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Risk Attitude Elicitation Methods: Do They Tell Similar Stories?¹

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Abstract

We focus on the comparison of risk attitudes elicited through three different procedures with the goal to analyse the consistency of risk attitudes. Rank correlations are utilized to measure the degree of association of the subjects' choices and principal component analysis is employed to find the main factors describing the specific characteristics of risk attributes. We observe patterns of consistency in risk attitudes between two methods and within the selected multidimensional method, too. We find an evidence that gender and subjects' cognitive abilities play a certain role in the consistency of risk attitudes. Participants' choices in popular Holt and Laury method and the other two methods show nearly no relation. The principal component analysis supports the validity of the distinctive nature of the three risk elicitation methods. We also identify another aspect which is common in the different risk context; we call it the payoff risk sensitivity.

Keywords: risk attitudes, preference elicitation

JEL Classification: G02, C81, C91

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Introduction

Economists and psychologists have been interested in eliciting attitudes towards risk mostly for two purposes. First, to test theories. The progress made in our understanding and description of risky decision making has evolved thanks to a very fruitful dialogue between empirical tests questioning the existing theoretical postulates and new approaches addressing the resulting conflicts between predicted and observed behaviour. Second, as an external explanatory factor of behaviour in contexts, in which a subject's attitude could presumably play a role. Both research agendas resulting from these two parallel endeavours implicitly assume that a subject's attitude elicited in one risky context should be related to the subject's risk attitude in a different context to some extent. The relevance of risk attitudes elicited in one context for decision-making in another context has not been addressed sufficiently nor systematically.

This paper focuses on the comparison of different risk attitude elicitation methods. Our goal is to find the level of consistency of risk attitudes in different experimental contexts. We also aim to identify if gender and subjects' cognitive abilities play any role in it. We use three different risk attitude elicitation methods in this study. They are based on the Holt and Laury (2002) procedure (HL), Crosetto and Filippin's (2013a) static version of the Bomb Risk Elicitation Task (BRET) and the Sabater-Grande and Georgantzis (2002) lottery-panel task (SGG). HL and BRET procedures are uni-parametric methods and SGG is designed as multi-dimensional instrument for risk attitude elicitation. We conducted a risk attitude survey. All decisions made are hypothetical because some domains, like large stakes and especially losses, were impossible to implement with real monetary rewards. Results reported in this paper come from 181 subjects, all Slovak university students. Based on the exploratory analysis we study results of the risk elicitation methods and patterns within them. We use Spearman's rank correlations to compare risk attitudes based on the three methods. We employ principal component analysis (PCA) to understand the nature of the risk behaviour in the different context of choices; the objective of the analysis using PCA is dimensionality reduction and identification of the key factors, which can capture specific attributes of the dataset.

The paper contributes to the existing literature in two areas. Firstly, we compare different risk attitude elicitation methods and we identify overlapping areas with regard to the context of the risk elicitation. Secondly, we carry out the risk attitude survey among population of Slovakia, thus broadening research related to risk attitudes in this region. The paper is structured as follows. The first section provides an overview of the literature. The second section describes selected risk elicitation methods and the third one explains the methodology. In the fourth section we present results, which are discussed in the fifth section. The last section concludes.

1. Literature Review

Main theoretical foundation of risk attitudes in the decision making under uncertainty is expected utility theory introduced by von Neumann and Morgenstern (1944). Well-known counterproposal to this view is prospect theory (Kahneman and Tversky, 1979). Several risk attitude elicitation methods have been developed to test the theories. Among many the most popular methods have been designed by Becker, DeGroot and Marschak (1964), Cox, Roberson and Smith (1982) and Holt and Laury (2002). Validity of risk elicitation tasks has been addressed on very few occasions² which has been pointed out by García-Gallego et al. (2012) and Crosetto and Filippin (2013b). Exceptionally, risk elicitation procedures have been shown to explain subjects' behaviour in strategic contexts.³ However, although the Holt and Laury (2002) procedure has been adopted more frequently than other tasks as a risk elicitation device, there is still no conclusive evidence on whether the test reasonably predicts the behaviour of a subject in a different, even risk-related task. Several studies have been carried out to compare different risk elicitation tasks and their results suggest that there is rather weak connection between them.

Bruner (2009) employed multiple price list task where increase in the expected value happens either by increasing the reward or the probability. He found that 58% of the subjects exhibited different risk preferences in the two different tasks. Deck et al. (2010) compared four risk elicitation methods and found weak correlations between the two static tasks and two dynamic tasks, but not among any other pair. Harbaugh, Krause and Vesterlund (2010) studied repeated choices of subjects in two procedures and reported that nearly 50% of the subjects changed their attitudes across the tasks. Goal of the study of Reynaud and Couverture (2012) was to test stability of risk preferences across four different elicitation methods and they found two of them⁴ being moderately correlated.

Crosetto and Filippin (2013a) compared their BRET method with three and Crosetto and Filippin (2013b) with four most frequently used risk elicitation procedures⁵ finding significant differences in the results and in the classification of subjects emerging from these procedures. Comparisons of different methods assume that subjects will try to maximise their utility in every period and every

² Well-known examples are Harrison (1990), Harbaugh, Krause and Vesterlund (2010), Bruner (2009) and Isaac and James (2000).

³ See for example, Sabater-Grande and Georgantzis (2002), and Charness and Villeval (2009) on the connection between risk taking and cooperation or Heinemann, Nagel and Ockenfels (2009) on uncertainty and coordination.

⁴ These were the methods based on Holt and Laury (2002), and Eckel and Grossman (2002),

⁵ The procedures introduced in Holt and Laury (2002), Eckel and Grossman (2002), Gneezy and Potters (1997) and finally in Lejuez et al. (2002).

situation, thus having stable approach to risk. Crosetto and Filippin (2013b) suggest that some subjects may choose to make more risky decisions in one task and more risk averse in another task to balance their previous decisions. Deck et al. (2013) conducted a laboratory study using multiple paid risk elicitation tasks and a risk attitude survey. Consistent with previous research, they indicated considerable within-subject variation in behaviour across tasks.

Comparative studies mentioned above generally claim that inconsistent behaviour can be explained by a subject's specific risk attitude in the given decision making context. To address this matter, we include one multidimensional method assuming its four different domains provide more comprehensive description of subject's risk attitude. We expect certain level of consistency of decisions across tasks, but not their uniformity, which would prove one of the domains being unnecessary. The other two selected methods are uni-parametric and we want to observe how much they relate to each other and to respective domains of a multidimensional method. Our first hypothesis is that domains of multidimensional method will be significantly (at least weakly) correlated with each other. Our second hypothesis is that each of the uni-parametric methods will be significantly (at least weakly) correlated with one or more domains of multidimensional method. We include testing for gender effects and effects of cognitive abilities.

2. Selected risk elicitation methods

We employ three different risk attitude elicitation methods in this study. One of the methods we use is perhaps the most popular approach for measuring risk tolerance in the lab. It is the one of Holt and Laury (2002) in which subjects are asked to make a series of binary choices over the lottery pairs with gradually increasing probabilities, where one of the lottery pairs is the safer choice. Table 1 provides an overview of the risk aversion classification based on lottery choices. The range of relative risk aversion in this classification is determined based on the following utility function:

$$U(x) = \frac{x^{1-r}}{1-r} \quad (1)$$

Authors further propose a "hybrid power-expo utility" function that exhibits both increasing relative risk aversion and decreasing absolute risk aversion. Major advantages that led to the popularity of the HL tables include its transparency to subjects (easy to explain and implement), and that it can be easily attached to other experiments where risk aversion may have an influence. Nevertheless, the HL method has also several disadvantages. For instance, one disadvantage is that it is quite sensitive to probability weighting since it uses variations of probabilities

instead of outcomes in its elicitation. Another disadvantage is that the HL tables need an expected utility framework in order to make predictions on the intensity of risk aversion. They are thus unable to classify subjects as being more or less risk averse without imposing expected utility on them.

Table 1

Risk Aversion Classification Based on Lottery Choices According to Holt and Laury

Number of safe choices	r (min)	r (max)	Risk preference classification
0	<	-1.71282	Highly risk loving
1	-1.71282	-0.946837	Highly risk loving
2	-0.946837	-0.486575	Very risk loving
3	-0.486575	-0.142632	Risk loving
4	-0.142632	0.146363	Risk neutral
5	0.146363	0.411456	Slightly risk averse
6	0.411456	0.67618	Risk averse
7	0.67618	0.970581	Very risk averse
8	0.970581	1.36839	Highly risk averse
9	1.36839	<	Stay in bed
10	-----	-----	Non-applicable

Source: Holt and Laury (2002), adjusted.

