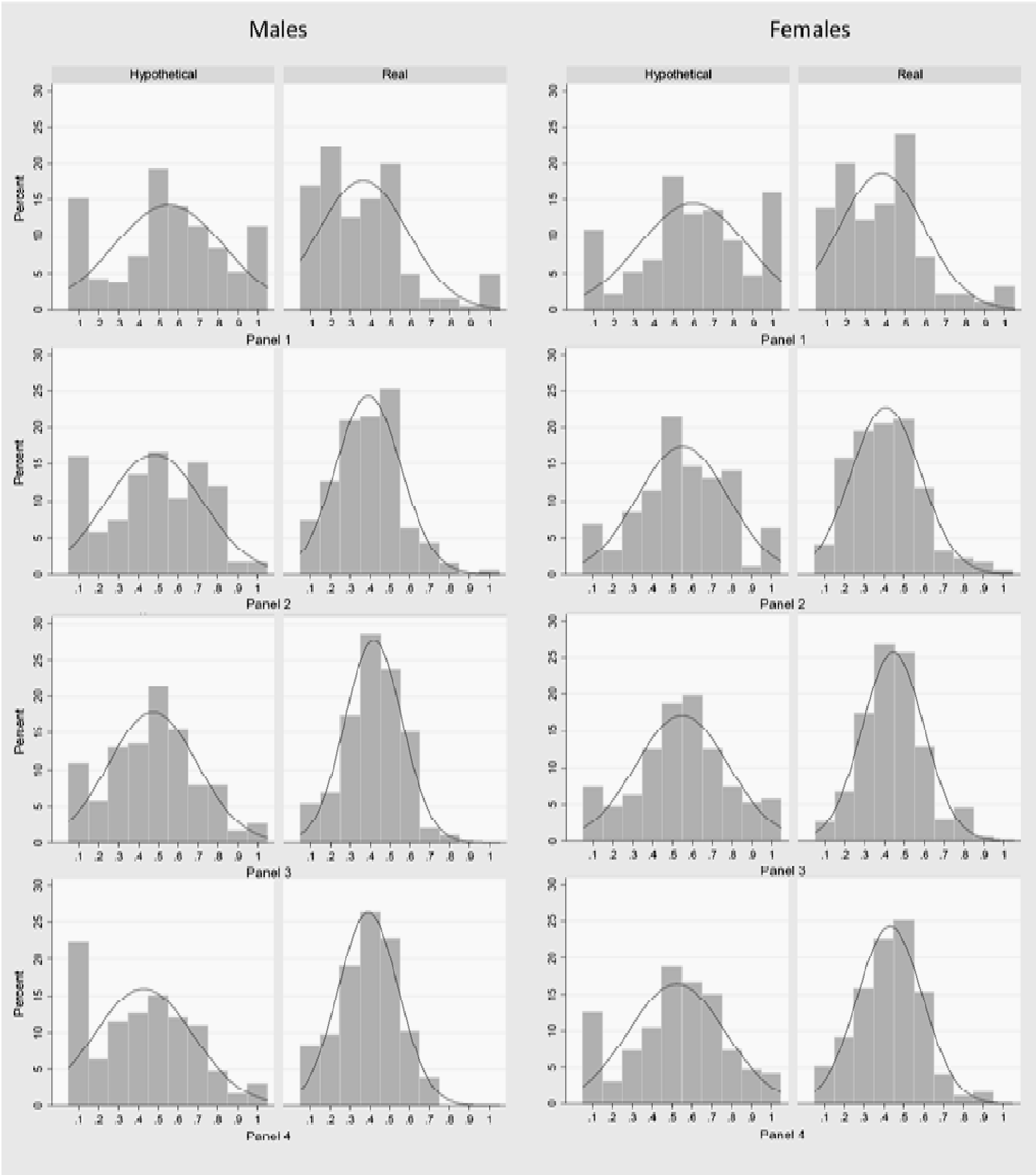

Figure 3. *Histograms of subjects' probability choices by panel, implementation conditions and gender.*

