Testing the Elicitation Procedure of the Minimum Acceptable Probability

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September 14, 2022

Abstract

Betrayal aversion has been shown to be an important determinant of trust (Bohnet and Zeckhauser, 2004). We study whether the way betrayal aversion is identified (as a difference in Minimum Acceptable Probabilities, MAPs) is affected by beliefs about one's prospects.

In a within-subject design, we find that MAPs are lower the worse the prospects one faces. This is similar to the distributional dependence of valuations elicited using the Becker–DeGroot–Marschak mechanism, of which MAPs are a special case. Our results suggest that distributional dependence should be accounted for when eliciting MAPs to isolate betrayal aversion.

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†Maastricht University. We thank Elias Tsakas, Mats Köster, Andrea Isoni and participants in the BEELab proposal meeting and those at the 2022 M-BEES and 2022 European ESA conferences for valuable comments.

1 Introduction

Individuals have often been found to prefer exposure to a randomly generated risk over exposure to an equiprobable risk generated by an opponent in a strategic situation. In the context of trust games, this strategic risk premium has been dubbed *betrayal aversion* (Bohnet and Zeckhauser, 2004). Many papers find that betrayal aversion is an important determinant of trust (Bohnet and Zeckhauser, 2004; Aimone et al., 2015; Fairley et al., 2016; Quercia, 2016; Bacine and Eckel, 2018; Butler and Miller, 2018; Polipciuc and Strobel, 2022).

Betrayal aversion is identified as the difference in first mover behavior in two games: a binary trust game—a version of the trust game (Berg et al., 1995)—and an equivalent game where the decision at the second node is made by a randomization device. In both games, first movers have to decide whether to keep their endowment or to send it to the second mover. If the first mover sends money, there is an efficiency gain. The second mover (either a real decision maker or a randomization device) decides whether to share the gain fairly or to keep most of it.

Typically first movers do not decide directly, but indicate their minimum acceptance probability (MAP). This is the lowest probability that first movers get a fair share back if they send money such that they prefer sending money over keeping their endowment. After all relevant second movers' decisions are collected, the actual probability of a fair split is calculated over the entire pool of second mover decisions. Then, the first mover sends the money if the actual probability is larger or equal to their minimum acceptance probability. If he does, the payoffs are decided by a randomly assigned second mover's decision.

The mechanism resembles the Becker–DeGroot–Marschak mechanism (Becker et al., 1964, in short, BDM). The MAP is elicited without first movers knowing how many second movers (devices) chose the favorable outcome at the second node. It is in a first mover's best interest to state the true MAP at which they he prefers sending money over not sending it.

For an expected utility maximiser, the MAP should be independent of his belief about the actual probability of fair sharing. This need not be the case for non-expected utility maximizers. A recent paper shows theoretically that the elicitation procedure of MAPs used in most papers on betrayal aversion leaves the door open to potential confounds for betrayal aversion such as "ambiguity attitudes, complexity, different beliefs, and dynamic optimization" if players are not rational expected utility maximizers (Li et al., 2020). Moreover, a couple of empirical papers which use more stringent identification procedures for betrayal aversion by controlling for first mover beliefs in the two games do not find betrayal aversion (Fetchenhauer and Dunning, 2012, the second experiment in Polipciuc, 2022), or find it to play a role for trusting only when beliefs are far more optimistic than is generally the case (Engelmann et al., 2021).

In this note, we use an online experiment to measure how much of what has been called betrayal aversion is due to distributional dependence, regardless of the source of risk being random or strategic. We remove the strategic component and show participants complete distributions over probabilities of the good (and bad) outcome of a lottery, and ask them to state their MAP for preferring the lottery over a safe payoff. When deciding about the MAP, participants do not know which lottery will be relevant, but they know the distribution from which the lottery will be drawn. Some refer to such situations as involving ambiguity,

others—as involving complex risks (the compound risk of which lottery will be selected and what the outcome of the lottery will be). In this paper, we refer to the situation as involving complex risk.[1]

Following Li et al. (2020), we expect a premium between the distribution mimicking the control condition in betrayal aversion studies and the distribution mimicking the binary trust game condition. We find the opposite to be true: the higher the expected probability of the favorable outcome, the higher the minimum acceptable probability required by participants to prefer the lottery.