Second method used in our paper is the Bomb Risk Elicitation Task (BRET), which is an intuitive procedure aimed at measuring risk attitudes introduced by Crosetto and Filippin (2013a). Subjects decide how many boxes to collect out of 100, one of which containing a bomb. Earnings increase linearly with the number of boxes accumulated, but are zero if the bomb is also collected. In the static version of the task, subjects face a 10 x 10 square in which each cell represents a box. They are told that 99 boxes are empty, while one contains a time bomb programmed to explode at the end of the task, i.e., after choices have been made. Subjects are asked to choose a number $k_i^* \in [0, 100]$ that corresponds to the number of boxes they want to collect, starting from the upper left corner of the square. The position of the time bomb ($b \in [1, 100]$) is determined after the choice is made by drawing a number from 1 to 100 from an urn. If $k_i^* \geq b$, it means that subject collected the bomb, which wipes out the subject's earnings. Otherwise the subject leaves the minefield without the bomb and receives certain monetary amount for every box collected. Authors assume classic constant relative risk aversion power utility function:

$$U(x) = x^r \quad (2)$$

and then

$$k^* = 100 \frac{r}{1+r} \quad (3)$$

which suggests that risk neutral subject should choose $k_i^* = 50$, with corresponding r from the range $[0.981, 1.020]$. Risk averse subject choose $k_i^* \leq 49$ with corresponding r from the range $[0.00, 0.98]$ and risk loving subject choose $k_i^* \geq 51$ with corresponding r from the range $[1.021, 68.275]$.

The third elicitation method we use in our study is the Sabater-Grande and Georgantzis (SGG) lottery-panel test designed by Sabater-Grande and Georgantzis (2002). It is implemented in our study as four different tasks, which we call different domains, corresponding to a different combination of low gains, high gains, low losses and high losses. Each domain consists of four different panels; each panel offers increasing at the same probabilities, with panel 1 offering the lowest and panel 4 the highest payoffs in the given domain. In each lottery, subjects can either win a payoff X with a probability p or on payoffs the other hand gain nothing (domains of low and high gains) or even lose some money (domains of low and high losses). Subjects choose one of the ten lotteries from each panel. The range of winning probabilities in all panels is the same (from 1 to 0.1 in steps of 0.1).

SGG lottery-panel test at the same time offers a range of different returns to risk so that a more risk averse subject might refuse to take risky options in the first or the second panel, but could be attracted to risky prospects when a high return is offered in panels 3 and 4. Thus, unlike uni-decision tests, this task may be used to classify subjects not only according to their willingness to take risks, but also with respect to their propensity to change across different risk-return combinations. Moreover, for a given risk aversion parameter, weakly monotonic transitions towards riskier choices are predicted as we move from panel 1 to panel 4 (García-Gallego et al., 2011). 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 individual subject, we can easily see that the test parsimoniously produces a panel rather than a single column of data. By the definition, this corresponds to a multi-dimensional description of individual attitudes towards risk.

Each of the HL and BRET approaches measure risk aversion parameter r with slightly different formula and thus lower r in HL corresponds to risk loving attitude while in BRET it describes risk aversion.⁶ Both methods distinguish three broad categories of risk averse, risk neutral and risk loving attitudes. SGG method does not provide straightforward mathematical formula to calculate risk aversion parameter r and it also does not distinguish between risk neutral and risk loving attitudes. SGG approach focuses on the effect of risk aversion across different domains and in the context of increasing stakes.

⁶ We can see in the formula (1) and formula (3) that there is a difference in the denominator being $1 - r$ in the HL method and $1 + r$ in the BRET method.

3. Methodology

To elicit the risk preferences, we conducted a controlled paper and pencil risk attitude experiments in April and May of 2013. These experiments have all features of controlled experiments apart from monetary incentives (the payments were hypothetical). That is why we refer to them as surveys in this text. The surveys were conducted in university premises within nine sessions. Each session lasted approximately 1 hour, including instructions. A survey was divided into 2 parts: Risk elicitation tasks⁷ and Cognitive Reflection Test (CRT). To avoid any ordering effects,⁸ tasks were randomly mixed. Participation in survey was voluntary and all payments were hypothetical. The results reported in this study are from 181 subjects, students of undergraduate and master study programs recruited at the University of Economics in Bratislava. Total number of female students participating in the experiment was significantly higher (116 vs. 65).⁹ 113 subjects were full-time university students and 68 were part time students with different working backgrounds. They were students of both undergraduate and master study programs in economics and applied economy informatics. We have made an adjustment in the sample excluding subjects, whose choices did not make sense, could be random or could be made without actual understanding of the tasks.¹⁰ Based on HL method we excluded those, selecting 10 safe choices. Such subject chose the certain payoff of 200 EUR over the certain payoff of 385 EUR. Based on BRET method we excluded subjects who collected 100 boxes. This choice means losing any possible gain, because it is certain that the “bomb”, erasing all gains, is among 100 boxes. It may indicate that the person makes decisions randomly, or doesn't comprehend the lottery options.

We use CRT in this study in order to capture the different cognitive abilities of the subjects. Two types of cognitive processes have been distinguished and emphasized by researchers (e.g. Epstein, 1994; Sloman, 1996): one which is fast, impulsive and often emotionally charged and another one which is slower, more reflective and deliberately controlled. Stanovich and West (2000) named them as

⁷ It is important to mention that we did not change the design of the risk elicitation tasks. The parametrization was used as in original papers since our aim was not to devise a new methodology but to compare existing ones.

⁸ Ordering effect refers to the process of working through a series of choice tasks which could influence the stated preferences leading to choice outcomes that are dependent on the order in which a question is answered.

⁹ The proportion could be unbalanced due to the predominance of female students at the university (which is generally the case of students in social and economic sciences in Slovakia).

¹⁰ In total 198 subjects participated in the survey and we excluded 17. The results reported in this study are from 181 subjects.

“System 1” and “System 2”. These “dual process” theories of cognition became popular in accounts of risk perception and science communication thanks to Kahneman (2003). Frederick (2005) designed CRT as three problems. The three problems are not difficult and their solution is easily understood when explained. However, in all three problems there are seemingly intuitive answers that are incorrect and are chosen by impulsive subjects. The subject needs to overcome the initial and impulsive wrong answer in order to find the correct answer. We divide subjects into two groups based on their correct answers to CRT problems. First group represents lower cognitive abilities and consists of those subjects who gave 0 or 1 correct answers. Second group represents higher cognitive abilities and consists of subjects who solved 2 or 3 problems correctly. CRT subject instructions are included in the appendix.

When analysing data, we first provide exploratory analysis to study results of the risk elicitation methods and patterns within them. In order to compare the methods, we use Spearman’s rank correlations. Rank correlation is an appropriate method for comparing the continuous, discrete or ordinal variables. Unlike Pearson’s correlation coefficient, rank correlation coefficient does not measure the degree of linear association between the two variables but the similarity of their rankings. Moreover, it is not sensitive to outliers. There are several versions of rank correlation. Spearman correlation coefficient is a non-parametric version of Pearson correlation coefficient. It is a statistical measure of the strength of a monotonic relationship. Spearman correlation coefficient is calculated in such a way that in the formula for Pearson’s correlation coefficient the values of variables are replaced with their rank:

$$\rho = \frac{\sum_{i=1}^N (rX_i - r\bar{X})(rY_i - r\bar{Y})}{\sqrt{\sum_{i=1}^N (rX_i - r\bar{X})^2} \sqrt{\sum_{i=1}^N (rY_i - r\bar{Y})^2}} \quad (4)$$

where rX stands for ranks of variable X and rY stands for ranks of variable Y . Similar as Pearson correlation coefficient it takes on values from -1 to $+1$. Closer values to these limits denote stronger monotonic relationship.

Next, we use principal component analysis (PCA) to find the common patterns in risk attitudes. It is a statistical method for reducing a dimensionality of data. It attempts to represent original variables with a parsimonious set of their linear combinations that account for the substantial part of their variance. These linear combinations are known as principal components (or factors), they have a unit length and are orthogonal (i.e. linearly unrelated) to each other. The coefficients in the linear combinations are known as factor loadings.

The first step of the procedure is rather straightforward and consists in eigenvector decomposition of a correlation (or covariance) matrix. The first principal component corresponds to the highest eigenvalue and represents the highest proportion of variance. The second principal component corresponds to the second largest eigenvalue, etc. Since the correlation (or covariance) matrix is positive semi-definite, the eigenvalues are real numbers and their number is equal to the rank of a correlation matrix. If the original variables are not perfectly collinear, the number of principal components is equal to the number of original variables. Since the objective of PCA is dimensionality reduction, not all principal components are retained. Several rules are used, one of them is Kaiser criterion where only the principal components with corresponding eigenvalues higher than one are retained. Another one is selection procedure based on scree plot of eigenvalues. Other rules involve percentages of explained variability and percentage of uniqueness (percentage of unexplained variability by chosen factors).

