Core Hypotheses

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1 Preliminary

This documents details the core hypotheses we seek to test. For details on the experimental design, see the document "Experiment_description". Unless otherwise noted, we employ OLS regressions and test our hypotheses using two sided t-tests. Whenever we include multiple observations from the same subject, we cluster standard errors at the subject level. We will refer to coefficients as statistically significant if $p < 0.05$.

2 Part I: Mao pairs

Variable construction: Our analysis follows that of Dertwinkel-Kalt and Köster (2019). We first construct the variable $shift$. $shift$ is equal to one if a given subject chose the less skewed option for the maximal positive correlation but shifted to the more skewed option for maximal negative correlation. For the reverse choice pattern, $shift = -1$. Finally, $shift = 0$ when a subject chose the same lottery for both correlation structures.

In a first step, we aim to replicate the results of Dertwinkel-Kalt and Köster (2019), using data from the treatment CEESE. We run the following regression:

$$shift_{i,t} = c + \beta asymmetric_{i,t} + \epsilon_{i,t} \tag{1}$$

where i denotes a given subject and t a given Mao pair. The variable $asymmetric_{i,t}$ is a dummy that is equal to zero if the Mao pair is more symmetric (S=0.6) and one if it is more asymmetric (S=2.7). c is a constant and $\epsilon_{i,t}$ is an iid error term.

Hypothesis 1 concerns the constant, c. We test whether it is significantly different from zero. This corresponds to Dertwinkel-Kalt and Köster (2019)'s hypothesis 3a). We run an equivalent test on β. This corresponds to Dertwinkel-Kalt and Köster (2019)'s hypothesis 3b). We expect to find that c is positive and β is negative, both statistically significant.

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In a second step, we repeat the same procedure for the treatment CEO. We expect the coefficients to be reduced in magnitude. They might lose statistical significance.

In a third step, we run the following regression:

$$shift_{i,t} = c + \beta_1 asymmetric_{i,t} + \beta_2 CEESE_i + \beta_3 asymmetric_{i,t} * CEESE_i + \epsilon_{i,t} \quad (2)$$

where $CEESE_i$ is a dummy that is equal to one if subject i is in treatment CEESE and zero otherwise. Since CEO is the omitted category, the constant c will be an estimate of the shift in choices due to correlation effect. β_2 will be an estimate of the ESE. We can thus cleanly separate the effect of correlation structure and ESE (as long as they are additively separable). β_1 captures differences in $shift$ for the different levels of symmetry of the Mao pairs that are due to correlation effects, and β_3 estimates these differences which are due to ESE.

If only correlation effects are at play, we expect c and β_1 to be significantly different from zero (and to be positive and negative respectively), while β_2 and β_3 are not statistically significantly different from zero. If only ESE are at play, we should see the reverse. Finally, if both ESE and correlation effects are present, all coefficients should be significant.

3 Part II: Common consequence Allais Paradox

3.1 Occurrence of the Allais paradox under different correlation structures

Variable construction: We classify choices into AA, BB, AB, and BA, where the first letter indicates lottery choice for $z = a_l$, and the second one for $z = b$. Lottery A denotes the more risky option. AA and BB are in line with EUT, AB is in line with the Allais paradox, BA is reverse Allais paradox (interpreted as decision noise). We construct the dependent variable analogous to the way for the Dertwinkel-Kalt and Köster (2019) tasks. $shift$ is defined such that it is zero if a choice patterns was classified as AA or BB, $shift = 1$ for AB and $shift = -1$ for BA.

Regressing $shift$ on a constant (clustering SE at the subject level) allows to test whether the Allais paradox is triggered for a given presentation and correlation structure, net of decision noise. In the treatment CEESE, For positive correlation, we expect this constant not to be significantly different from zero. We expect a positive and significant constant when lotteries are independent. This replicates existing findings (see for instance Frydman and Mormann (2018) and Bruhin et al. (2018)). For choices in the treatment CEO, we expect the constant to be non-significant for the the maximally positive correlation structure. For the case in which lotteries are independent but ESE are controlled for, the constant will yield an estimate of the effects due to correlation effects, when ESE are controlled for.

3.2 Can the Allais paradox be turned on and off by changing the correlation structure?

In a second step, we aim to disentangle ESE from correlation effects. Note that testing whether changing the correlation structure changes the frequency of Allais compatible choices comes down to testing whether changes in the correlation structure changes choices for $z = a_l$. This is because the correlation structure cannot change when $z = b$.