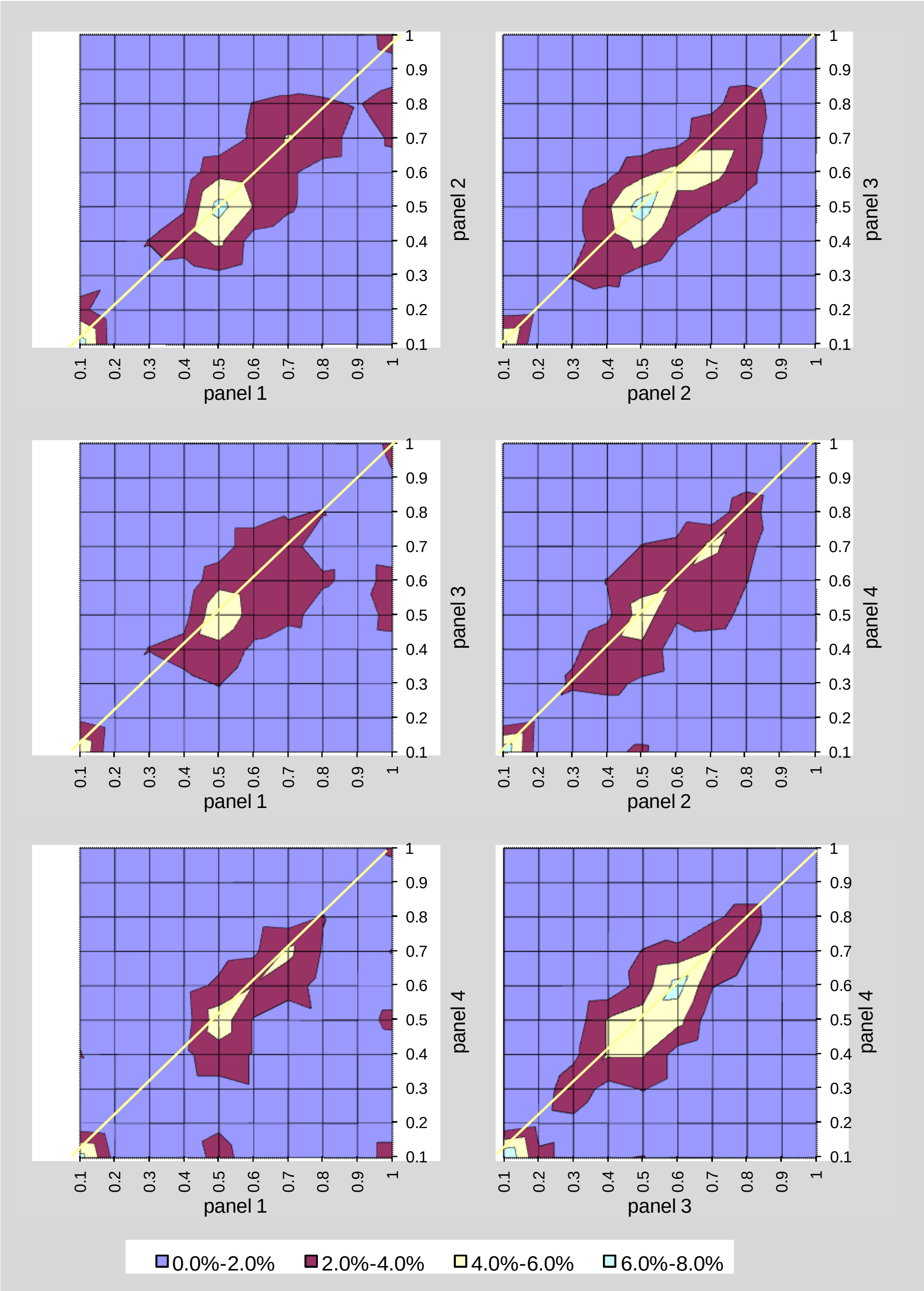

Figure 4. *Subject's choices across panel pairs for hypothetical payoff lotteries. Legend percentage ranges refer to proportion of subjects choosing combinations indicated in each chart label.*

