Eliciting Minimum Acceptable Probabilities

Pre-Analysis Plan

Martin Strobel Maria Polipciuc*

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*Maastricht University. Email: m.polipciuc@maastrichtuniversity.nl. We thank Elias Tsakas for valuable comments.

1 Main page description (public)

Interventions

Intervention(s)

We compare minimum acceptable probabilities (MAPs) for which a participant prefers a binary lottery to a sure payoff across treatments within individual. Individuals have to decide in randomized order in three scenarios (treatments). The treatments keep the sure payoff and the payoffs of the lottery fixed, but vary the distribution of the winning probability of the lottery.

Trial Start Date

Not applicable

Intervention Start Date

TBD

Intervention End Date

TBD

Primary Outcomes

Primary Outcomes (end points)

MAPs

Primary Outcomes (explanation)

The MAPs are elicited as thresholds for preferring a lottery to a sure payoff.

Experimental Design

Experimental Design

We elicit MAPs in an online experiment in a lottery similar to the *Decision Problem* in Bohnet and Zeckhauser (2004). Bohnet and Zeckhauser (2004) find that participants require a premium for being willing to trust someone compared to taking an equally risky bet with the same payoff externalities for an uninvolved person. They attribute this premium to betrayal aversion—an anticipatory disutility from exposing oneself to the risk of being betrayed.

In this study, we experimentally test a confounding explanation for this premium. We test whether participants' MAPs vary systematically as a result of the underlying distribution from which the probability of success of the lottery is drawn. We exogenously manipulate participants' probabilistic beliefs about this distribution by varying the different objective distributions from which the probability of success is drawn.

We then compare the resulting MAPs across treatments.

Experimental Design Details

See the pre-analyis plan

Randomization Method

Computer

Randomization Unit

Individual

Was the treatment clustered?

No

Planned Number of Observations

420 (based on sample size calculations in Appendix C)

Was IRB approval obtained (only for "In Development" and "On-going" trials)? If so, also

IRB Name

IRB Approval Date

IRB Approval Number

No, but the experiment has been approved in a BEELab proposal meeting at Maastricht University.

2 Introduction

The Minimum Acceptable Probability (MAP) is a threshold value for preferring to trust someone over accepting a sure payoff. It is elicited through a procedure similar to a Becker-DeGroot-Marschak mechanism (expressed as a required probability or absolute number of favorable outcomes).

The concept was introduced by Bohnet and Zeckhauser (2004) and it has been used—with slight variations—to elicit a determinant of trust, betrayal aversion, in a difference-in-difference design. Bohnet and Zeckhauser (2004) find that participants require a premium for being willing to trust someone compared to taking an equally risky bet with the same payoff externalities for an uninvolved person. They attribute this premium to betrayal aversion—an anticipatory disutility from exposing oneself to the risk of being betrayed.

As Li et al. (2020) note, this attribution rests on the assumption that participants are rational expected utility maximizers. Should participants not be rational expected utility maximizers, there are several possible confounding explanations for the premium found by Bohnet and Zeckhauser (2004) and subsequent studies, such as "ambiguity attitudes, complexity, different beliefs, and dynamic optimization" (Li et al., 2020, p. 275).

In this study, we test experimentally what the contribution of one such confounding explanation is to this premium. Specifically, we test whether participants'

MAPs change as a result of the underlying distribution from which the probability of success of the lottery is drawn. We remove the social and strategic aspects of a trusting decision, and study the MAP for accepting a risky lottery. The treatments exogenously vary the distribution from which the chance of the favorable outcome is drawn, thus manipulating participants' expectations about the lottery's winning chances.

Below we present the sample selection procedure, the experimental design, and the empirical strategy.

3 Research Strategy

This project will collect experimental data on an online platform dedicated to academic research (Prolific) in May 2021. Participants will be exposed to three treatments sequentially, in randomized order. In each of the treatments, participants have to state the MAP for which they prefer a lottery over a sure payment.

The pre-analysis plan will be registered at the AEA RCT registry before the start of the data collection.

3.1 Recruitment

Participants are registered users on the online platform Prolific. This platform is tailored for academic research, and gathers demographics about registered users. We will send an invitation to the experiment only to participants who have completed higher education, to increase the chances that task comprehension is not an issue. Our sample consists of residents of the United Kingdom.

4 Design

The study consists of three parts. The first part describes the task and asks comprehension questions. This part pays a fixed payoff. Only those who answer the comprehension questions correctly are directed to the second part, which is incentivized, and where we elicit participants' MAPs in three different scenarios. After this, those who complete the second part go through a survey (the third part), which is unincentivized. Uncertainty is resolved at the very end, when participants are informed about their payoff for the second part.