Usually, principal components obtained in this way are difficult to interpret and that is why the second step is used – rotation. This step assures a relatively simple structure of principal component matrix with respect to the original variables. If the goal is to simplify interpretation and polarize the factor loadings, i.e. factors are related to the original variables either strongly or not at all, varimax method is preferable.

4. Results

4.1. Descriptive Analysis

The Table 2 shows the descriptive statistics of the coherent sample of subjects' responses to risk elicitation tasks used in further analysis. The units of the variables correspond to the nature of a given task. In SGG panels the units are the probability of the win in the chosen lottery (between 0.1 – 1). In BRET the subjects chose the number of fields from 0 to 99. In HL method the response is measured by the number of safe options (from 0 to 9).

We report mean and standard deviation of the responses for the whole sample and then disaggregate the results based on two variables – gender (male/female) and the number of correct answers in Cognitive reflection test (CRT) – first category 0 or 1 correct answers and the second category 2 or 3 correct options.

When interpreting the results from Table 2, according to SGG method higher the probability chosen, more risk averse the subject is. Similarly, in HL method the risk aversion of the subject increases with the increase of safe options selected. However, in the BRET method the higher number of fields indicates decreasing

risk aversion. Based on SGG results we can see that subjects are on average more risk averse in high gains and high losses domains when compared to low gains and low losses. We also observe that subjects on average take more risk, when the stakes increase (within each domain).

Table 2

Descriptive Statistics

Risk elicitation method		All sample (N = 181)		Male (N = 65)		Female (N = 116)		CRT = 0 – 1 (N = 153)		CRT = 2 – 3 (N = 28)	
		Mean	St. dev.	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.
SGG low gains	Panel 1 (prob.)	0.51	0.31	0.54	0.32	0.50	0.31	0.52	0.31	0.50	0.31
	Panel 2 (prob.)	0.48	0.28	0.50	0.28	0.46	0.29	0.47	0.28	0.50	0.30
	Panel 3 (prob.)	0.46	0.26	0.52	0.25	0.43	0.26	0.46	0.26	0.48	0.27
	Panel 4 (prob.)	0.43	0.28	0.49	0.27	0.40	0.28	0.43	0.27	0.44	0.29
SGG high gains	Panel 1 (prob.)	0.70	0.28	0.72	0.25	0.69	0.29	0.69	0.28	0.73	0.26
	Panel 2 (prob.)	0.65	0.25	0.68	0.23	0.64	0.26	0.65	0.25	0.68	0.25
	Panel 3 (prob.)	0.63	0.25	0.67	0.23	0.61	0.25	0.63	0.25	0.63	0.22
	Panel 4 (prob.)	0.55	0.28	0.56	0.29	0.54	0.28	0.55	0.28	0.58	0.28
SGG low losses	Panel 1 (prob.)	0.50	0.28	0.53	0.27	0.49	0.28	0.50	0.27	0.54	0.29
	Panel 2 (prob.)	0.49	0.27	0.52	0.26	0.46	0.27	0.47	0.26	0.55	0.28
	Panel 3 (prob.)	0.47	0.25	0.52	0.25	0.45	0.25	0.47	0.25	0.50	0.25
	Panel 4 (prob.)	0.46	0.27	0.50	0.27	0.44	0.27	0.46	0.27	0.49	0.27
SGG high losses	Panel 1 (prob.)	0.72	0.26	0.72	0.24	0.72	0.27	0.72	0.27	0.72	0.23
	Panel 2 (prob.)	0.71	0.24	0.73	0.21	0.70	0.26	0.71	0.25	0.73	0.17
	Panel 3 (prob.)	0.71	0.24	0.69	0.24	0.72	0.24	0.71	0.25	0.70	0.18
	Panel 4 (prob.)	0.68	0.26	0.66	0.26	0.69	0.27	0.68	0.27	0.70	0.23
BRET	Number of fields	44.37	24.73	45.78	23.49	43.58	25.46	43.94	25.06	46.71	23.11
Holt-Laury	Safe options	5.14	1.75	4.94	1.53	5.26	1.86	5.16	1.72	5.07	1.92

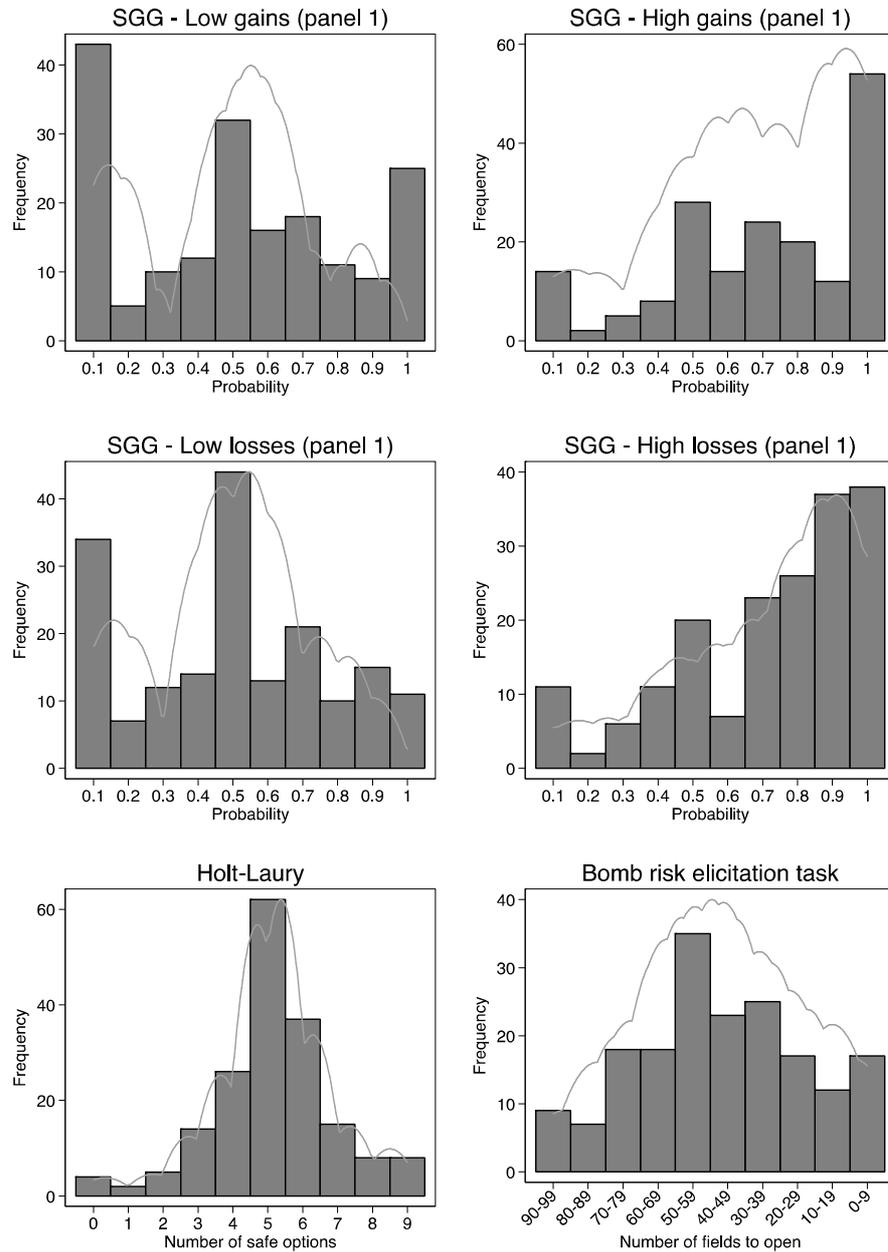
Source: Authors' calculations.

When comparing male and female subjects, average results suggest that males are on average little more risk averse than females in all domains of SGG method, except for high losses domain, where differences are very small and not monotonic. On the other hand, average choices of HL and BRET methods indicate little more risk averse attitude of females. However, based on the two-sided t-test¹¹ we conclude that gender differences are not statistically significant, except for panel 3 and 4 in SGG low gains domain.

We see only very small differences in risk attitudes based on CRT results. Subjects with higher cognitive abilities based on average of choices in SGG method are slightly more risk averse but only in high gains and low losses domains. There is no actual difference in low gains and high losses domains. Average results of BRET and HL methods suggest that subject with lower cognitive abilities are slightly more risk averse. Also in this case, we conclude that gender differences are not statistically significant based on the two-sided t-test.

¹¹ t-test results are not reported in this paper, but they are available from authors upon request.

Figure 1
Histograms and Kernel Density Functions for Participants' Choices



Note: Whole sample (N = 181).

Source: Authors' calculations.

Average values have a limitation in that they reduce information contained in the dataset into one number. That is why next step of our descriptive analysis is to look at and compare distribution patterns. To this end we compare histograms and empirical kernel density functions.

Figure 1 presents histograms and kernel density functions for participants' choices. For each domain of SGG method we select only one panel as a representative for the given domain. We chose the panel where the greatest dispersion in answers was observed.¹² In order to facilitate the comparison with other methods we binned values for BRET into 10 categories and we reversed x-axis so that risk averse choices are on the right-hand side.