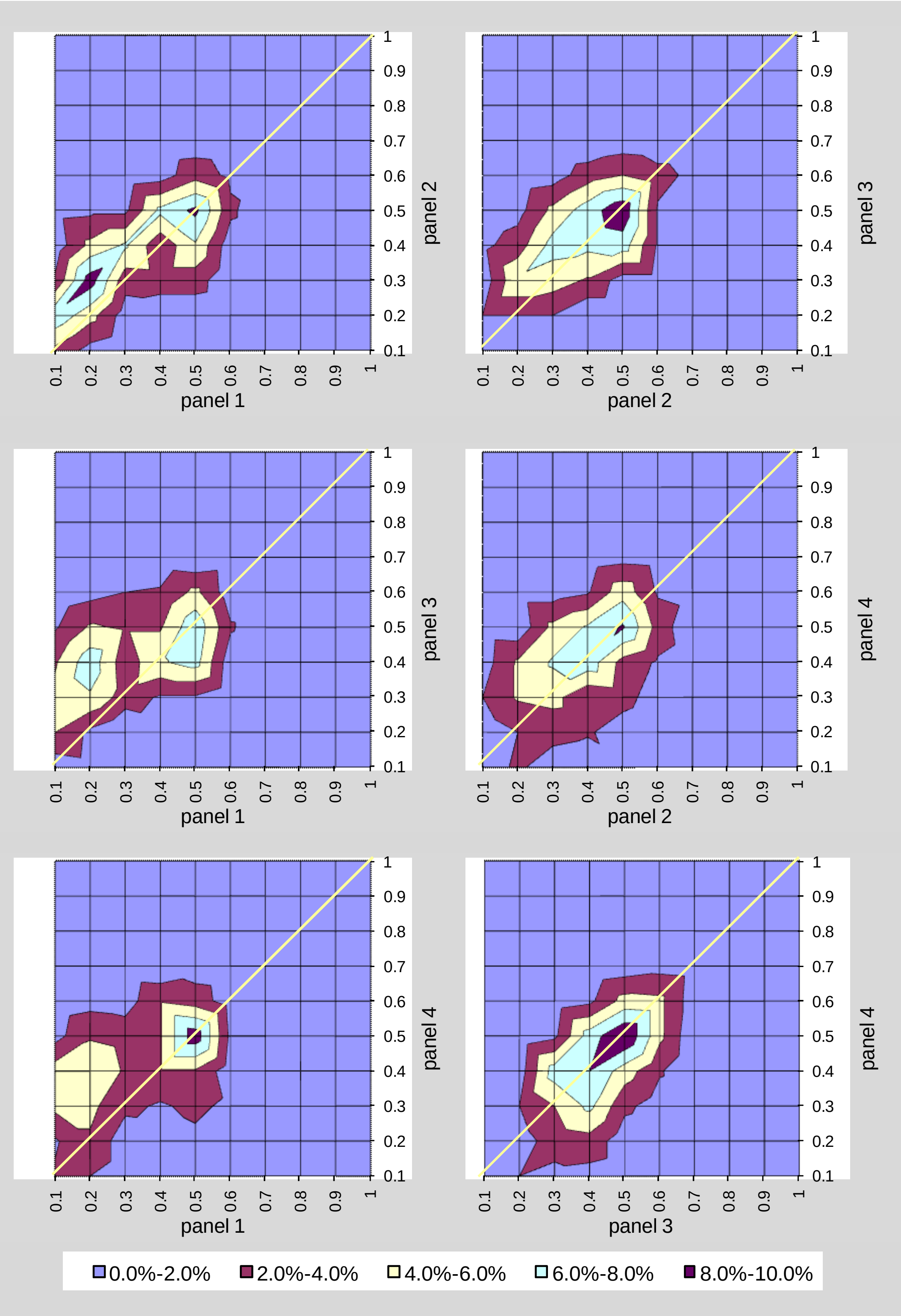

Figure 5. *Subjects' choices across panel pairs for real payoff lotteries. Legend percentage ranges refer to proportion of subjects choosing combinations indicated in each chart label.*