While this is at odds with our expectations, it ties in with findings from the empirical literature on distributional dependence of willingness to pay (WTP) as elicited through the BDM mechanism. Similarly to betrayal aversion, theoretical literature has pointed out that the BDM mechanism is not incentive compatible if players are not rational expected utility maximizers (Karni and Safra, 1987; Horowitz, 2006). This is because individuals face uncertainty regarding the price of the good at stake and additional uncertainty about whether they will buy the good or not. If their utility function is influenced by these uncertainties, changing the price distribution of the good might influence their valuation of the good (here, the MAP). Several empirical papers find this to be the case for the BDM: generally, the higher the expected price of the good, the higher the WTP (for a short review of this literature, see Tymula et al., 2016). The results of Tymula et al. (2016) are partly consistent with theories of reference-dependent preferences (Kőszegi and Rabin, 2006, 2007; Wenner, 2015).

Our results suggest that (i) the way MAPs are elicited is sensitive to subjective

[1] Ambiguity aversion and attitudes to complex risks are positively correlated (Armantier and Treich, 2016).

beliefs, so these should be taken into account in order not to confound valuation, and (ii) the way subjective beliefs influence valuation is not in line with results of the toy model in Li et al. (2020).

The paper is structured as follows. Section 2 describes the experimental design and procedures. Section 3 sets forth the hypothesis. Section 4 presents the results. Section 5 explains how our results inform the existing literature and suggests directions for future research.

2 Design and procedures

We use a within-subject design, with each subject being exposed to all treatments sequentially. In each treatment, participants see a graphical representation of a distribution over lotteries with two possible outcomes (high and low), but varying probabilities for each outcome. A lottery will be drawn at random from the distribution. This means in some treatments it is more likely to get a lottery with a high chance of a high payoff than in others. We use three distributions over lotteries. The distributions are ordered in terms of the expected payoff over the entire distribution, as their name suggests: the Good, the Bad, and the Uniform (the Good $>$ the Uniform $>$ the Bad).

To make the task easy to understand, we present lotteries via 32 wheels of fortune with 15 sectors each. Dark blue sectors symbolize the high payoff (£4), light blue sectors—the low payoff (£1). The sure payoff (the payoff participants receive if no wheel is spun) is £2. In each treatment, participants see the wheels sorted in ascending order by the probability of the favorable outcome, with the 32 wheels equally distributed over 4 rows. Figure 1 below shows the distribution of

lotteries for the Good treatment.

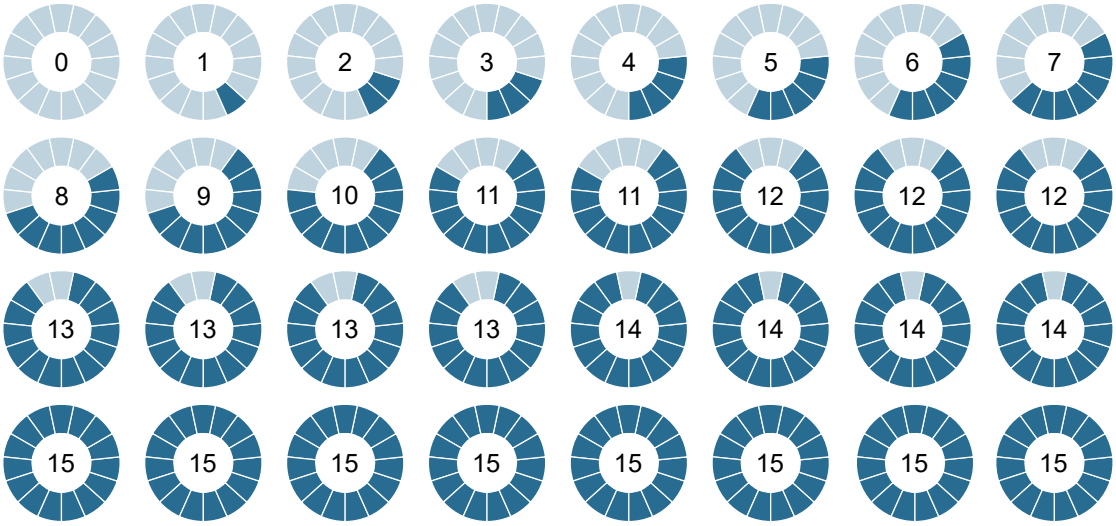

Figure 1: The Good distribution

Two of the three distributions are meant to emulate treatments in papers on betrayal aversion. The Uniform distribution has equal chances of occurrence for each of the possible wheels. We assume that this is what participants expect to face in treatments with decisions made by randomization devices, unless specified otherwise.[2] The Bad distribution has an overall chance of a high payoff similar to the share of trustworthy respondents in Western samples in papers on betrayal aversion (0.2895) (e.g. Bohnet and Zeckhauser, 2004; Bohnet et al., 2008). The distribution in Good mirrors the one in Bad: its overall expected chance of a high payoff is one minus that in Bad (0.7105), it has the same variance and minus the skewness of the Bad distribution. We included this distribution to check if departures from the Uniform distribution in either direction yield effects of similar size (albeit reverse sign) on reported MAPs. Table 1 presents the distributions.