4.2. Consistency of the Risk Attitudes within the Multidimensional SGG Method

We use Spearman rank correlation to analyse relationships between choices across various domains of multidimensional SGG method. Table 3 provides summary of correlations of SGG domains.¹³ When comparing different panels within each of the four SGG domains, we find significant strong correlations between them (from 0.50 to 0.88) with just one exception of high gains domain (correlation between panel 1 and 4 = 0.39). The correlation between panel 1 and panel 4 is always the weakest in each domain. Thus, we find evidence for strong consistency in the same risk context represented by a domain, with correlations becoming weaker as the difference between the stakes becomes bigger.

Table 3

Spearman Rank Correlation between SGG Domains – Summary

	SGG low gains	SGG high gains	SGG low losses	SGG high losses
SGG low gains	0.711 (0.56 – 0.88)			
SGG high gains	0.341 (0.23 – 0.55)	0.582 (0.39 – 0.72)		
SGG low losses	0.503 (0.40 – 0.61)	0.269 (0.15 – 0.43)	0.700 (0.50 – 0.82)	
SGG high losses	0.240 (0.17 – 0.35)	0.300 (0.13 – 0.38)	0.256 (0.08 – 0.38)	0.717 (0.55 – 0.83)

Source: Authors' calculations,

First value is an average of correlations between all 4 panels within each domain. Values in parentheses represent the range of correlations. Full results are reported in appendix. All correlations were statistically significant at 5% level.

¹² Sabater-Grande and Georgantzis (2002) used this approach to select a representative panel for the domain.

¹³ Full results are reported in appendix.

When we compare different SGG domains with each other, we find mostly moderate correlations (exceptionally exceeding 0.50). Strong correlations are between low gains and low losses (average correlation 0.503). We also observe that panels 4 across all domains are always most correlated with each other (average correlation 0.444, with range 0.35 – 0.61). Overall we find strong connections of choices within respective domains and weaker links across domains, with low gains and low losses showing the closest similarity.

We also find that choices of male subjects are more correlated in domains of low gains and low losses and then in high gains and high losses when compared to females. On the other hand, cognitive abilities do not play any role in this regard.¹⁴

4.3. Consistency of the Risk Attitudes Elicited through Different Methods

In this part, we also use Spearman rank correlation to determine the consistency of risk attitudes across various risk elicitation methods. Tables 4, 5 and 6 present the results of correlations between HL and BRET, SGG and HL, and SGG and BRET, including the male and female comparison and comparison of subjects with lower and higher cognitive abilities. BRET is represented by number of fields open, HL by number of safe options and SGG by probabilities. The higher number of fields open in BRET indicates lower risk aversion, while the higher number of safe options in HL and higher probability in SGG indicates higher risk aversion. Therefore, negative correlations between BRET and other methods are the sign of their consistency.

Table 4

Spearman Rank Correlation of HL and BRET Tests

	Holt-Laury				
	all	male	female	CRT = 0 – 1	CRT = 2 – 3
	N = 181	N = 65	N = 116	N = 153	N = 28
BRET	-0.0406	0.081	-0.0906	-0.0639	0.0601

BRET is represented by number of fields open and HL by number of safe options.

HL is represented by number of safe options and SGG by probabilities.

Source: Authors' calculations.

First of all we obtain a very low and statistically insignificant correlation (Spearman correlation coefficient = -0.04) between the HL and the BRET methods, with no difference in results for males or females, neither for subjects with different cognitive abilities. These two uni-parametric methods seem to produce unrelated risk attitudes.¹⁵

¹⁴ The corresponding results are presented in appendix.

Table 5
Spearman Rank Correlation of HL and SGG Methods

		Holt-Laury				
		all	male	female	CRT = 0 – 1	CRT = 2 – 3
		N = 181	N = 65	N = 116	N = 153	N = 28
SGG low gains	panel 1	0.1083	0.03	0.1508	0.1475	-0.0953
	panel 2	0.1771*	0.1209	0.2159*	0.2314*	-0.0872
	panel 3	0.113	0.099	0.1449	0.1515	-0.0989
	panel 4	0.1508*	0.3161*	0.0933	0.1729*	0.0364
SGG high gains	panel 1	0.0786	0.2537*	0.0049	0.1022	-0.0343
	panel 2	0.1274	0.1213	0.1317	0.1659*	-0.0707
	panel 3	0.0352	0.0848	0.0166	0.0392	0.0107
	panel 4	0.0756	0.2743*	-0.0234	0.0602	0.1911
SGG low losses	panel 1	0.0523	0.0814	0.0453	0.1048	-0.1845
	panel 2	0.051	0.1612	0.0124	0.0666	-0.0024
	panel 3	0.0222	0.212	-0.0572	0.0178	0.075
	panel 4	0.0428	0.2834*	-0.0622	0.0734	-0.0963
SGG high losses	panel 1	0.1512*	0.2852*	0.0867	0.1762*	0.0602
	panel 2	0.1251	0.2137	0.0887	0.1643*	-0.0537
	panel 3	0.0986	0.2807*	0.0056	0.1437	-0.1029
	panel 4	0.1747*	0.3858*	0.0717	0.1779*	0.2207

Source: Authors' calculations.

When we obtain correlations between the HL test and the SGG choices made in the four different domains, we observe only weak correlations and only in some panels in the low gains and high losses domains for all subjects (Spearman correlation coefficient is between 0.1 – 0.18). Otherwise there are no significant correlations.

However, there is a difference when we consider gender – there is some consistency (moderate correlations) of male subjects' risk attitude elicited through HL and SGG for high stakes (panel 4) across all domains; Spearman correlation coefficient is between 0.27 – 0.39. For female subjects, there is almost no significant correlation across all domains and all panels (with just one exception of panel 2 in low gains domain). Risk decisions of subjects with higher cognitive abilities were utterly unrelated between HL and SGG methods (from the perspective of statistical significance).

However, subjects with more impulsive decision making (with CRT = 0 – 1) showed some relations through weak correlations in several panels across low gains, high gains and high losses domains (Spearman correlation coefficient is between 0.17 – 0.23).

¹⁵ Both HL and BRET allow calculation of relative risk aversion parameter r based on constant relative risk aversion utility function. Since the transformation is monotonic (for HL and BRET only) and Spearman rank correlations compare rankings of two variables, the results obtained using risk aversion parameter instead of raw values gave nearly identical results. Results are not reported in this paper, but they are available from authors upon request.

Table 6

Spearman Rank Correlation of BRET and SGG Methods

		BRET				
		all	male	female	CRT = 0 – 1	CRT = 2 – 3
		N = 181	N = 65	N = 116	N = 153	N = 28
SGG low gains	panel 1	-0.2111*	-0.3647*	-0.1418	-0.1893*	-0.3517
	panel 2	-0.1883*	-0.2924*	-0.1435	-0.1487	-0.4406*
	panel 3	-0.2092*	-0.3831*	-0.1327	-0.1716*	-0.4655*
	panel 4	-0.2733*	-0.3465*	-0.2458*	-0.2269*	-0.5216*
SGG high gains	panel 1	-0.1978*	-0.2214	-0.1992*	-0.1869*	-0.2544
	panel 2	-0.2203*	-0.2277	-0.2235*	-0.1948*	-0.3684
	panel 3	-0.1830*	-0.2538*	-0.1521	-0.1699*	-0.2543
	panel 4	-0.1579*	-0.2079	-0.1443	-0.1475	-0.2295
SGG low losses	panel 1	-0.0683	-0.2366	0.0129	-0.0102	-0.4101*
	panel 2	-0.0865	-0.2935*	0.0074	-0.0358	-0.4127*
	panel 3	-0.1003	-0.3251*	0.0117	-0.0419	-0.4819*
	panel 4	-0.1282	-0.3657*	-0.0135	-0.0737	-0.4847*
SGG high losses	panel 1	-0.0707	-0.0655	-0.0757	-0.0345	-0.2877
	panel 2	-0.0594	-0.0729	-0.0624	-0.0532	-0.1546
	panel 3	-0.0478	-0.0393	-0.0498	-0.0497	0.0071
	panel 4	-0.1523*	-0.0961	-0.1739	-0.1928*	0.0906

BRET is represented by number of fields open and SGG by probabilities.

Source: Authors' calculations.

The correlation between BRET and SGG methods reveal some pattern of consistency and at the same time we observe differences based on gender and cognitive abilities. We discern weak but significant correlation for all subjects (Spearman correlation coefficient is between 0.16 – 0.27) in domains of low and high gains (all panels); otherwise choices are not significantly correlated. The results in low gains domain seem to be driven by males.

Male subjects are on average moderately consistent with their risk attitude according to BRET and two SGG domains (7 of 8 panels in low gains and low losses domains); Spearman correlation coefficient is between 0.29 – 0.39.