Variable construction: We therefore construct the following variable. $shift$ is defined such that it is zero if a given subject chose the same lottery regardless of the correlation structure. $shift = 1$ if a given subject chose lottery A (the riskier lottery) for $z = a_l$ when the lotteries are independent and B (the safer lottery) when they are maximally positively correlated. $shift = -1$ for the reverse pattern.

We run the following regression:

$$shift_{i,t} = c + \beta CEESE_{i,t} + \epsilon_{i,t} \tag{3}$$

c estimates the fraction of choice pairs exhibiting the Allais paradox due to changing the correlation structure from maximal positive to independent, when controlling for ESE. β estimates the fraction of Allais compatible choice pairs due to ESE in the treatment CEESE. Note that the number of events is not the same in CEESE and CEO when lotteries are independent. However, according to salience theory, this does not matter, meaning that correlation effects should be equivalent in both treatments. Therefore β is a valid estimate for the fraction of Allais compatible choice pairs due to ESE in the treatment CEESE. We expect β to be positive and significant. We expect c to be small and that it might not reach statistical significance.

4 Part III: Dominant and Dominated Lotteries

Salience Theory predicts that subjects choose the dominant lottery in both cases, that is when the domination is state-wise as well in as in the case of FOSD. A salient thinker will always choose a state-wise dominant option. Changing the correlation structure from positive to negative should only reinforce these preferences. However, the positive correlation structure makes it easier for subjects to note that one lottery is superior. We therefore predict that subjects will choose the dominated option less often when the correlation structure is positive than when it is negative.

To test this, to stick with our previous approach, we construct a variable $shift_{i,t}$, that is equal to 1 if a subject i chose the dominant lottery for the choice pair t for the negative correlation structure (FOSD) but not for the positive correlation structure (state-wise dominant). For the reverse pattern, shift is equal to -1. If no change occurs when the correlation structure is changed, $shift = 0$. We then regress $shift_{i,t}$ on a constant and test whether this constant is equal to zero.

$$shift_{i,t} = c + \epsilon_{i,t} \tag{4}$$

We expect c to be negative and statistically significant. A shift towards the dominated lottery due to changing the correlation from maximally positive to maximally negative can be interpreted as evidence against salience theory.

5 Part IV and V: Same Marginal Lotteries

We construct a dummy $skew_{i,t}$ that is equal to one if subject i chose the lottery with the higher relative skewness for choice t. We also construct a dummy that is equal to 1 if subjects received immediate feedback on a given choice. We then run the following regression

$$skew_{i,t} = c + \beta feedback_{i,t} + \epsilon_{i,t} \tag{5}$$

By testing whether c is equal to 0.5 (the random choice benchmark), we test for preferences for positive relative skewness when subjects do not receive immediate feedback. We also test if β is different from zero. If it is positive and significant, this will be interpreted as evidence in favor of regret theory.

To further test for differences in relative skewness seeking due to feedback, we calculate, for each subject i, the average of the variable $skew_{i,t}$. We call this the relative skewness seeking score (RSSS). We compute the RSSS both for choices with and without immediate feedback. The score ranges from 0 to 1. We then test for differences in the distribution of relative skewness seeking scores with and without feedback. To this end, we perform a Wilcoxon signed-rank test, at $p = 0.05$.

6 Further Analysis

6.1 Does relative skewness seeking predict skewness seeking?

We use the fraction of choices of the more positively skewed option part I (regardless of the correlation structure) as a measure for individual's absolute skewness seeking. We call this the skewness seeking score (SSS). (We consider part I choices because the Mao pairs control for EV and variance). We consider choices from both treatments.

If there are differences in choices due to feedback, we use the RSSS for choices without feedback. If there are no differences due to feedback, we use the average of the RSS for the case with and without feedback.

We then regress the score for skewness seeking on individuals score for relative skewness seeking. We test if β is statistically significant. (linear regression, robust standard errors, t-test at $p = 0.05$)

$$SSS_i = c + \beta RSSS_i + \epsilon_i \tag{6}$$

6.2 Robustness Check

We will check the robustness of our findings to excluding subjects who

- failed a comprehension test at the beginning of the experiment at least three times before succeeding.
- chose a state-wise dominated lottery.

References

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