[2]We assume participants in the *Risky Dictator Game* in Bohnet and Zeckhauser (2004) had such a distribution in mind.

Table 1: The treatments: the distribution of chances of a high payoff

	# of wheels		
# of high payoff sectors	The Good	The Bad	The Uniform
0	1	8	2
1	1	4	2
2	1	4	2
3	1	3	2
4	1	2	2
5	1	1	2
6	1	1	2
7	1	1	2
8	1	1	2
9	1	1	2
10	1	1	2
11	2	1	2
12	3	1	2
13	4	1	2
14	4	1	2
15	8	1	2
Total # of wheels	32	32	32

Participants are told that one of the wheels will be drawn at random, with all wheels having an equal chance to be drawn. They are asked to state a *minimum acceptable frequency* (which we refer to as MAP, for easier comparison with papers on betrayal aversion): the lowest number of dark blue sectors in the randomly drawn wheel such that they prefer to spin the wheel instead of receiving the sure payoff.[3] Specifically, they have to answer: "Which wheels would you like to spin for your bonus?" by inserting an integer between 0 and 15 in the blank space: "I prefer to spin wheels which have at least _____ dark blue sectors."

The experiment was conducted online using Qualtrics. Participants were UK residents registered on a platform for conducting academic studies (Prolific). Since the elicitation of MAPs is rather complex (Quercia, 2016; Polipciuc, 2022), we opted for participants who had at least a bachelor's degree. The study was pre-registered at the AEA RCT Registry (`https://doi.org/10.1257/rct.7776-1.1`).

The study had three stages: a set of eliminatory comprehension questions, the three decisions, and a post-experimental questionnaire.[4] Those who completed the experiment (went only through the comprehension questions) spent a median time of 12.4 (5.9) minutes and earned on average 3.96 (1) UK pounds.[5]

[3]We decided to use frequencies instead of probabilities because there is evidence that participants have an easier time expressing choice this way (Quercia, 2016).

[4]In the post-experimental questionnaire, respondents answered an unincentivized question to determine their ambiguity aversion, a version of a cognitive reflection test (Frederick, 2005; Thomson and Oppenheimer, 2016) adapted by the authors, a question about the subject they studied for their most recent degree, a general risk taking question (Dohmen et al., 2011), a question about their aspiration level for earnings from participating in a survey, a couple of questions to check their anchoring susceptibility, from which an anchoring score can be computed (Cheek and Norem, 2017), a set of questions about their optimism/pessimism, the revised Life Orientation Test (Scheier et al., 1994) and a brief sensation seeking scale, BSSS-4 (Stephenson et al., 2003).

[5]Participants were paid £1 for going through the comprehension questions (regardless of the correctness of their answers). Those who answered the comprehension questions correctly earned

3 Hypothesis

Let p be the probability of the high payoff and $1-p$ the probability of the low payoff of the lottery. The distribution of p (and consequently, of $1-p$) varies between treatments. Based on Li et al. (2020) we assume that what has been called betrayal aversion could be due to such differences in the underlying distribution of p.

Specifically, we adapt the toy example in Appendix A in Li et al. (2020) to predict the optimal MAP in each treatment. We additionally assume that participants treat complex bets similarly to how they treat ambiguous bets (for supporting evidence, see Armantier and Treich, 2016). This leads us to expect the following ordering of MAPs:[6]

Hypothesis 1 *The MAP in Good (more mass on high values of p) is lower than the MAP in Uniform (a uniform distribution over p), which is lower than the MAP in Bad (more mass on low values of p).*

$$MAP_G < MAP_U < MAP_B \tag{1}$$

We also consider the alternative hypothesis ($MAP_B < MAP_U < MAP_G$). This could be true if participants anchor their MAPs on visual or numerical cues of the distributions, such as the mean.

an additional £1, £2 or £4 for one of their decisions.

The high average earnings of those who completed the experiment are due to a coding error which we detected after running the experiment. Instead of decisions in all three treatments being equally likely to be selected, only those in Good and Uniform were selected, each with equal probability. This led all participants who had completed all stages of the experiment to have a higher chance of a higher payoff. This error did not affect decisions, but only which decision was selected for payment. Participants were informed about the error after the experiment.

[6]For details, see Appendix A.5.

4 Results

4.1 The estimation sample

Table 2 describes the sample. Treatment was assigned in order to balance the number of participants exposed to each of the six possible orderings of treatments. 275 of the 450 participants answered the eliminatory comprehension questions correctly and completed the experiment. Since assignment to treatment happened before participants had gone through the comprehension questions, this leads to slightly different sizes of the subsamples for the six orderings.