As mentioned above, participants in the experiment are asked to state their MAP in a *Decision Problem* (Bohnet and Zeckhauser, 2004): what is their MAP for taking a gamble rather than accepting a sure payoff? The experiment uses a within-subject design. The complete instructions are available in Appendix XYZ.

Below we present the main task in more detail.

4.1 Explanation of the main task in Part 1

See the document 'Explanation.pdf'.

4.2 Part 2

In each treatment, subjects are faced with a different distribution of the possible states of the world. Each state of the world is represented by a wheel of fortune with 15 sectors. Sectors are either dark blue (worth the high payoff of £4) or light blue (worth the low payoff of £1).

Each of the three treatments consists of 32 different wheels, which can be ordered by the overall expected value over all wheels in the treatment. We call the three treatments: the Good (the treatment with the highest expected value over all 32 wheels, where the distribution of the favorable outcome is left skewed), the Bad (the treatment with the lowest expected value over all 32 wheels, where the distribution of the favorable outcome is right skewed), and the Uniform (the expected value is in-between the ones in the other treatments, and the distribution of the favorable outcome is uniform).

The Bad and the Uniform distribution were chosen to reflect potential distributions imagined by participants in Bohnet and Zeckhauser (2004) and Bohnet et al. (2008) in the Trust Game and in the Decision Problem, respectively. Specifically, the Bad distribution has an expected probability of a dark blue sector over all 32 wheels of 0.2895, close to p^* in the Trust Game. The Uniform distribution is plausibly what participants expected to face in the Decision Problem: an overall probability of a dark blue sector over the 32 wheels of 0.5.

Payoffs are determined by a two-stage lottery with objective probabilities. In Stage 1, one of the 32 wheels is randomly drawn. In Stage 2, the number of dark blue sectors in the randomly selected wheel is compared with the participant's MAP. Should this number be equal to or exceed her MAP, the participant spins the virtual wheel for her payoff. Should the number be lower than her MAP, the wheel is not spun, and the participant receives the intermediate safe payoff of £2.

Participants who have answered the comprehension questions in Part 1 correctly see the pictures in Figures 1, 2, 3 in randomized order.[1] Each picture is accompanied by the following text:

Consider the wheels above. Which wheels do you prefer to SPIN for your bonus?

[1] The code for the spinning wheels is an adaptation of the wheel in: `https://github.com/tschiemer/qualtrics-gambling`, developed by Philip Tschiemer and Marc Hoeglinger.

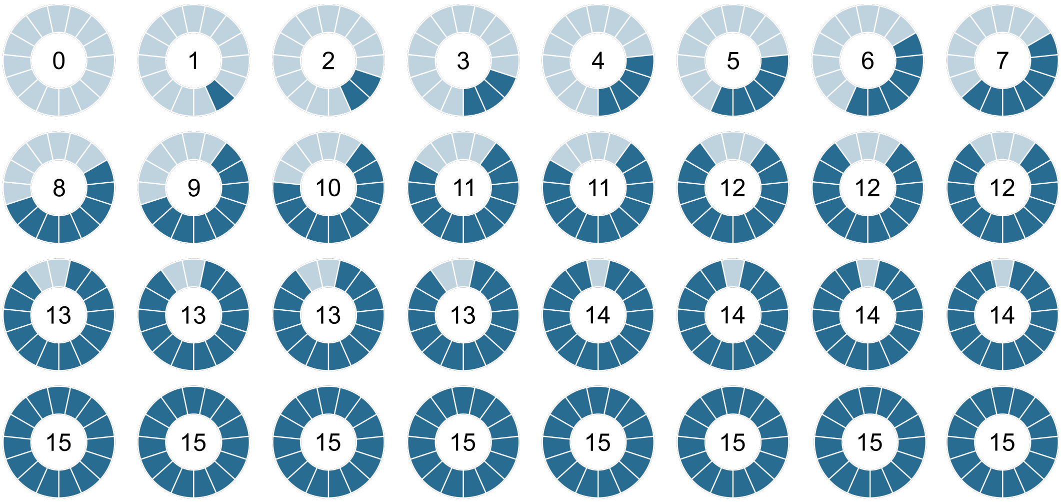

Figure 1: Left skewed distribution ('The Good')