Female subjects are seldom consistent in their risk attitude derived from BRET and SGG methods, there is no clear pattern. There is a weak correlation for only some panels of low and high gains in SGG domains (Spearman correlation coefficient is between 0.20 – 0.25). Interestingly, similar to males, the subjects with higher cognitive abilities seem to be consistent with their risk attitudes in BRET method and SGG domains of low gains and low losses; we obtain moderate to strong correlations (0.35 – 0.52). Decisions of subjects with lower cognitive capacity in BRET method are only weakly correlated (yet the coefficients are statistically significant) with low and high gains domains of SGG method.

4.4. Studying Latent Common Dimensions of Risk Attitudes

We use principal component analysis (PCA), which should help us to understand the nature of the risk behaviour. The objective of PCA is dimensionality reduction, finding the main factors best explaining particular characteristics of the data. Our survey provides us with 18 choices per subject in total; 16 are obtained from SGG method and one from HL and BRET methods each.

Firstly, we use Kaiser criterion and PCA gives us five factors with eigenvalue higher than one. These factors capture 76% of subjects' choice variance. However, uniqueness of HL and BRET is 65% and 72% respectively, i.e. there is large proportion of unexplained variability in these two methods. That is why we increase the number of retained factors to seven. The choice of number of retained factors is also supported by scree plot of eigenvalues, where the flat part of the plot starts with the eighth eigenvalue.

Table 7

Principal Component Analysis

Rotated Factor Loadings (pattern matrix) and Unique Variances

Variable	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Uniqueness
SGG lg p1	0.0950	0.2977	0.8357	0.1456	-0.0661	0.0910	-0.1044	0.1592
SGG lg p2	0.1227	0.2467	0.8868	0.1441	0.0358	0.1039	-0.0630	0.1009
SGG lg p3	0.1219	0.2996	0.7999	0.1695	0.2329	-0.0311	-0.0666	0.1671
SGG lg p4	0.1297	0.2997	0.6248	0.1592	0.5109	0.0330	-0.1542	0.1917
SGG hg p1	0.1633	0.1643	0.1160	0.8448	-0.1653	0.0498	-0.1190	0.1751
SGG hg p2	0.1909	0.0990	0.1442	0.8527	0.1364	0.1102	-0.1035	0.1644
SGG hg p3	0.2197	0.0679	0.2471	0.7478	0.2830	-0.1078	0.0021	0.2352
SGG hg p4	0.0658	0.1063	0.1787	0.5843	0.6142	0.0550	-0.0240	0.2302
SGG ll p1	0.0772	0.7720	0.3602	0.1718	-0.2678	0.0241	0.0060	0.1666
SGG ll p2	0.1674	0.8910	0.2590	0.1418	-0.0411	0.0040	0.0025	0.0891
SGG ll p3	0.1422	0.8397	0.2579	0.0656	0.2829	-0.0661	-0.0164	0.1192
SGG ll p4	0.1721	0.7367	0.1904	0.0198	0.5170	0.0219	-0.0663	0.1189
SGG hl p1	0.8295	0.1493	0.1918	0.1406	-0.1831	0.0472	-0.0288	0.1966
SGG hl p2	0.9174	0.1684	0.0971	0.1483	-0.0180	0.0210	-0.0346	0.0967
SGG hl p3	0.8850	0.1025	0.0560	0.1493	0.1685	-0.0572	0.0138	0.1489
SGG hl p4	0.7370	0.0706	0.0661	0.1218	0.4656	0.1607	-0.1167	0.1764
BRET	-0.0516	-0.0147	-0.1315	-0.1135	-0.0420	-0.0230	0.9767	0.0108
Holt-Laury	0.0447	-0.0195	0.0916	0.0511	0.0287	0.9794	-0.0227	0.0260

Source: Authors' calculations.

Table 7 presents rotated factors loadings (factor loadings higher than 0.45 are in bold – they represent substantial correlation between the factor and given variable); we use these results to interpret individual factors. Factor 1 is mainly determined by all four panels of the high losses domain; factor 2 by all panels of the low losses domain; factor 3 by all panels of the low gains domain; factor 4 by all panels of the high gains domain. Each of them captures between 14 – 17% of the variance. Therefore, the order of factors 1 – 4 is not important; their explanatory

value is nearly equivalent. Factor 5 is a specific and we will analyse it in the next paragraph. Factors 6 and 7 present the evidence that risk attitudes obtained by the HL and BRET methods represent a specific risk dimension not captured by SGG multidimensional method. Proportion of explained variance is about 6% for each of them. See Table 8 for a detailed report.

Each of the first 4 factors represents a different dimension of risk attitude. Each of them can be described as a mean measure of risk aversion in a specific risk environment (domains of high or low losses, and high or low gains). The higher is the score of each of the factors, the more risk averse the subject is and vice versa.

Table 8

Proportion of Variance Explained by Rotated Factors

Factor	Variance	Difference	Proportion	Cumulative
Factor 1	3.11605	0.02987	0.1731	0.1731
Factor 2	3.08619	0.06486	0.1715	0.3446
Factor 3	3.02133	0.43518	0.1679	0.5124
Factor 4	2.58616	1.05971	0.1437	0.6561
Factor 5	1.52645	0.47902	0.0848	0.7409
Factor 6	1.04743	0.00394	0.0582	0.7991
Factor 7	1.04349	.	0.058	0.8571

Source: Authors' calculations.

Factor 5 can be seen as a measure of a subject's sensitivity to variations in the return to risk. There is a pattern in every domain of SGG: the factor loadings are always negative in panel 1 and they gradually increase reaching a maximum in panel 4. Panel 4 offers the highest gains among all four panels while the potential loss (or zero gain option) remains the same. This factor reacts on the amount of payoff, which is at stake. Factor 5 can be described as an additional measure of risk attitudes. We call this dimension *the payoff risk sensitivity*. Risk averse subjects (*payoff risk sensitive*) will prefer safer options in higher panels. Therefore, the higher is the value of the factor, the more risk averse the subject is in the context of potential high gains (the loss is the same for all panels in each domain). Risk neutral subject (*payoff risk sensitive*) will choose same (or similar) options across the four panels within the domain. Risk loving subjects (*payoff risk sensitive*) will prefer risky options in higher panels. The lower is the value of the factor, the more risk loving (*payoff risk sensitive*) the subject is. Factor 5 explains 8.5% of the variance of subjects' choices, which is about one half the explanatory power of each of factors 1 to 4. Noteworthy, HL and BRET are not related to this factor at all (factor loadings are close to zero).

The disaggregation of a sample based on gender or cognitive abilities did not bring any particular additional insights.¹⁶ The patterns in the whole sample remain

approximately valid in these sub-samples. The risk attitudes elicited by HL and BRET continue to be unrelated to each other and to those gained using SGG method. Some changes occurred in the structure of the risk attitudes elicited by multidimensional SGG method, though. Males seem to associate low gains and low losses domains; formerly two distinctive factors identified in the whole sample collapse into one. When considering the payoff risk sensitivity factor, the results for whole sample seem to be driven by males. For female subjects the factor loadings are smaller compared to males and the payoff risk sensitivity factor is more associated with panels 1 than panels 4.¹⁶

The latent factors underlying the risk attitudes of people with lower cognitive abilities do not differ much from those uncovered in the whole sample either. Here, the risk payoff sensitivity factor is slightly less linked to the low losses and high losses panels. In the sub-sample of subjects with higher cognitive abilities we report that five factors explaining the risk attitudes elicited by SGG method collapsed into three factors, however this may be a consequence of a small size of the sub-sample.

5. Discussion

First we conduct exploratory analysis. Based on SGG results we can see that subjects are on average more risk averse in high gains and high losses domains when compared to low gains and low losses. When we analyse frequency of choices we observe that the riskiest options are the most frequent in low gains and low losses SGG domains whereas they nearly disappear in high gains and high losses SGG domains. This finding supports the notion that the context of decision making plays an important role. Next, when comparing the choices within the same domains, we observe that subjects on average take more risk, when the stakes increase. The common pattern, where subjects have chosen higher winning probability (with smaller reward) in the decisions involving higher stakes, was reported also by Holt and Laury (2002).

When comparing male and female participants, results suggest that there are no significant differences in their risk attitudes based on HL and BRET methods and partially also on SGG method. Exceptions are the two panels of SGG low gains domain, where males are on average little more risk averse than females. We suggest that some of the well-known gender effects¹⁷ reported on risky decision

¹⁶ Results are not reported in this paper, but they are available from authors upon request.

¹⁷ There is a long list of literature on gender differences in risk taking claiming that males are more risk tolerant than females. For meta-analysis of 150 studies see Byrnes, Miller and Schafer (1999).

making may be due to differences in subjects' sensitivity to risk premium variations. However, a research on similar sample of university students by Baláž et al., 2013 concluded, that there was no difference in risk attitudes between the genders. When we compare subjects based on their cognitive abilities, results indicate that there are no significant differences in their risk attitudes.