Table 2: Characteristics of the estimation sample

	Age	Share male	Sample size
Good–Uniform–Bad	30.956	0.333	45
	(8.808)	(0.477)	
Uniform–Bad–Good	33.538	0.346	52
	(9.074)	(0.480)	
Bad–Good–Uniform	37.114	0.523	44
	(11.071)	(0.505)	
Good–Bad–Uniform	33.132	0.491	53
	(9.174)	(0.505)	
Bad–Uniform–Good	32.429	0.333	42
	(9.423)	(0.477)	
Uniform–Good–Bad	33.333	0.205	39
	(10.103)	(0.409)	
Total	33.411	0.378	275
	(9.685)	(0.486)	

Notes: The table shows averages per sequence. Standard deviations in parentheses.

4.2 Behavior in the experiment

First, we present summary statistics for all decisions, by treatment and by decision order. Next, we run nonparametric tests and ordinary least squares regressions to test the hypothesis. P-values for nonparametric tests are from two-sided tests.

Table 3 presents the average MAP by treatment over all decisions and by decision order. This table already suggests that the hypothesis is not supported by the data, as the average MAP is highest in Good, followed by Uniform, followed by Bad (except for the second decision).

Table 3: Descriptive statistics: MAPs by treatment

	All decisions	First decision	Second decision	Third decision
The Good	9.531	9.571	9.458	9.553
	(2.503)	(2.270)	(2.500)	(2.750)
The Uniform	8.844	8.890	8.368	9.227
	(2.382)	(2.392)	(2.119)	(2.539)
The Bad	8.615	8.093	9.124	8.512
	(2.522)	(2.597)	(2.491)	(2.387)
N	825	275	275	275

Notes: The table shows averages per treatment. Each participant made three decisions in randomized order. Standard deviations in parentheses. Possible answers were integers between 0 and 15.
Coefficients of The Good and The Bad differ between models, but only from the fourth digit or farther after the decimal point.

A nonparametric Page's L test confirms this: there is strong evidence that the ordering is the opposite to the one hypothesized ($MAP_B < MAP_U < MAP_G$, p-value < 0.001).[7]

In Table 4 we present results of ordinary least square regressions of MAPs.

[7]Page's L test has the null hypothesis that all possible orderings are equally likely. The alternative hypothesis is that a specified order is the increasing order of alternatives. The Stata command is *pagetrend*.

Model (1) contains as regressors only dummy variables indicating the treatment. Model (2) adds age and gender as explanatory variables. Model (3) additionally includes risk attitudes. Model (4) also includes dummy variables for the order in which participants were exposed to treatments. In all models, standard errors are clustered at the individual level.

Table 4: Linear regressions on Minimum Acceptable Frequencies

Dependent variable:	Minimum acceptable frequency			
	(1)	(2)	(3)	(4)
The Good	0.687***	0.687***	0.687***	0.687***
	(0.099)	(0.099)	(0.099)	(0.099)
The Bad	−0.229***	−0.229***	−0.229***	−0.229***
	(0.070)	(0.070)	(0.070)	(0.070)
Age		0.005	0.006	0.006
		(0.013)	(0.013)	(0.014)
Male		−0.047	0.030	−0.029
		(0.286)	(0.284)	(0.283)
Risk attitudes (0–10)			−0.172**	−0.152**
			(0.074)	(0.074)
Sequence				
Uniform–Bad–Good				0.490
				(0.408)
Bad–Good–Uniform				−0.008
				(0.434)
Good–Bad–Uniform				1.173***
				(0.412)
Bad–Uniform–Good				−0.150
				(0.434)
Uniform–Good–Bad				0.469
				(0.433)
Constant	8.844***	8.696***	9.520***	9.066***
	(0.144)	(0.460)	(0.593)	(0.627)
N	825	825	825	825

Notes: Standard errors clustered at the individual level in parentheses. The baseline treatment is the Uniform distribution. The baseline sequence is Good–Uniform–Bad. Risk attitudes are measured on a 0–10 scale, where 0 is very risk averse and 10 is very risk loving.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In all four specifications, participants ask for 0.687 more dark blue sectors

(yielding a high payoff) on average in Good compared to Uniform to be willing to spin the selected wheel (p-value < 0.001 in all specifications). They also ask for 0.229 fewer dark blue sectors in Bad compared to Uniform (p-value $= 0.001$ in (4)). More risk loving individuals have lower MAPs (p-value $= 0.04$ in (4)).