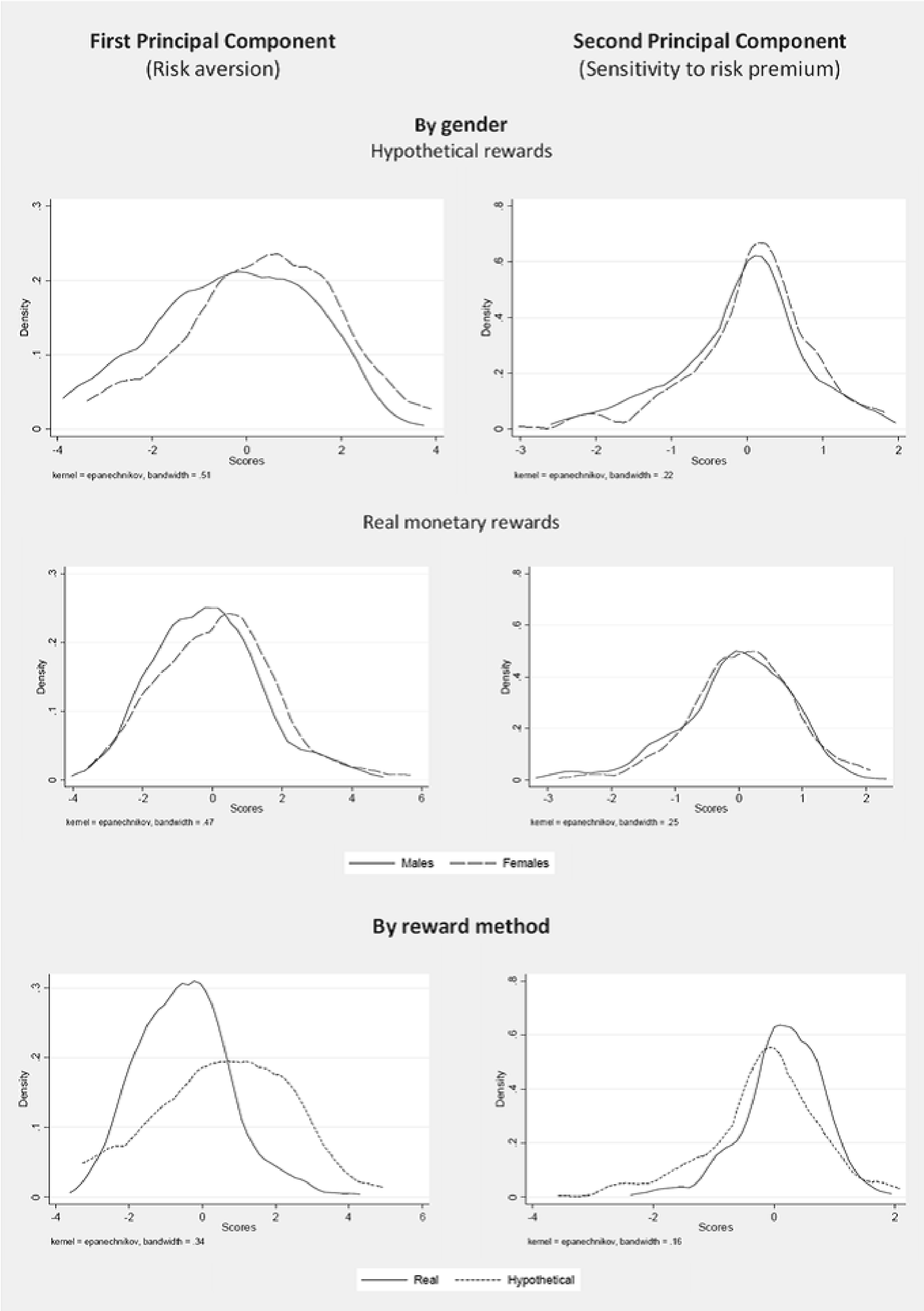

Figure 6. *Kernel density estimates for first and second component scores, by gender and reward method.*

A3: Tables

Component	Eigenvalue	Percentage (%)	Cumulative %
Comp. 1	2.742 ***	68.54	68.54
Comp. 2	0.670 ***	16.75	85.29
Comp. 3	0.307 ***	7.67	92.96
Comp. 4	0.282 ***	7.04	100
	Panel	**Coefficient**	**Std. Error**
Comp. 1			
	Panel 1	0.489 ***	0.016
	Panel 2	0.517 ***	0.013
	Panel 3	0.521 ***	0.013
	Panel 4	0.472 ***	0.017
Comp. 2			
	Panel 1	-0.577 ***	0.029
	Panel 2	-0.372 ***	0.035
	Panel 3	0.317 ***	0.036
	Panel 4	0.654 ***	0.027

*** significant at 1% level of confidence.

Table 1. *Cumulative percentages of components eigenvalues (top) and loads per component (bottom).*

Dependent variable: price

Variable	Coefficient	Std. Errors
dummy_loose (t-1)	95.09 ***	5.63
period	-1.55 ***	0.18
dummy_t1	73.63 ***	18.54
dummy_t2	68.10 ***	18.59
dummy_t3	-4.57	18.64
pc1_scores	**-7.54** *	4.02
pc2_scores	**-20.24** ***	6.95
constant	461.70 ***	14.53

Number of obs = 8820
Number of groups = 180

Breusch and Pagan LM test for random effects
chi2(1) = 13584.52
Prob > chi2 = 0.0000

(*) significant at 10% confidence level, (**) significant at 5% confidence level,
(***) significant at 1% confidence level.

Table 2. *Random effects GLS regression: Pricing explained by risk attitudes.*

A4: Utility and probability-weighting function estimation: An econometric approach

Although the test is not designed to be used as a method of mapping decisions into parameter spaces, the results obtained here can be used to estimate probability weighting and utility function parameters, as is often done with other tests of risk attitudes based on choices among different probability-prize combinations. We present here the results from such an exercise, based, among others, on Abdellaoui et al. (2010) and Harrison and Rutström (2009). We estimate maximum likelihood models, adapting the structural model of binary choice to the context of choices among more than two alternatives.

Firstly, we estimate a standard Constant Relative Risk Aversion (CRRA) utility function, assuming expected utility theory (EUT). We assume that utility is defined by

$$U(X_j) = \frac{X_j^{(1-\alpha)}}{1-\alpha} + \varepsilon_i$$

Where, X_j is the lottery prize of lottery j, α is the parameter to be estimated and ε_i is unobserved stochastic influences. Under EUT, the value associated with the lottery satisfies:

$$EU_j = p_j \frac{X_j^{(1-\alpha)}}{1-\alpha}$$

Given the observed choices X_i, the subjects' probability of selecting the choice category represented by $y_i = j$ over all other choice categories is:

$$p(y_i = j|X_i,) = p\left(EU_{ij} > EU_{ik}\right) \forall j \neq k\ .$$

Assuming that ε_i is independently and identically distributed (IID) according to a logistic distribution,

$$p(y_i = j|X_i,) = \frac{e^{EU_{ij}}}{\sum_{k=0}^{9} e^{EU_{ik}}}$$

the log likelihood of the multinomial logit model is:

$$\ln \mathcal{L} = \sum_{i=1}^{N} \sum_{j=0}^{9} z_{ij} \ln \left(\frac{e^{EU_{ij}}}{\sum_{k=0}^{9} e^{EU_{ik}}}\right).$$

Secondly, we estimate maximum likelihood models, assuming Rank Dependent Utility Theory (RDUT). We consider the Tversky and Kahneman (1992) probability weighting function:

$$w_j = \frac{p_j^{\gamma}}{\left(p_j^{\gamma} + (1-p_j\ )^{\gamma}\right)^{\frac{1}{\gamma}}}$$

Under RDUT, the value associated with a lottery X satisfies:

$$EU_j = w_j \frac{X_j^{(1-\alpha)}}{1-\alpha}$$

We estimate the models using the clustering method that allow us the possibility of correlation between responses by the same subject. The standard errors on estimates are corrected for the possibility that the 4 responses are clustered for the same subject.

Estimation results are reported below in Table A1. All coefficients reported are significant at 1% confidence level. Under EUT, the CRRA coefficient is 0.64 that indicates that our subjects are risk averse. Under RDUT, the CRRA coefficient is again 0.64, which implies that our utility estimates are consistent across different theories, while the probability weighting function parameter is less than 1 and very close to previous estimates obtained in Tversky and Kahneman (1992) and several other studies thereafter.

	Expected Utility		Rank-Dependent Utility	
	Coefficient	Std. Errors	Coefficient	Std. Errors
α	0.64***	0.00	0.64***	0.00
γ			0.68***	0.00
Subjects 785				
N 3140				

(***)significant at 1% confidence level

Table A1.*Parameters estimates of Expected Utility and Rank-Dependent Utility theories*

As shown in Figure A1, the estimated probability-weighting function has the usual shape corresponding to overestimation of small probabilities and underestimation of large ones. Thus, our results can be easily used to infer parameter estimates corresponding to our subject' choices, although, as mentioned in the main text, the relevant dimensions relevant for empirical analysis aimed at explaining behavior in other contexts are those corresponding to the two principal components underlying observed behavior.

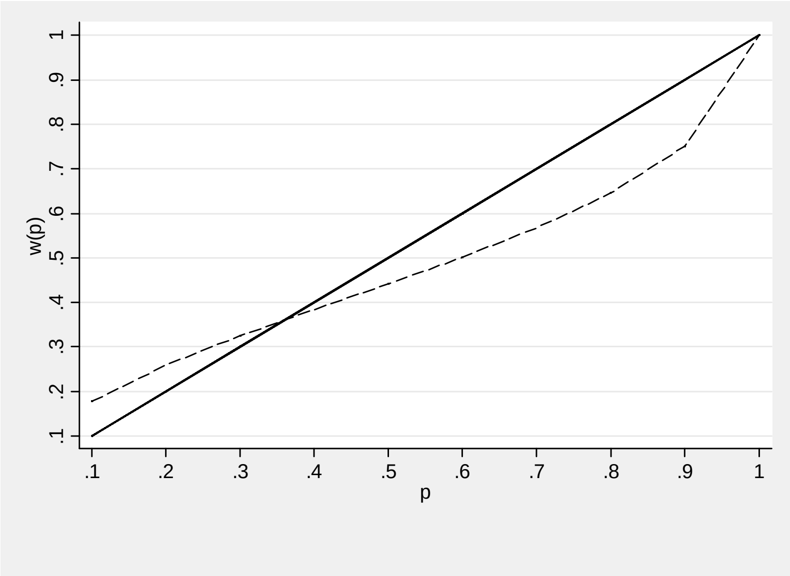

Figure A1. *Tversky and Kahneman (1992) probability weighting function.*

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