Based on rank correlations between choices across various domains of multi-dimensional SGG method, we find evidence for strong consistency in the same risk context represented by a domain, with correlations becoming weaker as the difference between the stakes becomes bigger.

On the other hand, the links across SGG domains are weaker, albeit low gains and low losses exhibit certain degree of similarity, driven primarily by males. Cognitive abilities do not seem to make any difference. This finding is compatible with previous results reported by Brañas, Guillen and Lopez del Paso (2008) who had shown that behaviour in the SGG test is independent of the subject's mathematical skills.

When we compare the three risk elicitation methods, we find almost no association between subjects' choices in HL and BRET. Next we look at HL and SGG methods and find rather weak and rare consistency within low gains and low losses SGG domains. Further analysis revealed that the result was driven by male participants and those with lower cognitive abilities. Certain pattern of consistency was uncovered for males; they were consistent across all domains in the context of highest stakes (panels 4). Surprisingly no consistency in choices of subjects with higher cognitive abilities was found at all. Overall HL approach exhibits very low levels of correlation with all the versions of the methods implemented in this study. This could be due to embedding bias¹⁸ reported by Bosch-Domènech and Silvestre (2006; 2013) and Abdellaoui, Driouchi and L'Haridon (2011).

When analysing the correlations between the risk elicitation methods, we report consistency of BRET and SGG methods. In the whole sample the consistency is found between BRET and low and high gains SGG domains. However, there is a different pattern for males and participants with higher cognitive abilities. They both seem to identify BRET with low gains and low losses SGG domains (correlations are moderate to strong). On the other hand, females and subjects with lower cognitive abilities appear to associate BRET with high gains SGG domain.

¹⁸ Authors tested the HL method and when some items were removed from the lists, it yielded a systematic decrease in risk aversion and scrambled the ranking of individuals by risk aversion. It was named *embedding bias* by Bosch-Domènech and Silvestre (2006). Authors suggested that: "... it might be related to empirical phenomena and theoretical developments where better prospects increase risk aversion" (p. 465).

PCA method enables us to study common dimensions of risk attitudes. This tool helps us to disentangle the complex system of risk attitudes elicited using 18 related tasks. We have identified seven factors which explained all of 18 tasks in a satisfactory way (uniqueness of each variable was less than 24%). Four of these factors correspond to four different domains of multidimensional SGG method. Therefore, results suggest that each of these domains indeed measures a different aspect of subject's risk attitude. Other two factors correspond to HL and BRET method respectively. The most interesting finding is the existence of independent dimension capturing risk attitudes of participants in the context of potential high payoff (factor 5). This factor reacts on the amount of reward, which is at stake and we call it *the payoff risk sensitivity*.

From the viewpoint of the main research question on the level of consistency of risk attitudes in different experimental contexts we find that each HL, BRET and SGG methods seem to measure distinctive aspect of the risk attitudes. Moreover, HL and BRET methods appear to be completely unrelated to each other despite the common theoretical grounding.¹⁹

Numerous methods have been used to measure risk in the laboratory and many others could be designed. The three methods that we use were selected for two reasons. First, these tasks have been used in previous studies eliciting risk attitudes; and second, all the tasks are static. Despite the fact, that our results could be empowered by using monetary incentives, we think the risk attitudes elicited from these methods are still valid. In fact, we believe that this mixed evidence provides some impulse for future research, both in developing new and refining existing methods to measure risk taking.

Conclusion

We have used three distinct risk attitude elicitation methods to find the degree of consistency of risk attitudes in different experimental contexts. Subjects' risk attitudes elicited from uni-parametric HL and BRET methods are not associated with each other at all, which is rather unexpected result. It is the same between HL and SGG method. However, there is consistency between BRET and two domains of SGG method; gender and cognitive abilities play an important role here as well. We also find various levels of similarity between different domains of multidimensional SGG method, but risk attitudes are neither identical nor completely unrelated. These findings are supported by factor analysis; here we

¹⁹ Authors of HL and BRET methods link them to constant relative risk aversion utility function, which implies that risk attitudes they capture (based on relative risk aversion parameter r) should be compatible.

identified another dimension which we call *the payoff risk sensitivity*. We suggest that more cautious approach should be adopted by researchers in economics and psychology regarding the validity of the existing risk attitude measurement methods. Multidimensional or at least a multiple-method approach is the only way of accounting for the similarities and differences among risk attitudes elicited in different conditions.

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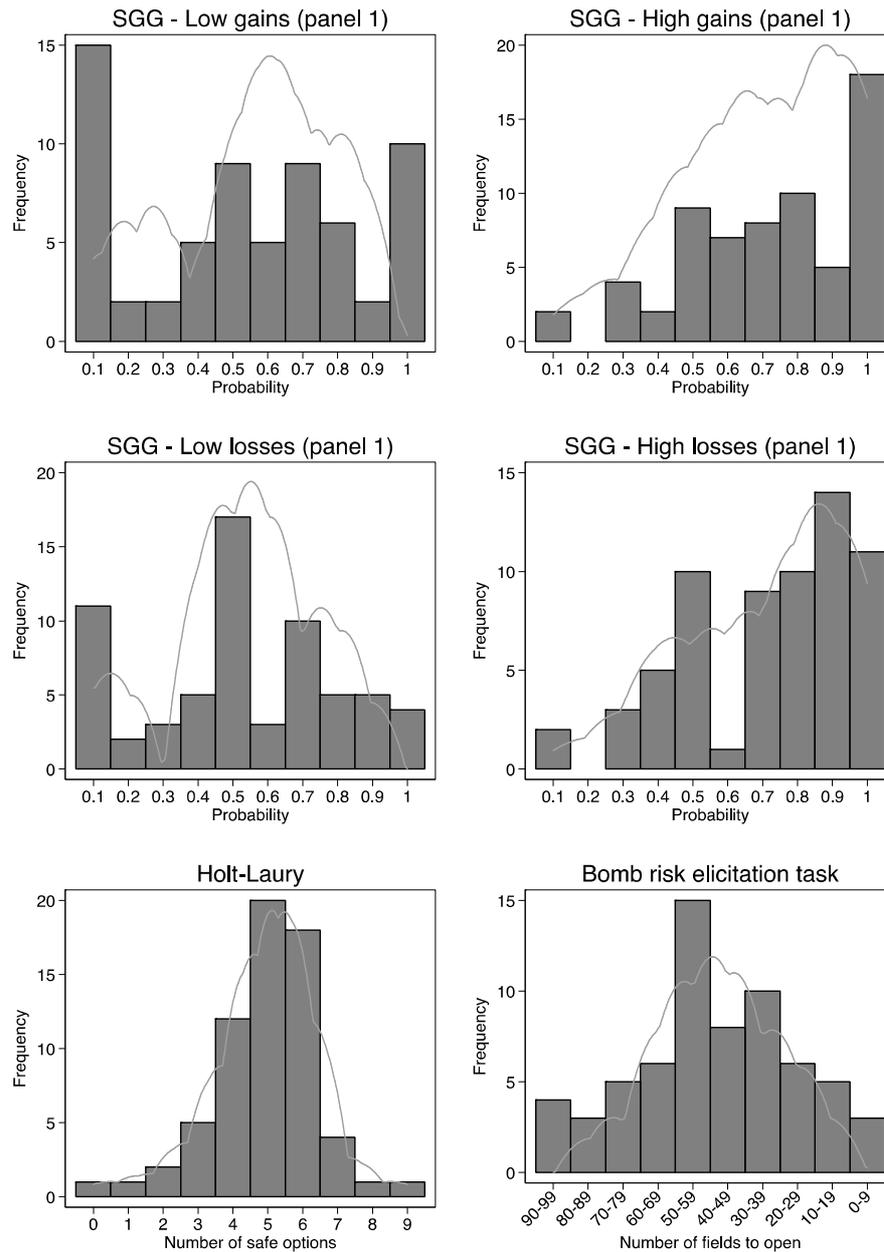
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Appendices