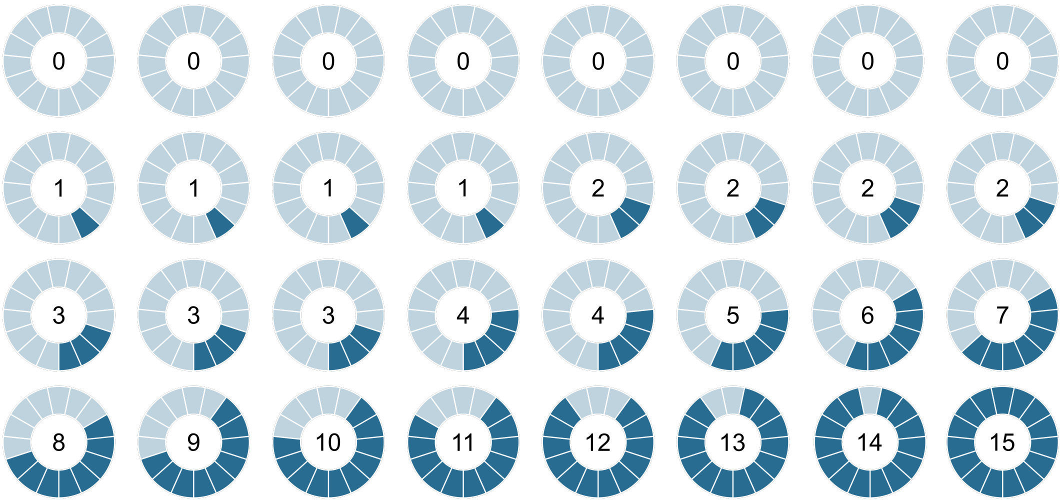

Figure 2: Right skewed distribution ('The Bad')

Please enter an integer between 0 and 15.

I prefer to SPIN wheels which have at least ... dark blue sectors.

If the randomly selected wheel has fewer than ... dark blue sectors, I DON'T SPIN it. My bonus is £2.

If the randomly selected wheel has ... or more dark blue sectors, I SPIN it. My bonus is

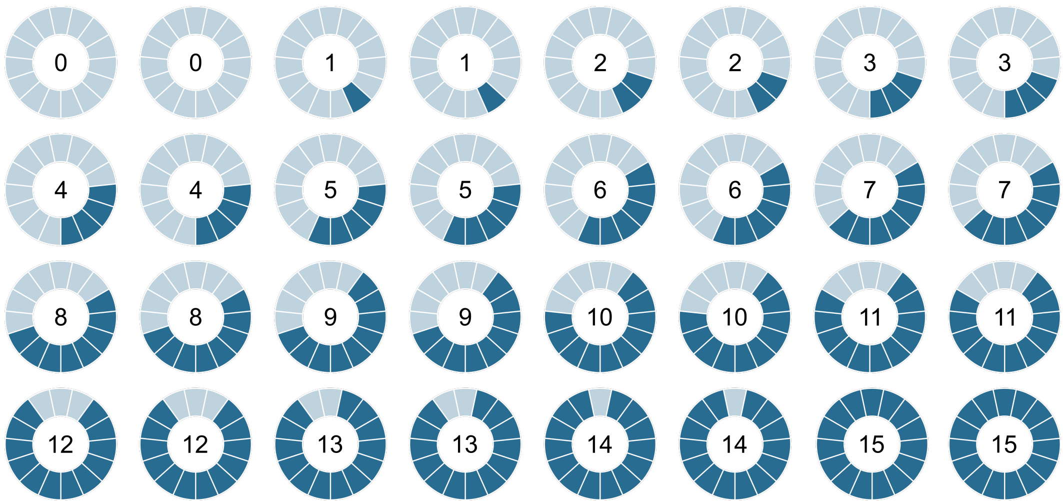

Figure 3: Uniform distribution ('The Uniform')

- *£1 if the selected wheel lands on light blue, and*
- *£4 if it lands on dark blue.*

They have to fill in the text in the bold italicized sentence (which is not bold nor italicized in the version participants see). The rest of the '...' are interactive, and are automatically filled in (and/or updated) with the participant's input.

4.3 Survey questions in Part 2

Participants answer the following type of questions:

- an adapted cognitive reflection test (Frederick, 2005; Thomson and Oppenheimer, 2016);
- 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);
- a brief sensation seeking scale, BSSS-4 (Stephenson et al., 2003).

Additional information will be requested from Prolific, who can provide data on participants' age, gender, household spending decision making, and investment behavior.

5 Empirical Strategy

Should participants be expected utility maximizers, their MAPs should not differ between the three treatments. This would be in line with what Bohnet and Zeckhauser (2004) and Bohnet et al. (2008) assume.

In their Appendix A, Li et al. (2020) show by means of a numerical example that if participants are not expected utility maximizers, ambiguity aversion alone could generate the pattern attributed to betrayal aversion. Since there is evidence that attitudes towards complex risks and attitudes towards ambiguity are correlated (Armantier and Treich, 2016), we redo their numerical exercise for our three distributions: the Good, the Bad and the Uniform in Appendix A. For this calculation we thus assume that participants view the tasks as complex risky situations—and this underlies their inverse-s-shaped probability weighting.