The only sequence order which differs significantly from the baseline (Good–Uniform–Bad) is Good–Bad–Uniform: MAPs are significantly higher than in the baseline. Since the sequence indicators pick up the value in Uniform, the values for MAPs in Uniform differ significantly between these two sequences, with the one in Good–Bad–Uniform being significantly higher than the one in Good–Uniform–Bad (p-value $= 0.004$, Mann-Whitney test). While we do not have a straightforward explanation for this difference, we notice that the first decision (which is Good in both sequences) already differs significantly between these sequences, with MAP in Good–Bad–Uniform being significantly higher than the one in Good–Uniform–Bad (p-value $= 0.003$, Mann-Whitney test). Since at that point the sequence of events and information participants faced in the two treatments was identical, this difference cannot be a treatment effect or an order effect.[8,9]

Result 1. *Participants set the lowest requirement to be willing to take a randomly drawn lottery in Bad, followed by Uniform, followed by Good.*

Subjects' MAPs are stickier if they start with Good than with the other two: the intra-individual standard deviation over all three MAPs is lower if the first

[8] We used ordinary least squares regressions for ease of interpretation of the coefficients. Since the dependent variable is categorical and ordered, we also used ordered logit models (not reported).

The results are qualitatively similar: compared to Uniform, MAPs between 1 and 8 are less likely in Good (more likely in Bad) and MAPs between 9 and 15 are more likely in Good (less likely in Bad).

[9] In a robustness check, we reran the regressions separately for each ordering. The signs of the effects are the same for each ordering as for the pooled sample, even if some effects do not reach significance in these smaller samples.

decision is in Good than if it is in one of the other two treatments (Mann-Whitney test, p-value = 0.02). Table 5 shows the results of running specifications (1)–(3) in Table 4 on first decisions only. Since the skewed effect of stickiness is not present, deviations in MAP in Good and in Bad do not differ in absolute size (Wald test for equality of coefficients in (3), p-value = 0.87). The smaller coefficient in Bad over all three decisions is thus due to more pronounced stickiness when facing prospects that worsen than when facing prospects that improve over time.

Result 2. *Within individual, MAPs are stickier for participants who face the Good first than for those who face one of the other two distributions first.*

Table 5: Linear regressions on Minimum Acceptable Frequencies: first decision

Dependent variable:	Minimum acceptable frequency		
	(1)	(2)	(3)
The Good	0.681 *	0.731 **	0.682 *
	(0.352)	(0.355)	(0.353)
The Bad	−0.797 **	−0.794 **	−0.783 **
	(0.363)	(0.367)	(0.364)
Age		0.018	0.019
		(0.015)	(0.015)
Male		−0.194	−0.113
		(0.303)	(0.303)
Risk attitudes (0–10)			−0.174 **
			(0.076)
Constant	8.890 ***	8.333 ***	9.189 ***
	(0.253)	(0.573)	(0.680)
N	275	275	275

Notes: The baseline treatment is the Uniform distribution. Risk attitudes are measured on a 0–10 scale, where 0 is very risk averse and 10 is very risk loving.
* p < 0.10, ** p < 0.05, *** p < 0.01.

We speculated that such an ordering of MAPs is possible if individuals anchor

on visual or numerical cues offered by the distributions. If this were true, then the effects should be reduced if we add an interaction term between the individual anchoring score (Cheek and Norem, 2017) as measured in the post-experimental questionnaire and the treatments. This is however not the case: if we include the interaction term in models in Table 4, the coefficients of The Good and The Bad keep their magnitude and significance levels. Treatment effects do not differ for those who are more or less susceptible to anchoring. Someone who is one standard deviation less susceptible to anchoring than the mean (in either direction) asks for a MAP which is higher by approximately 0.58 (significant at 10% level, results available on request).

A suggestion we received after the data collection was that instead of thinking in terms of MAPs, subjects might be attracted to the visual center of the distributions.[10] Should this be the case, the ordering of MAPs would coincide with the one we observe for a mechanical reason. In order to test this, we rerun the specifications in Table 4, but we use as dependent variable the number of wheels which, if randomly selected, are relevant for the participant's payoff. In other words, this is the number of wheels which—given the participant's MAP—if selected, would be spun. We consider this assumption to be supported if either (i) treatment does not influence the number of wheels potentially spun and this number is close to 16 in all treatments (half of the 32 wheels available) or (ii) treatment influences significantly the number of wheels potentially spun, but the coefficients of the treatment variables are small in a "real-world" sense.

Table 6 shows that in Uniform, approximately 14 wheels are potentially spun for payoff on average. While this is close to the expected 16 wheels, the number

[10]We thank Mats Köster for this suggestion.