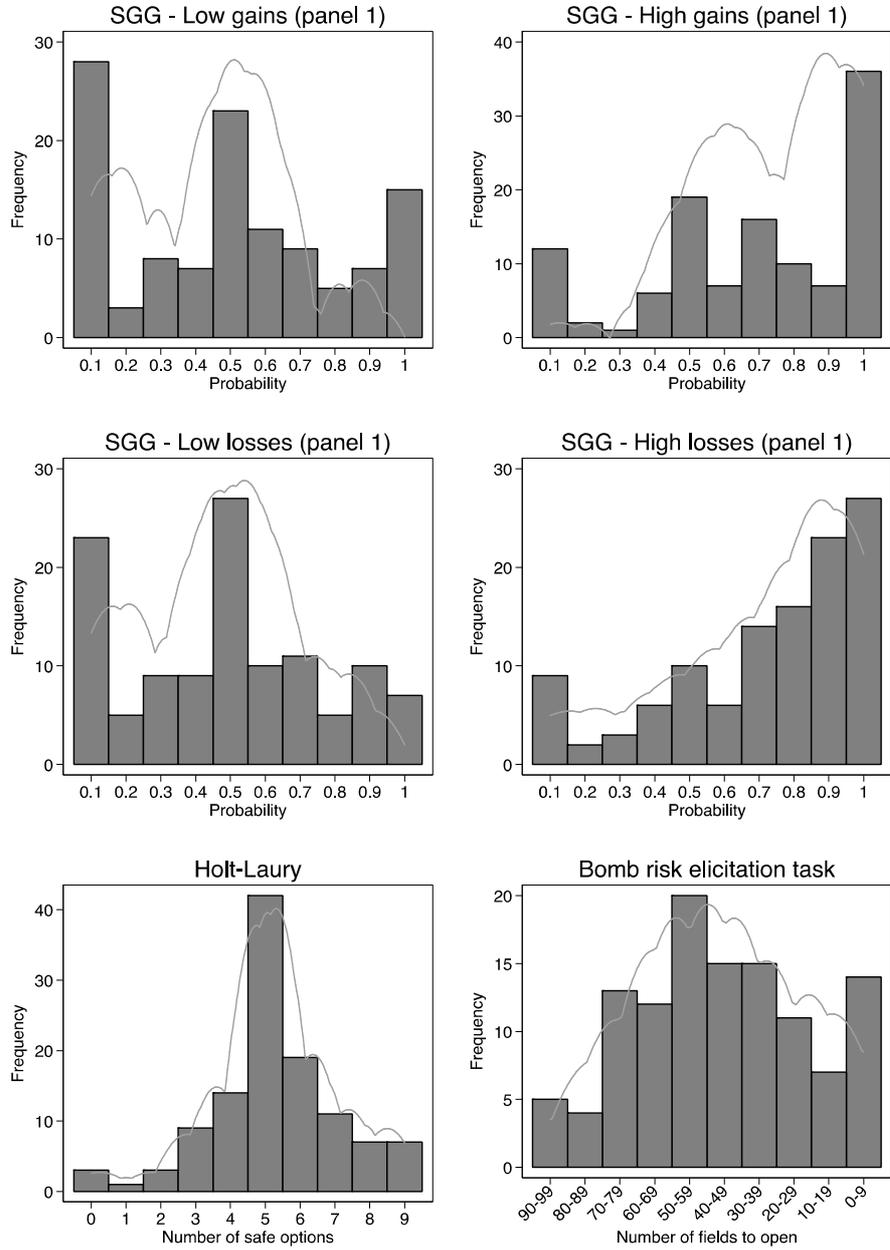
Appendix 1

Histograms and Kernel Density Functions Participants' Choices by Gender and CRT



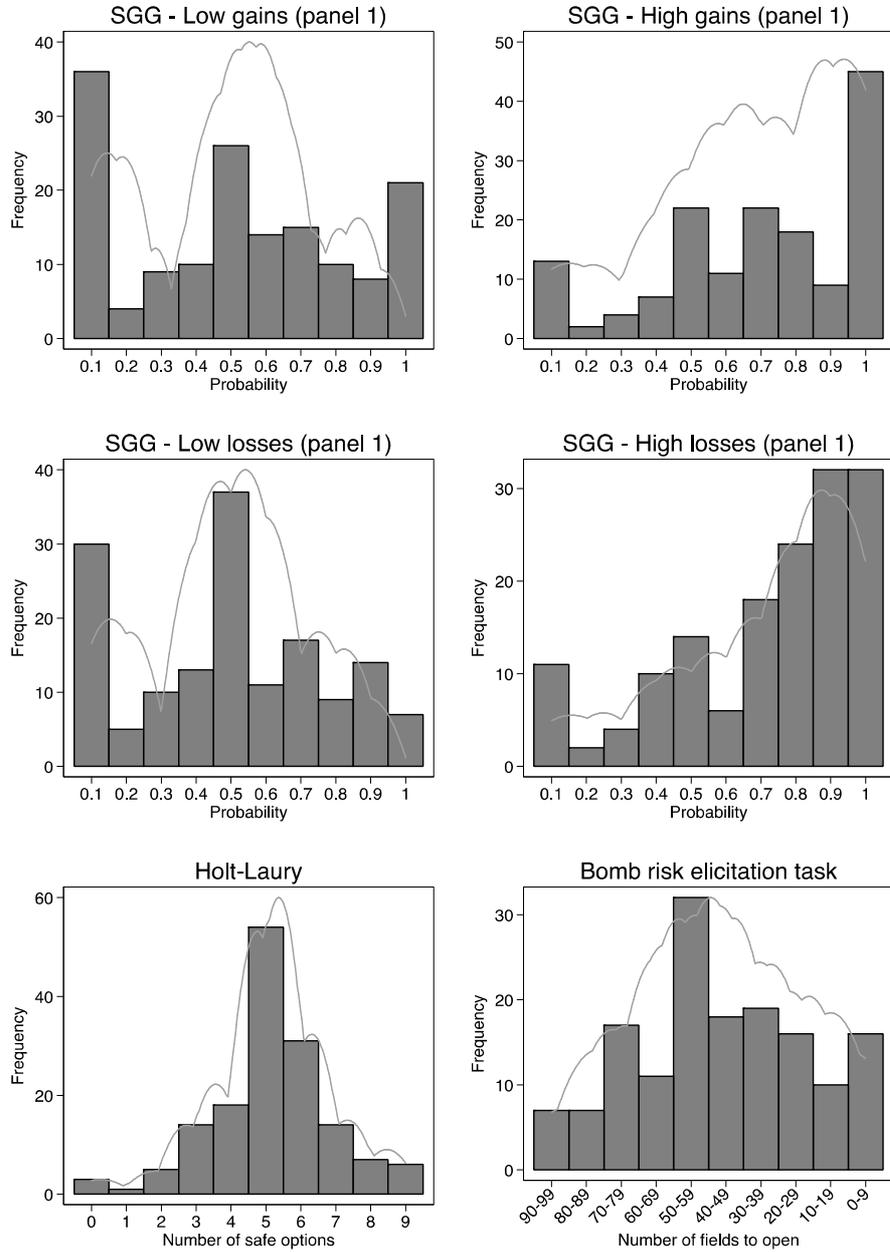
Note: Males (N = 65).

Source: Authors' calculations.



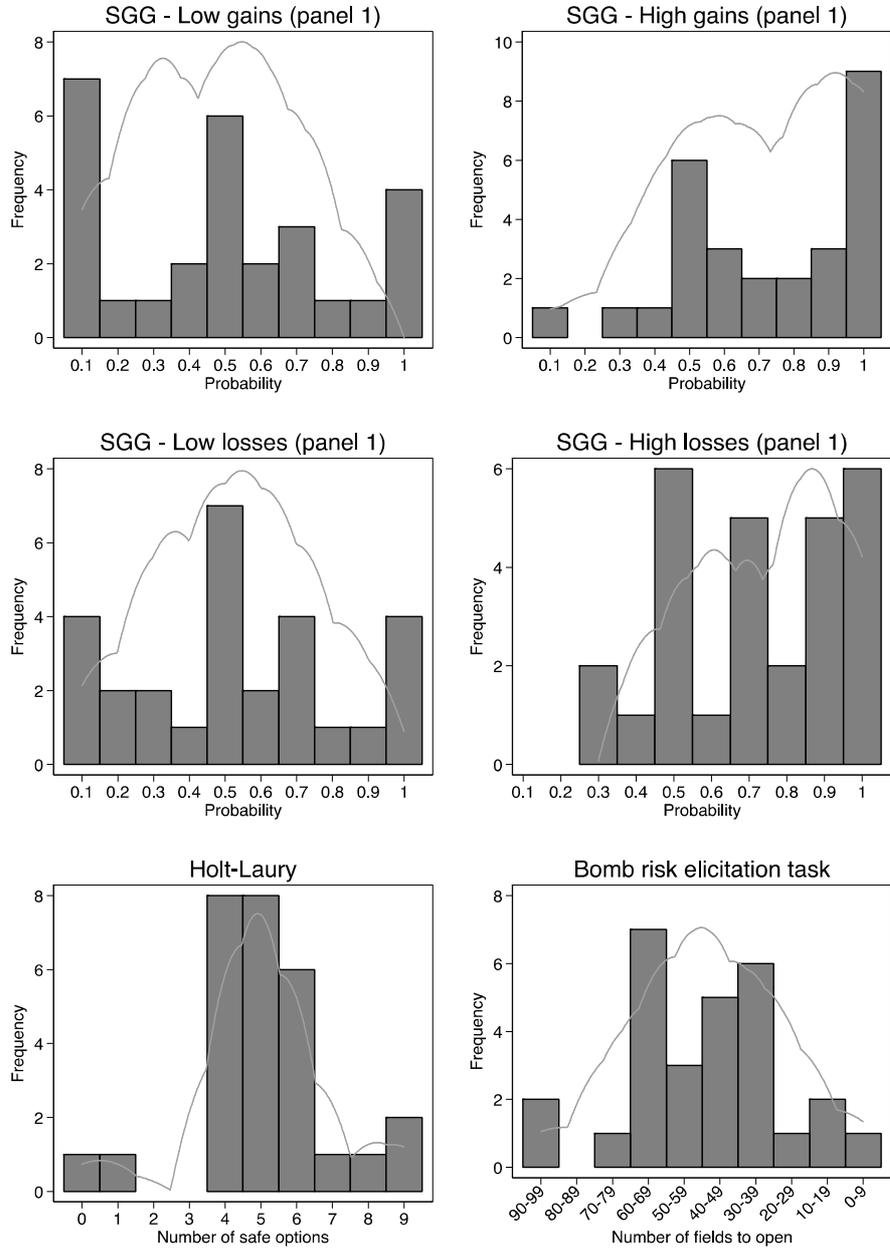
Note: Females (N = 116).