This calculation leads to the following hypotheses.[2]

[2]For details, see Appendix A.

5.1 Hypotheses

5.1.1 Main hypotheses

Hypothesis 1 *The MAP in the Good treatment (more mass on high values of p^*) is lower than the MAP in the Bad treatment (more mass on low values of p^*).*

Hypothesis 2 *The MAP in the Good treatment (more mass on high values of p^*) is lower than the MAP in the Uniform treatment (a uniform distribution over p^*).*

Hypothesis 3 *The MAP in the Bad treatment (more mass on low values of p^*) is higher than the MAP in the Uniform treatment (a uniform distribution over p^*).*

5.1.2 Heterogeneity

Since the MAP is a way to gauge (complex) risk aversion, we expect that in the same treatment females state higher MAPs than males on average.

Hypothesis 4 *Within each treatment, females require higher MAPs on average than males.*

Our treatments vary the objective distribution of the winning probability. How subjects process these probabilities might depend on things like (i) their optimism/pessimism etc. These heterogeneity analyses will be based on subsamples resulting from answers to the post-experimental survey.[3]

Hypothesis 5 *Within each treatment, more optimistic individuals require lower MAPs on average than pessimistic individuals.*

[3] Gender is among the demographics which we can obtain from Prolific.

5.2 Specifications and Analysis

We present the OLS regressions which will be used to test the hypotheses. Additionally, we will also run non-parametric Mann-Whitney U tests and Friedman tests / Page L trend tests, to check whether the MAPs in all treatments are from the same distribution.

The main hypotheses (1–3) will be tested using the following regression:

$$MAP_i = \beta + \beta_L L + \beta_R R + \epsilon_i \tag{1}$$

where MAP_i is the MAP chosen by participant i, L is an indicator which takes the value of 1 if the decision was made in the Good treatment, R is an indicator which is 1 if the decision was made in the Bad treatment and ϵ_i is a random error term. Standard errors in the estimation will be clustered at the individual level.

For heterogeneity analyses, we will interact all terms in equation (1) with an indicator variable corresponding to each specific hypothesis. For instance, for Hypothesis 5, all terms will be interacted with indicator variable F_i, which takes the value 1 if the participant is female:

$$MAP_i = \beta + \beta^F F_i + \beta_L L + \beta_L^F L F_i + \beta_R R + \beta_R^F R F_i + \epsilon_i \tag{2}$$

The formal statements of the hypotheses are in Appendix B.

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Appendix A Numerical Example

Li et al. (2020) show in their Appendix A that—even in the absence of betrayal aversion—a different effect of ambiguity attitudes in the *Risky Dictator Game* and in the *Trust Game* may lead to the strategic premium observed in papers on betrayal aversion.

We apply their numerical example to the three distributions used in our study. We make the following assumptions:

- the utility of outcomes is fixed. We consider $U(£4) = 1$, $U(£1) = 0$, and $U(£2) = 1/3$;[4]
- 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:

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

- we use $\alpha = 0.65$ and $\beta = 1.0467$, which according to Li et al. (2020) are the values most commonly found for risky probability weighting;
- participants use "forward" evaluation: they consider the three possible outcomes, and take into account their probabilities;
- participants have the following rank dependent utility function:

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

[4] We set the utility of the safe payoff such that $U(£2) = x \times U(£4) + (1 - x) \times U(£1)$, where $x \in [0, 1]$.

where $P(£4)$ is the probability of receiving the high payoff, $P(£2)$ the probability of receiving the safe payoff, and $P(£1)$ the probability of receiving the low payoff.

In this case, the MAPs which maximize participants' utility in the three treatments are: $MAP_L = 7$ ($RDU = 0.628$), $MAP_U = 8$ ($RDU = 0.495$), and $MAP_R = 9$ ($RDU = 0.439$).

Appendix B Hypothesis Testing

B.1 Hypothesis 1

$H0 : \beta_L - \beta_R = 0$

$H1 : \beta_L - \beta_R < 0$

B.2 Hypothesis 2

$H0 : \beta_L = 0$

$H1 : \beta_L < 0$

B.3 Hypothesis 3

$H0 : \beta_R = 0$

$H1 : \beta_R > 0$

B.4 Hypothesis 4

Within each treatment:

$H0 : \beta^F = 0$

$H1 : \beta^F > 0$

or

$H0 : \beta^F + \beta^F_L = 0$

$H1 : \beta^F + \beta^F_L > 0$

or

$H0 : \beta^F + \beta^F_R = 0$

$H1 : \beta^F + \beta^F_R > 0$

B.5 Hypothesis 5

Analogous to Hypothesis 4.

Appendix C Sample size calculations

The Stata code below (actually, attached) builds heavily on Example 2 in Campos-Mercade (2018).