Table 6: Linear regressions on wheels potentially spun for payoff

Dependent variable:	Wheels potentially spun for payoff			
	(1)	(2)	(3)	(4)
The Good	7.378 ***	7.378 ***	7.378 ***	7.378 ***
	(0.192)	(0.192)	(0.192)	(0.193)
The Bad	−6.785 ***	−6.785 ***	−6.785 ***	−6.785 ***
	(0.159)	(0.159)	(0.159)	(0.160)
Age		−0.009	−0.010	−0.011
		(0.021)	(0.021)	(0.022)
Male		0.166	0.057	0.147
		(0.462)	(0.462)	(0.459)
Risk attitudes (0–10)			0.242 *	0.209 *
			(0.123)	(0.123)
Sequence				
Uniform–Bad–Good				−0.840
				(0.617)
Bad–Good–Uniform				0.084
				(0.663)
Good–Bad–Uniform				−1.921 ***
				(0.654)
Bad–Uniform–Good				0.139
				(0.686)
Uniform–Good–Bad				−0.736
				(0.653)
Constant	14.313 ***	14.539 ***	13.380 ***	14.151 ***
	(0.288)	(0.745)	(0.986)	(1.027)
N	825	825	825	825

Notes: Standard errors clustered at the individual level in parentheses. The baseline treatment is the Uniform distribution. The baseline sequence is Good–Uniform–Bad. Risk attitudes are measured on a 0–10 scale, where 0 is very risk averse and 10 is very risk loving.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

of wheels varies significantly for the other two treatments. In Good, subjects are willing to spin approximately 7.4 more wheels—the equivalent of an additional row of wheels. In Bad, subjects are willing to spin approximately 6.8 fewer wheels.[11] We conclude that while there is a potential "pull towards the visual center" effect, it cannot explain the results.

Another suggestion was that our results could be explained by the range-frequency theory (Parducci, 1965; Parducci and Perrett, 1971).[12] This theory states that when presented with stimuli (physical, such as sounds or weights, but also monetary rewards), participants bin the stimuli into categories depending on the available range of stimuli and on their frequency. Participants do this as a compromise between (i) dividing the available range into equal shares and (ii) ensuring that each bin has an equal share of stimuli. If participants consider that only certain categories are acceptable risks, this can lead to the MAP ordering observed in our data. We provide a numerical example of such a rationale in Appendix B.

5 Discussion

In this note, we test a necessary assumption for the way betrayal aversion has been elicited in the past to be incentive compatible. This assumption is that the underlying distributions of probabilities of outcomes in two treatments which are contrasted to isolate betrayal aversion do not influence behavior. If these underlying distributions do have an influence on behavior, then betrayal aversion is misidentified.

[11] The results are similar for the sample of first decisions.

[12] We thank Andrea Isoni for this suggestion.

We remove the social/strategic aspects of the original game and exogenously manipulate underlying distributions in three treatments. Two of these treatments aim to emulate plausible distributions imagined by subjects in studies on betrayal aversion. We find a difference in behavior between treatments, but of the opposite sign to our expectation: the more favorable the distribution of lotteries that one faces, the better the lotteries one is willing to accept have to be. We thus find a distributional dependence of risk attitudes as elicited using MAPs, but of the opposite sign than the predictions of the toy example in Li et al. (2020). This result implies that betrayal aversion should be identified after controlling for subjective beliefs.

The result is consistent with several theories. A first type of such theories are theories of reference-dependent preferences which predict that individuals will be more risk loving when endowed with more risky options. Since our experiment was not meant to disentangle between competing theories, several of them could explain our results—for instance, the one in Kőszegi and Rabin (2006, 2007) or the one of Wenner (2015). These theories state that expectations (which we manipulated exogenously by changing the underlying distribution of lotteries) act as reference points. Modifying expectations modifies the gain-loss component of the utility function, such that higher expectations may make the same outcome less desirable. Alternatively, changing expectations could directly affect consumption utility: if one derives self-image utility from one's consumption, a change in expectations could change which goods are more desirable and thus, which ones offer a boost in self-image for the owner (Strahilevitz and Loewenstein, 1998; Marzilli Ericson and Fuster, 2011). With better options overall, the bar to determine which of them increase one's status will be placed higher. A second theory which could

explain the result is the range-frequency model (Parducci, 1965; Parducci and Perrett, 1971). This theory explicitly considers that when evaluating the intensity of a stimulus, participants take into account both the range and the frequency of available stimuli. By changing the frequency, as we do in the treatments, one changes the components of the categories construed by the participant. If only certain categories are deemed acceptable (e.g. risks worth taking), this can affect decisions in a way which aligns with the results.

We chose the distributions for the treatments such that the overall chance of a high payoff was close to the probability of trustworthiness in the original studies on betrayal aversion. Further decisions about the Bad (Good) distribution were based on the condition that optimal MAPs be different in the three treatments using the parameters in the toy example of Li et al. (2020) and additional assumptions detailed in Appendix A.5. Many distributions fit this criterion and our choice at this point was arbitrary. Future evidence about how people conceptualize random versus strategic risk and ambiguity could inform experimental designs able to reconcile results from betrayal aversion studies with those on the flexible valuation of risky goods.

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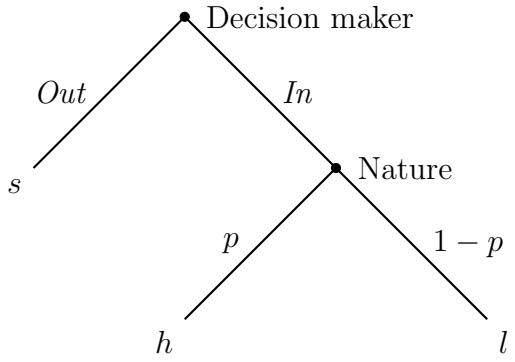
Appendix A Theoretical Benchmarks

A.1 The Game

We analyze an extension of a simple one-player lottery choice. The decision maker (DM) decides whether to stay *Out* and receive a safe outcome s or to move *In* and play a lottery which pays a high outcome h with probability p or a low outcome l with probability $1-p$. We assume that the DM's utility function $U(.)$ is continuous and differentiable in the set of outcomes. Also, $l < s < h$.

The DM does not know p when making his decision. What he knows is that p is distributed with density $f(p)$ and has full support on the interval $[0, 1]$. The DM makes his decision contingent on p. More precisely, we ask him about his minimum acceptable probability, MAP. If p happens to be smaller than MAP, then DM stays *Out*, otherwise he goes *In*. The following figure gives a graphical representation.[13]



In the following we look at different benchmarks. In particular, we are interested in whether and how the optimal minimum acceptable probability MAP* depends on the distribution of p.

[13]For simplicity, we do not explicitly depict the fact that the DM makes a decision contingent on p.

A.2 Expected Utility Theory

Assume the DM to have a utility function $U(\cdot)$. In an expected utility framework, utility is strictly increasing with outcome. Hence, we have

$$U(l) < U(s) < U(h) \tag{2}$$

In this appendix, we consider the MAP as a probability i.e. MAP $\in [0, 1]$. The DM wants to choose his MAP such that he maximizes his expected utility $U(MAP)$ which is

$$\begin{aligned} U(MAP) &= \int_{p=0}^{MAP} f(p) \cdot U(s)\, dp + \int_{p=MAP}^{1} f(p) \cdot [p \cdot U(h) + (1-p) \cdot U(l)]\, dp \quad (3) \\ &= \int_{p=0}^{MAP} f(p) \cdot U(s)\, dp - \int_{p=1}^{MAP} f(p) \cdot [p \cdot U(h) + (1-p) \cdot U(l)]\, dp \quad (4) \end{aligned}$$

We use the Fundamental Theorem of Calculus to derive the first order condition:[14]

$$\frac{\partial U(MAP)}{\partial MAP} = f(MAP) \cdot U(s) - f(MAP) \cdot [MAP \cdot U(h) + (1 - MAP) \cdot U(l)] \stackrel{!}{=} 0 \tag{5}$$

The density function $f(p)$ has full support. Therefore, $f(MAP)$ is positive and we can simplify the expression to

$$MAP^* = \frac{U(s) - U(l)}{U(h) - U(l)} \tag{6}$$

[14] From the differentiability of $U(.)$ and $\frac{\partial U(MAP)}{\partial MAP}(0) > 0$ and $\frac{\partial U(MAP)}{\partial MAP}(1) < 0$, we can conclude that at least one local maximum exists. If the solution of the FOC is unique, then it must be this maximum.

The optimal MAP* is independent of the distribution of p. Thus, an expected utility maximizer should not be influenced by it.

A.3 Outcome Based Add-ons

The result of Section A.2 holds if the utility function of the DM is extended by other elements that are based on outcomes. For example, the DM might receive extra (dis-) utility from playing the lottery. Or he might feel additional happiness or regret in case the outcome of the lottery is high or low, respectively. Such add-ons lead to a different MAP*, but do not change the fact that it is independent of the distribution of p.

A.4 Probability Weighting

Experimental evidence shows that humans have difficulties in handling probabilities. In particular, they seem to overestimate small probabilities and underestimate large ones.[15] In the following we assume the DM to have a continuous probability weighting function $w : [0,1] \to [0,1]$ with $w(0) = 0$ and $w(1) = 1$. This gives the DM the following utility function:[16]

$$U(MAP) = \int_{p=0}^{MAP} f(p) \cdot U(s)\, dp + \int_{p=MAP}^{1} f(p) \cdot [w(p) \cdot U(h) + w(1-p) \cdot U(l)]\, dp \tag{7}$$

[15] Back in 2000, Starmer (2000, p. 348–349) mentioned research spanning 50 years which supports this. This still holds true today, e.g. see Li et al. (2020, Figure 4 on p. 276).

[16] Probability weighting is not compatible with the axiomatic framework of expected utility theory. We use the notion of utility in a broad sense covering also non-expected utility theories.

This leaves us with the FOC:

$$U(s) - [w(MAP) \cdot U(h) + w(1 - MAP) \cdot U(l)] = 0 \tag{8}$$

From the assumptions about the weighting function and $U(l) < U(s) < U(h)$, it follows that this equation has at least one solution (Theorem of Bolzano). As in Section A.2, all solutions are independent of the distribution of p.[17, 18]

A.5 Rank Dependent Utility

In this section, we present the assumptions we made in order to derive the hypothesis. Unlike in the previous appendices, we focus on a numerical calculation.

We adapt the toy example in Li et al. (2020) and make the following assumptions:

- the utility of outcomes is fixed. We consider $U(high) = U(£4) = 1, U(low) = U(£1) = 0$, and $U(safe) = U(£2) = 1/3$;[19]
- participants use a probability weighting function because they perceive the tasks to involve complex risks. Similar to Li et al. (2020), we use Prelec's (1998) *compound invariance* function:

$$w(p) = (exp(-(-ln(p))^{\alpha}))^{\beta}$$

[17] We may get to a unique solution of equation (8) if we place additional requirements on the outcomes $U(\cdot)$ and/or on $w(p)$. Two possibilities are: 1.) A unique solution is guaranteed if $w(p)$ is strictly increasing and symmetric, i.e. $w(1-p) = 1 - w(p)$ or 2.) A unique solution is guaranteed if $w(p)$ is strictly increasing and the utility of the low outcome including all possible add-ons is set to zero, i.e. $U(l) = 0$.

[18] In case of multiple solutions, we assume the distribution of p does not offer cues which lead to selecting a different optimum MAP in each treatment.

[19] $U(safe) = 1/3$ was chosen because, given the data on betrayal aversion, it makes a mildly risk-averse player indifferent between accepting any lottery and the safe payoff.

- we use $\alpha = 0.65$ and $\beta = 1.0467$, which according to Li et al. (2020) are the most common values for risky probability weighting;
- participants use "forward" evaluation: they consider the three possible outcomes and take into account their probabilities, as resulting from the probability weighting function above;
- participants have the following rank-dependent utility function (Schmeidler, 1989), in which an act generated by a choice of MAP leads to:

$$RDU = w(P(£4)) \times 1 + (w(P(£4) + P(£2)) - w(P(£4))) \times (1/3)$$

where $P(£4)$ is the probability of receiving the high payoff for a ceratin MAP in the respective treatment, $P(£2)$ the probability of receiving the safe payoff, and $P(£1)$ the probability of receiving the low payoff (which does not appear in the utility function, as the utility of the low payoff is considered to be 0).

In this case, the MAPs which maximize participants' utility in the three treatments are: $\text{MAP}_\text{G} = 7$ ($RDU = 0.628$), $\text{MAP}_\text{U} = 8$ ($RDU = 0.495$), and $\text{MAP}_\text{B} = 9$ ($RDU = 0.439$).

Appendix B Range-frequency model: a numerical example

According to the range-frequency model, participants categorize stimuli according to range and frequency, and then evaluate them based on a compromise between

the two ways of classification.

Let us assume that a participant uses four bins to categorize stimuli: bad lotteries, not OK lotteries, OK lotteries, and good lotteries. When using the range criterion, this participant bins existing lotteries in all treatments in the following way:

Category	Dark blue sectors
Bad	0, 1, 2, 3
Not OK	4, 5, 6, 7
OK	8, 9, 10, 11
Good	12, 13, 14, 15

If she bins lotteries according to frequency, she arrives at the following division in each treatment:

Category	Dark blue sectors
	The Good
Bad	0, 1, 2, 3, 4, 5, 6, 7
Not OK	8, 9, 10, 11, 12
OK	13, 14
Good	15
	The Uniform
Bad	0, 1, 2, 3
Not OK	4, 5, 6, 7
OK	8, 9, 10, 11
Good	12, 13, 14, 15
	The bad
Bad	0
Not OK	1, 2
OK	3, 4, 5, 6, 7
Good	8, 9, 10, 11, 12, 13, 14, 15

If she thinks only categories OK and Good are acceptable and compromises between the two divisions of stimuli, she could report the following MAPs: $MAP_G = 10.5$, $MAP_U = 8$, $MAP_B = 5.5$. As she gives more weight to the frequency criterion, choices get closer to one another.