Source: Authors' calculations.



Note: CRT = 0 or CRT = 1 (N = 153).

Source: Authors' calculations.



Note: CRT = 2 or CRT = 3 (N = 28).

Source: Authors' calculations.

Appendix 2

Spearman Rank Correlation between SGG Domains

		SGG low gains				SGG high gains				SGG low losses				SGG high losses			
		p1	p2	p3	p4	p1	p2	p3	p4	p1	p2	p3	p4	p1	p2	p3	p4
SGG low gains	p1	1															
	p2	0.87	1														
	p3	0.67	0.77	1													
	p4	0.56	0.64	0.76	1												
SGG high gains	p1	0.32	0.30	0.26	0.23	1											
	p2	0.30	0.31	0.35	0.34	0.72	1										
	p3	0.28	0.35	0.46	0.44	0.53	0.67	1									
	p4	0.27	0.31	0.38	0.54	0.39	0.55	0.63	1								
SGG low losses	p1	0.57	0.50	0.48	0.40	0.30	0.22	0.23	0.18	1							
	p2	0.51	0.51	0.54	0.46	0.32	0.27	0.31	0.25	0.79	1						
	p3	0.47	0.51	0.59	0.56	0.23	0.25	0.31	0.32	0.60	0.82	1					
	p4	0.42	0.44	0.49	0.61	0.14	0.28	0.27	0.43	0.50	0.68	0.82	1				
SGG high losses	p1	0.23	0.25	0.26	0.23	0.32	0.30	0.31	0.13	0.34	0.30	0.20	0.20	1			
	p2	0.20	0.22	0.24	0.23	0.35	0.32	0.34	0.19	0.24	0.34	0.27	0.25	0.83	1		
	p3	0.17	0.21	0.24	0.26	0.28	0.35	0.36	0.21	0.14	0.28	0.29	0.27	0.68	0.81	1	
	p4	0.22	0.27	0.27	0.35	0.27	0.38	0.34	0.36	0.08	0.23	0.29	0.38	0.55	0.65	0.77	1

Source: Authors' calculations.

Appendix 3

Spearman Rank Correlation between SGG Domains by Gender and CRT – Summary

	SGG low gains		SGG high gains		SGG low losses		SGG high losses	
	male	female	male	female	male	female	male	female
	N = 65	N = 116	N = 65	N = 116	N = 65	N = 116	N = 65	N = 116
SGG low gains	0.68	0.72						
SGG high gains	0.37	0.33	0.59	0.58				
SGG low losses	0.62	0.42	0.25	0.27	0.68	0.70		
SGG high losses	0.26	0.24	0.45	0.23	0.24	0.28	0.68	0.74

	SGG low gains		SGG high gains		SGG low losses		SGG high losses	
	CRT = 0 – 1	CRT = 2 – 3	CRT = 0 – 1	CRT = 2 – 3	CRT = 0 – 1	CRT = 2 – 3	CRT = 0 – 1	CRT = 2 – 3
	N = 153	N = 28	N = 153	N = 28	N = 153	N = 28	N = 153	N = 28
SGG low gains	0.69	0.71						
SGG high gains	0.34	0.34	0.56	0.58				
SGG low losses	0.48	0.50	0.27	0.27	0.69	0.70		
SGG high losses	0.25	0.24	0.29	0.30	0.24	0.26	0.76	0.72

Source: Authors' calculations.

Values are an average of correlation between all 4 panels within each domain. Full results are available from authors upon request.

Instructions for the HL

Your decision sheet shows ten decisions listed on the left. Each decision is a paired choice between “Option A” and “Option B.” You will make ten choices and record these in the final column, but only one of them may determine your earnings.

Imagine, that a ten-sided die that will be used to determine payoffs; the faces are numbered from 1 to 10 (the “0” face of the die will serve as 10.) the first throw of die select one of the ten decisions to be used, and a second time determine what the payoff will be for the option (A or B) you chose. All payoffs from this round are hypothetical and will not be paid to you.

Option A If die roll is:	Option B If dice roll is:	Decision number	Decision
1 then payment is 200; 2, 3, 4, 5, 6, 7, 8, 9 or 10 then payment is 160	1 then payment is 385; 2, 3, 4, 5, 6, 7, 8, 9 or 10 then payment is 10	1	
1 or 2 then payment is 200; 3, 4, 5, 6, 7, 8, 9 or 10 then payment is 160	1 or 2 then payment is 385; 3, 4, 5, 6, 7, 8, 9 or 10 then payment is 10	2	
1, 2 or 3 then payment is 200; 4, 5, 6, 7, 8, 9 or 10 then payment is 160	1, 2 or 3 then payment is 385; 4, 5, 6, 7, 8, 9 or 10 then payment is 10	3	
1, 2, 3 or 4 then payment is 200; 5, 6, 7, 8, 9 or 10 then payment is 160	1, 2, 3 or 4 then payment is 385; 5, 6, 7, 8, 9 or 10 then payment is 10	4	
1, 2, 3, 4 or 5 then payment is 200; 6, 7, 8, 9 or 10 then payment is 160	1, 2, 3, 4 or 5 then payment is 385; 6, 7, 8, 9 or 10 then payment is 10	5	
1, 2, 3, 4, 5 or 6 then payment is 200; 7, 8, 9 or 10 then payment is 160	1, 2, 3, 4, 5 or 6 then payment is 385; 7, 8, 9 or 10 then payment is 10	6	
1, 2, 3, 4, 5, 6 or 7 then payment is 200; 8, 9 or 10 then payment is 160	1, 2, 3, 4, 5, 6 or 7 then payment is 385; 8, 9 or 10 then payment is 10	7	
1, 2, 3, 4, 5, 6, 7 or 8 then payment is 200; 9 or 10 then payment is 160	1, 2, 3, 4, 5, 6, 7 or 8 then payment is 385; 9 or 10 then payment is 10	8	
1, 2, 3, 4, 5, 6, 7, 8 or 9 then payment is 200; 10 then payment is 160	1, 2, 3, 4, 5, 6, 7, 8 or 9 then payment is 385; 10 then payment is 10	9	
If dice roll is 1, 2, 3, 4, 5, 6, 7, 8, 9 or 10 then payment is 200;	If dice roll is 1, 2, 3, 4, 5, 6, 7, 8, 9 or 10 then payment is 385;	10	

Instructions for the BRET

1	2	3	4	5	6	7	8	9	10
11	12	13	14	15	16	17	18	19	20
21	22	23	24	25	26	27	28	29	30
31	32	33	34	35	36	37	38	39	40
41	42	43	44	45	46	47	48	49	50
51	52	53	54	55	56	57	58	59	60
61	62	63	64	65	66	67	68	69	70
71	72	73	74	75	76	77	78	79	80
81	82	83	84	85	86	87	88	89	90
91	92	93	94	95	96	97	98	99	100

On the paper you see a field composed of 100 numbered boxes. Behind one of these boxes a time bomb is hidden; the remaining 99 boxes are empty. You do not know where the time bomb is. You only know that it can be in any place with equal probability. Your task is to choose how many boxes to collect. Boxes will be collected in numerical order. So you will be asked to choose a number between 1 and 100.

If you happen to have collected the box in which the time bomb is located, you will earn zero. If the time bomb is located in a box that you did not collect you will earn an amount in euro equivalent to the number, you have chosen divided by ten. All payoffs from this round are hypothetical and will not be paid to you.

Please, indicate how many boxes would you like to collect

Instructions for CRT

Please answer following questions within the interval of 90 seconds.

1. A bat and a ball cost 1.10 USD in total. The bat costs \$1.00 more than the ball. How much does the ball cost?
2. If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets?
3. In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake?