



Bachelor thesis

UNETHICAL BEHAVIOR IN GROUPS AND OPTIMAL PUNISHMENT MECHANISMS

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Abstract

Unethical behaviors such as dishonesty, cheating, and corruption happen frequently at an individual level as well as at an organizational level. Recent Experimental evidence suggests that there is stronger inclination to behave immorally in organisations. We investigated individual behaviour within groups under two punishment mechanisms. The first punishment mechanism penalizes the individual solely whereas the second penalizes the group collectively. Our findings suggest that there are no significant differences in behaviour under individual punishment mechanisms, nor under group punishment mechanisms.

Introduction

Honesty is at the heart of numerous economic activities. Organisations can be broken down to a conglomerate of groups of individuals. In our research we try to understand the motives behind immoral behaviour within groups and investigate different mechanisms to alter it.

It was 1968 when Gary Becker brought dishonest actions to a rational economic framework, he argued that the decision maker faces a trade-off between the expected costs of punishment and the benefits from engaging in immoral behaviour. Becker argued that a rational agent should opt for parking the car illegally closer to her destination in order to get to the meeting in time (Becker, 1968).

Experimental Psychology and Economics suggest otherwise. Evidence show that the proportion of dishonest actions is surprisingly little, even when payoffs are ultimately beneficial. In a two-player sequential game, the first participant, *the sender* is told the result of a six-sided die roll that he then has to report to her partner *the receiver*. Each outcome related report {1..6} had different payoffs for the sender and the receiver that only the sender knew about. Telling the truth resulted in equal payoffs of €20. The sender had the option to lie about the outcome of the die roll to influence the payoffs. Some reports attached higher payoff for them than for their partners i.e. €30 vs €10. Others were the other way around. In the case where reporting the actual die roll resulted in payoffs worse than lying for both subjects i.e. €10 each. 35% of senders refused to lie demonstrating pure lie aversion. (Uri Gneezy, 2011).

Furthermore in a meta study that analysed 72 experimental studies containing 362 treatment conditions from 32,503 subjects covering 43 countries discovered through standardisation of participants' payoffs to a scale between -1 and 1 where -1 is the lowest possible payoff and +1 is the highest that average standardised report was 0.216 where 0 represents the truthful report without lying. This meant that subjects forewent about 3 quarters of the potential gains from lying (Abeler, Nosenzo, & Raymond, 2016).

Experiments also suggest that we lie more in groups. Between 2010 and 2011 experiment sessions involving 288 subjects ran in the laboratories of the university of Bonn and the university of Cologne, some participants were randomly assigned to a group that consists of two people- *group treatment*. Others participated individually- *Individual treatment*. They investigated lying under different compensation schemes, *individual treatment* scheme and *group treatment* scheme. Participants were presented with a die and were asked to report the

first die roll outcome. Higher outcome contributed on 1:1 to higher points except for 6, reporting 6 resulted in 0 points, therefore participants had an incentive to lie whenever a die roll outcome was not equal to 5. For the individual treatment the payoff was equal to the number of points, but in the group treatment it was an equal split of both participants' number of points. In case of truthful reports, the expected number of points should be $\frac{(1+2+3+4+5+0)}{6} = 2.5$ points. The experiment showed that the proportion of lies in the group treatment was significantly higher than the individual treatment. An average report in individual treatment was 3.31 points compared to 3.86 points. (Julian Conrads, 2011). Another similar experiment was conducted where the group treatment consisted of 3 randomly assigned members. They allowed participants to communicate via chat before reporting the result of a commonly witnessed die roll aiming to investigate group communication and its impact on coordination- *reporting the same communicated value in the chat*. found that the fraction of dishonest reports was 28.2% lower in the individual treatment compared to the one group treatment and 24.8% lower in the another group treatment (89.7% and 86.3% vs 61.5%) (Kocher, Schudy, & Spantig, 2020). Perhaps due to a more dispersed feeling of responsibility.

From the above literature we can assume that there are mental costs associated with lying, explanation could be self-image, religious orientations, intrinsic beliefs...etc. In our experiment we investigate new punishment mechanisms to escalate mental costs and demote immoral behaviour. Similar to previous experiments we operationalise immoral behaviour in lying. We precisely introduce potential supervision under two punishment schemes, an individual punishment, and a group punishment.

Experimental Design

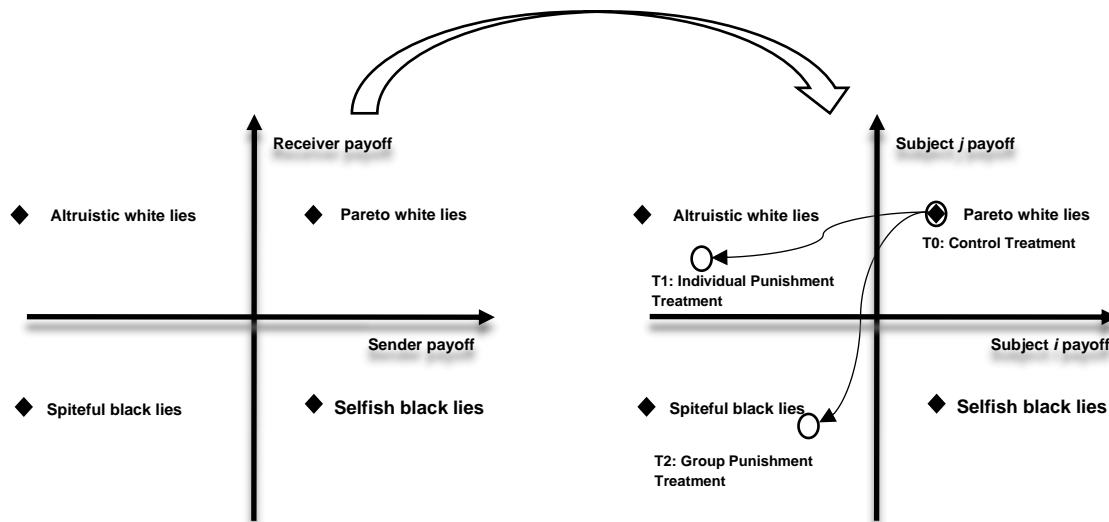


Figure 1: Taxonomy of lies under changes in payoffs.

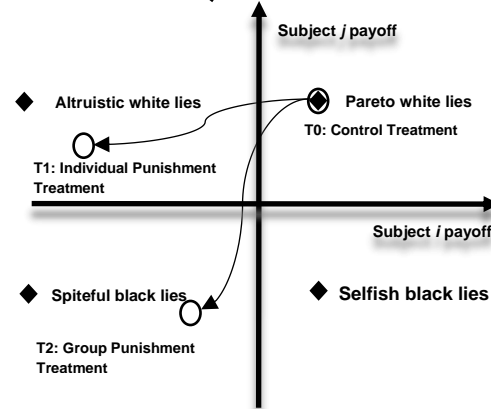


Figure 2 : Applying Gneezy's model to our experimental setup; the hollow circles represent the payoffs in case of getting caught lying from the perspective of the sender.

i.e., If the sender gets caught lying in our Individual punishment treatment, this will result in getting lower payoff in relation to their partner.

Based on his 2011 Experiment (Uri Gneezy, 2011) argued that not all lies are equal. He demonstrated different classification of lies in a two-player domain by employing his aforementioned cheating game represented in **Figure 1**. The dimensions illustrate the receiver's individual payoffs in case the sender lies. A *pareto white lie* is a lie that benefits both subjects, an *altruistic white lie* benefits the liar's partner at her own cost, a *spiteful black lie* harms both subjects and a *selfish black lie* benefits the liar at the cost of her partner. We extend Gneezy's vision to our experiment. In our experiment we introduce potential supervision. There's a probability that a subject is supervised and in case of cheating their payoffs is altered. In principle, all lies are *pareto white lies* as presented in the first quadrant of **Figure 2**. In case of supervision, they are then re-distributed to other quadrants -*different lies*.

Our Experiment employs a simple one-shot decision task consisting of a simple cheating game. We are interested in whether an organization or rather an individual within an organization would commit an immoral behaviour. We reside to a parsimonious design, a dichotomous coin toss. This is desirable to curb the 'cheat by a little' effect- this is for instance when participants lie in reporting die rolls. They lie but not to the full extent (Julian Conrads, 2011; Kocher, Schudy, & Spantig, 2020). In our experiment each participant is randomly assigned to a group that consists of two participants, henceforth subject *i* and subject *j*. Subjects then watch a series of three consecutive coin tosses on a computer and are asked to report the result of the second

coin toss, whether it was heads or tails. heads is associated with a value $v_i(Heads) = 5$ whereas tails is associated with a value $v_i(Tails) = 0$. These values are later *involved* in the treatment-specific payoff calculation.

The Experiment employs a between-subjects design consisting of a control group and two treatment groups. In contrast to the control group (T0), both the Individual punishment treatment (T1) and the group punishment treatment (T2) include potential supervision. Subjects in the treatment groups are informed about the mechanism of supervision. The potential supervision is implemented in the form of a compound lottery, namely, a two-stage lottery in which the outcomes from the first-stage randomisation are themselves lotteries. The lotteries represent a Poisson distribution. The first lottery is on the group level, whilst the second is on the individual level; Whether a group will be selected (0.5 probability) and if so, only one subject will be randomly selected for supervision, illustrated in **Figure 3**. Groups upon which supervision is to be conducted are selected with a probability of 0.5, then only one of the two subjects is randomly selected for supervision, yielding a probability $p = 0.25$ that a subject gets supervised. Subjects cannot tell whether they are supervised or not.

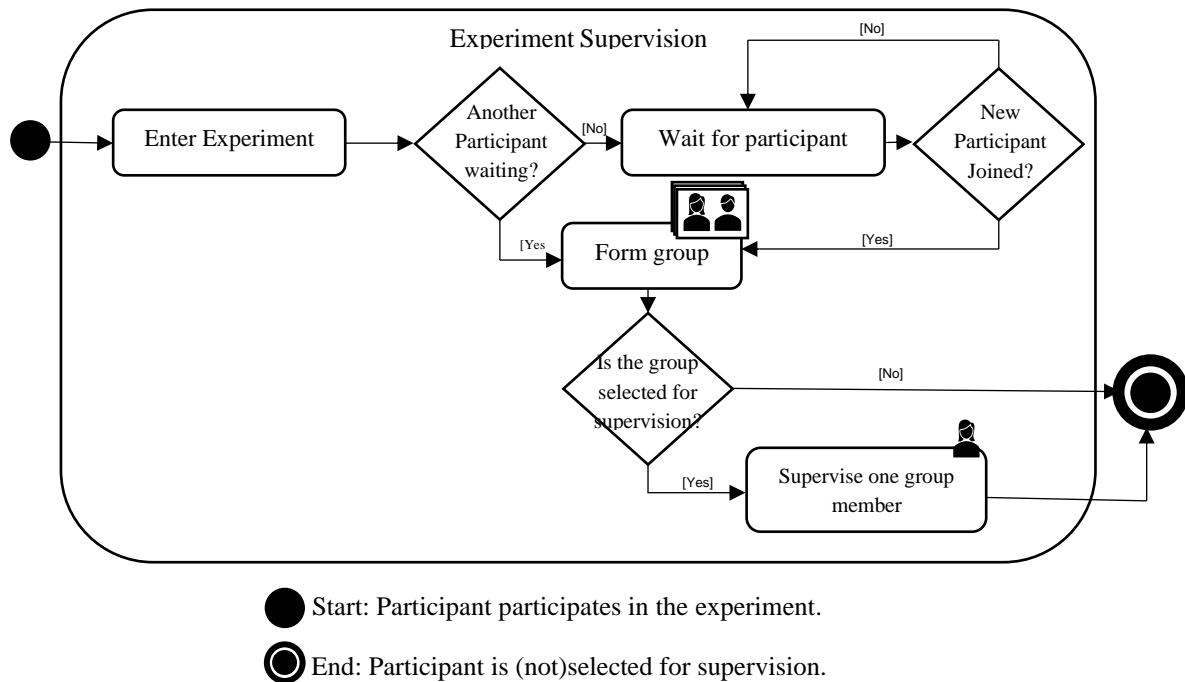


Figure 3: Informal activity diagram representing the supervision scheme from the experiment

Subjects' payoffs in the control group (T0) are determined by an equal split of the group's joint earnings: $\pi_i = \frac{v_i+v_j}{2}$. This is also true in the other treatments, (T1) and (T2) in case of no supervision or no lying. The payoffs only differ from the control treatment when a subject lies while being supervised. In this case the payoffs are determined as follows:

- Treatment 1 (individual punishment): subject i (committing the lie) earns $\pi_i = -1 + \frac{v_j}{2}$, while subject j gets the benefit of subject i 's lie but is not affected by the punishment. subject j receives the payoff: $\pi_j = \frac{v_i+v_j}{2}$.
- Treatment 2 (group punishment): Both subjects i (committing the lie) and j get $\pi_i = \pi_j = -1 + \frac{v_j}{2}$. This means that, not only subject j gets no benefit from subject i 's lie, but also shares the same punishment.

The pareto white lie in **Figure 2** only remains as such in the control treatment, where there is no supervision. In the individual punishment treatment (T1) subject j still benefits from subject i 's lie, this leads subject i to think that in the worst case their partner would benefit, similar to altruistic lies. In the group punishment treatment (T2) both subjects suffer akin to spiteful black lies.

Behavioural Predictions and Hypotheses

| | Control | T1 | T2 |
|---|---------|--|-------|
| $E[\pi_i Lie_i]$ | 2.5 | $0.75 \cdot 2.5 + 0.25 \cdot (-1) = 1.625$ | |
| $E[\pi_j Lie_i]$ e contra $E[\text{Externality}]$ | 2.5 | 2.5 | 1.625 |
| $E[\text{Joint payoffs} Lie_i]$ | 5 | 4.125 | 3.250 |
| $E[\text{Inequality} Lie_i]$ | 0 | -0.875 | 0 |

Table 1: Expected payoffs from lying¹ in (€).

In **Table 1** we represent the expected additional payoffs of subject i and subject j given that subject i is motivated to lie (i.e. witnesses tails). In the first row we calculate the expected payoff of subject i acknowledging that they do not have any knowledge regarding what their partners witness or report. In the control treatment (T0) there's no punishment. subject i 's payoff from lying is $\frac{5}{2} = €2.5$. In the punishment treatments (T1) and (T2) subject i gains €2.5 when not supervised and punished by losing €1 when supervised. Thus subject i 's payoff from lying is $0.75 \cdot 2.5 + 0.25 \cdot (-1) = €1.625$ in the punishment treatments.

We then take subject j 's viewpoint when subject i lies. In the control treatment, subject j earns €2.5 as benefit from subject i 's lie. This is because the individual payoff as is an equal split. In the individual treatment (T1). Subject j can only benefit from subject i 's lie; hence, subject j earns €2.5 from subject i 's lie. In the group punishment treatment (T2) subject j shares the same punishment as subject i earning €1.625 from subject i 's lie.

Having calculated subject i 's and subject j 's expected payoffs given that subject i lies, we add up the individual payoffs across treatments to calculate the expected joint payoff. Moreover, by deducting both subjects payoffs, we calculate the expected inequality. The payoff design generates a trade-off between efficiency seeking behaviour and inequality aversion behaviour that we could validate by introducing a social value orientation test.

The main outcome of the experiment is the share of dishonest reports from the overall number of reports. Lying is generally always payoff maximising across all treatments. Additionally, the expected payoff from lying is higher in the control treatments compared to the punishment

¹ The table shows the additional payoffs from the lie and **not** the total payoffs. In order to determine the total payoff, we have to consider the report of subject j , but, as mentioned earlier, subject i does not know about subject j 's report or what they witness, hence we focus on the viewpoint of subject i . We assume that subject i only lies to report Heads, a beneficial lie.

treatments €2.5 opposed to €1.625, thus we expect the proportion of dishonest reports to be higher in the control group when compared to the treatment groups.

Hypothesis 1: The share of dishonest reports in the control group is higher than the share of dishonest reports in the treatment groups:

$$H1: \frac{Nr. \text{ Dishonest Reports } (T0)}{N(T0)} > \frac{Nr. \text{ Dishonest Reports } (T1+T2)}{N(T1+T2)}$$

(Julian Conrads, 2011) proposed that lying was more pronounced under team incentives because it could arguably be *whiter*. Afterall, they are doing something good for the other team member. Although our experiment employs a different design, we notice that in the individual punishment treatment a lie has similar consequences. In the worst case it benefits the other participant which may lower the mental costs associated to the lie and serves as a justification for committing immoral behaviour.

Hypothesis 2: The share of dishonest reports in the individual punishment treatment is equal to the share of dishonest reports in the group punishment treatment:

$$H2: \frac{Nr. \text{ Dishonest Reports } (T1)}{N(T1)} > \frac{Nr. \text{ Dishonest Reports } (T2)}{N(T2)}$$

Implementation

The experiment is implemented in Python and HTML using otree framework (Chena et al., 2016). The experiment is deployed in the form of three separate applications, one for each treatment. They were later deployed on Heroku's cloud platform. It's crucial for us that the participants understand how their reports impact the calculation of their individual and the group payoff, hence on the first page² of the experiment we discuss the payoff calculations specific to the assigned treatment. This page contains the formulas along with examples to help the participants understand the payoff calculation mechanism. Furthermore, we include control questions in the form of a quiz. Participants are given experiment outcomes i.e. 'subject *i* reports heads although they witnessed tails, subject *j* reports tails and witnessed tails. Subject *j* was supervised, what is subject *i*'s individual payoff?' For this we can also use the following notation (1,0;0,0;2).

² A screenshot is provided in the appendix

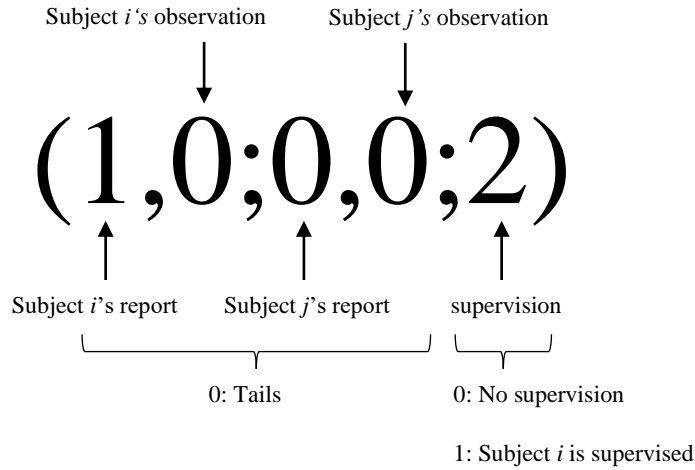


Figure 4: Experiment Notation

The first pair of numbers represent subject i 's report followed by what they observed. The second pair of numbers represent report and observation for subject j . The last number represent the supervision. 0 means that the computer is not supervising any subject. 1 means that the computer is supervising subject i . while 2 means that that the computer is supervising subject j . This is highlighted in **Figure 4**.

The control questions section contains three similar multiple-choice questions where participants are asked to select the correct individual payoffs. Participants are also asked to revise the formulas in case of wrong attempts and cannot proceed to the experiment unless they answer all questions correctly. It's worth mentioning that we monitor the participants during the quiz, we are able to find out how many questions they got wrong, how many times they got wrong and what answers they selected for each question. The first question, arguably the easiest, presents the scenario $(0,0;0,0;0)$ while the second $(0,0;0,1;2)$ and the third $(0,1;0,0,1)$. All participants were asked the same questions regardless of the treatment they were assigned, only their individual payoffs differed.

On the second page participants are equally likely to watch one of two tapes. Both tapes present three consecutive fair coin tosses. Tape I shows heads in the second coin toss while tape II shows tails. The tape is presented only once and lasts approximately 13 seconds. After watching the tapes participants are proceeded to the final page of the experiment where they are asked to report the outcome of the second coin toss.

Once a participant finishes the experiment, they can progress to the next application, a questionnaire. The questionnaire contains optional questions about age, gender and nationality and finishes with a confrontation question; ‘You witnessed x and reported y , can you please explain your intention?’. Where x represents what the subject witnessed, and y represents what they reported. The participants are provided with a textbox below that can accommodate up to 200 characters to insert their answers. The purpose of this is to further validate from the subject’s explanation that they fully understood the payoff mechanism and additionally gain insights about how the participants respond in these types of situations.

After the questionnaire, subjects proceed to the payoff page where they are informed about their individual payoff as well as the group’s payoff. In case the other subject is not yet done with the experiment part, a waiting page³ will be prompted with a blue loading bar until the other participant finishes the experiment. As presented earlier, payoff calculations require inputs from both subjects.

³ A screenshot is provided in the appendix

Results

The experiment has been sent out conveniently via link using Heroku. The candidates were family members but mostly friends from different backgrounds 29/32 with mean age of 26 and 47% female. 9 participated in the control treatment (T0), 5 participated in the individual punishment treatment (T1) and 18 in the group punishment treatment (T2). The analysis results and statistics were implemented in R.

We first investigate whether the participants managed to easily understand the experiment. We find that given the initial experiment set-up 61% of participants answered the control questions correctly on the first attempt. On the other hand, 39% arguably benefitted from the inclusion of the control questions. **Figure 5** demonstrates our findings.

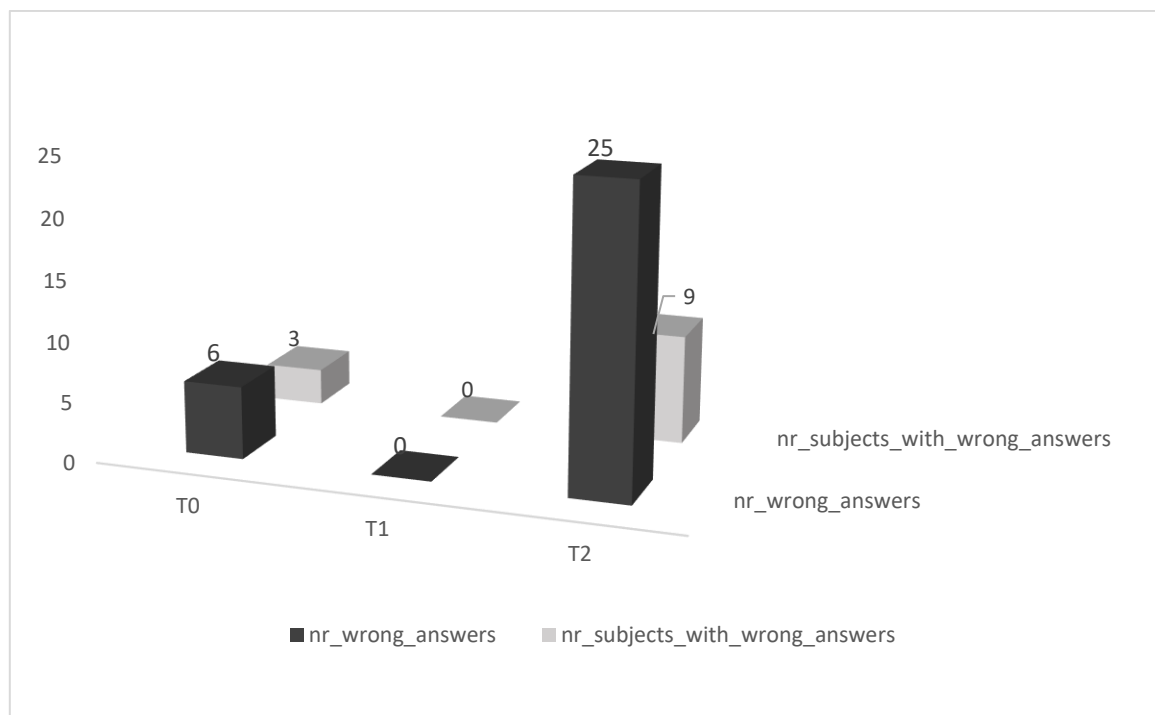


Figure 5 Control Questions Analysis: On the x-axis we see the different treatments, on y axis we see the number of wrong answers to the 3 control questions and behind on the y-axis we see the number of participants that made the wrong answers. For instance, we see that in the Group punishment treatment (T2) 9 subjects committed 25 mistakes.

We then investigate the realisations of our model. Based on our experimental design we expect heads to show up 50% of the time. Since we have 32 subjects, we expect 16 to be shown heads. We also expect 25% of participants to be supervised, that is 8. This is presented in **Figure 6** followed by **Figure 7**.

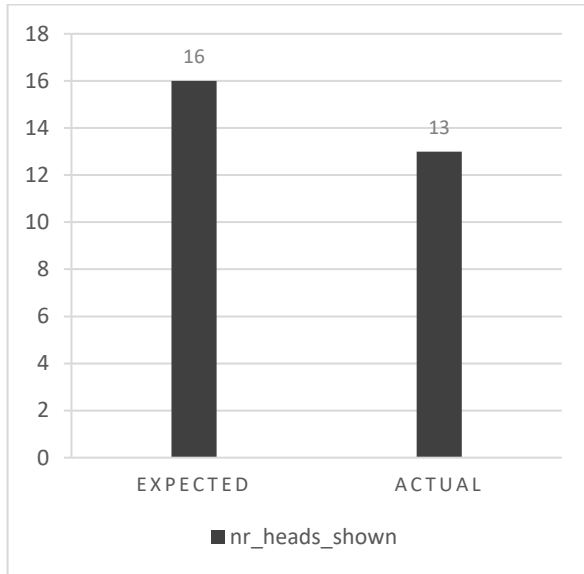


Figure 6: Heads showed up only 13 times. This also means that 13 subjects had no motivation at to lie.

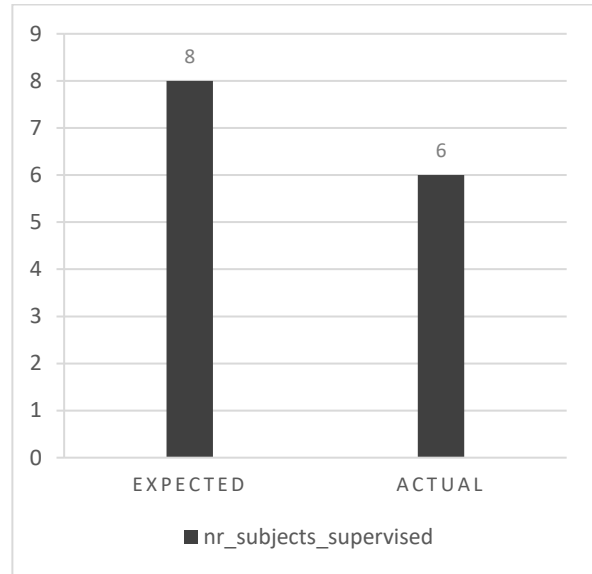


Figure 7 Number of subjects supervised is 6.

The Actual number of heads outcomes and the actual number of subjects supervised are slightly below expectations but not far off. 13 against 16 and 6 against 8 respectively (approx.. 20% off), this is due to our small sample size. **Figure 8** represents a summary of the results. In the upper part we can see the distribution of participants reports and depending on what they have witnessed and on the treatment, they participated in. It shows that there were four non-beneficial lies where the participants reported tails although they witnessed heads, of which two candidates reported in the questionnaire that they confused heads with tails.

| Control Group (T0) | | | | Individual Punishment (T1) | | | | Group Punishment (T2) | | | |
|--------------------|-------|----------|-------|----------------------------|-------|----------|-------|-----------------------|-------|----------|-------|
| | | Reported | | | | Reported | | | | Reported | |
| | | Heads | Tails | | | Heads | Tails | | | Heads | Tails |
| Witnessed | Heads | 3 | 2 | Witnessed | Heads | 2 | 0 | Witnessed | Heads | 4 | 2 |
| | Tails | 1 | 3 | | Tails | 2 | 1 | | Tails | 7 | 5 |

| | Number of dishonest subjects | Number of total subjects |
|----------------------------|------------------------------|--------------------------|
| Control Group (T0) | 3 | 9 |
| Individual Punishment (T1) | 2 | 5 |
| Group punishment (T2) | 9 | 18 |

Figure 8: Summary Matrix containing the number of subjects. The number subjects are classified according to what they witnessed and what they reported. This is across all three treatments. Right diagonal entries represent true reports. In the lower half we present a table showing the number of subjects who lied in relation to the total number of subjects per treatment. We can see that the group punishment treatment (T2) had the largest number of subjects as well as the highest number of lies.

Our first hypothesis was that the proportion of dishonest reports in the punishment treatments (T1) and (T2) is lower in comparison to the control group (T0). Our assumption was, since there is neither punishment nor supervision, subjects would be more tempted to misreport the outcome of the coin toss to earn a higher payoff.

$$H1: \frac{Nr. Dishonest Reports (T0)}{N(T0)} > \frac{Nr. Dishonest Reports (T1+T2)}{N(T1+T2)}$$

We test this against the null hypothesis, namely, that there is no difference between the proportion of dishonest reports in the punishment treatments (T1) and (T2) in comparison to the control group (T0).

$$H_{null}: \frac{Nr. Dishonest Reports (T0)}{N(T0)} = \frac{Nr. Dishonest Reports (T1+T2)}{N(T1+T2)}$$

Before conducting any statistical tests, we discovered that the proportion of dishonest reports in the punishment treatments (T1) and (T2) was higher than in the control treatment (T0) as presented in **Figure 9**. 0.4783 against 0.3333. This contradicts our hypothesis H1.

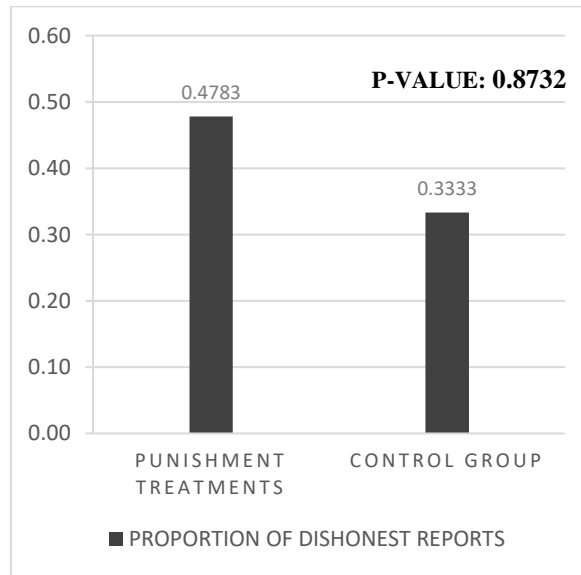


Figure 9: The proportion of dishonest reports in the punishment treatments combined (T1) and (T2) in relation to the proportion of dishonest reports in the control group (T0). We notice counter intuitively that the proportion of dishonest reports in the punishment treatments is higher than in the case of no supervision.

We resided to the non-parametric Fischer's exact test after discovering that the Chi-squared test conditions were violated, the expected values inside the cells must be greater than five. This condition is violated as shown in **Table 2**.

The p-values for the statical tests were insignificant. Fisher's exact test resulted in a p-value of

| | Honest Reports | Dishonest Reports |
|------------|----------------|-------------------|
| Control | 5.0625 | 3.9375 |
| Treatments | 12.9375 | 10.0625 |

Table 2: The Chi-squared Expected values of honest and dishonest reports per treatments according to H1.

0.8732. This is justified by the unlikeliness of such hypothesis given that we encounter the opposite. We fail to reject the null hypothesis at significance level of $\alpha = 0.05$ as the p-value is bigger than 0.05; we fail to reject our null hypothesis, that there is no difference between the proportions of dishonest reports in the punishment treatments (T1) and (T2) and the proportion of dishonest reports in the control group (T0) against our claim H1.

Our Second hypothesis was that the proportion of dishonest reports in the individual punishment treatment (T1) would be higher than that in the group punishment treatment (T2). We assumed that subjects can better justify their lie because it always benefits their partner, even if they get caught.

$$H2: \frac{Nr. Dishonest Reports (T1)}{N(T1)} > \frac{Nr. Dishonest Reports (T2)}{N(T2)}$$

We test this against the null hypothesis, namely, that there is no difference between the proportion of dishonest reports in the punishment treatments (T1) in comparison to the group treatment (T2).

$$H_{null}: \frac{Nr. Dishonest Reports (T1)}{N(T1)} > \frac{Nr. Dishonest Reports (T2)}{N(T2)}$$

We find that the proportion of dishonest reports in the group punishment (T2) is higher than in the individual punishment (T1) as presented in **Figure 10**. This is evidence that do not support the claim H2.

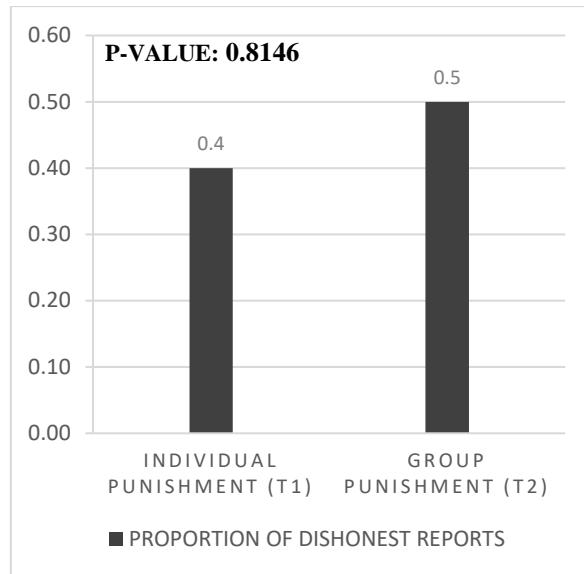


Figure 10: The proportion of dishonest reports in the group punishment treatment (T2) is higher than the proportion of dishonest reports in the individual punishment (T1).

We applied the same statistical tests, Fisher's exact test and permutations test with $N=1000$. We again resided to the non-parametric Fischer's exact test after discovering that the Chi-squared test conditions were violated, the expected values inside the cells must be greater than five. This condition is violated as shown in **Table 3**.

| | Honest Reports | Dishonest Reports |
|--------------------------------------|----------------|-------------------|
| Individual punishment treatment (T1) | 2.6086 | 2.3913 |
| Group punishment treatment (T2) | 9.3913 | 8.6087 |

Table 3: The Chi-squared Expected values of honest and dishonest reports per treatments according to H2.

The p-values for the statical tests were insignificant. Fisher's exact test resulted in a p-value of 0.8146. This is justified by the unlikeliness of such hypothesis given that we encounter the opposite. hypothesis at significance level of $\alpha = 0.05$ as the p-value is bigger than 0.05; we fail to reject that there is no difference between the proportions of dishonest reports in the individual punishment treatment (T1) and the proportion of dishonest reports in the group punishment treatment (T2) against our claim H2.

After conducting our statistical analysis, we concluded that we do not have evidence to reject that the proportion of lies are the same against both hypotheses H1 and H2. Although the experiment results show opposite effects when it came to both hypotheses our statistical analysis show that there is not enough evidence supporting such claims either. We fail to reject that the proportion of misreported coin tosses are the same across treatments for both claims. We share the raw data and the source code of the analysis in the appendix. In the next section we discuss the limitations which may have led to these results.

Limitations and Acknowledgements

Experimental limitations

Due to time restriction we could not accommodate more participants. Therefore, the number of participants was significantly low. Ideally, we would have hoped for at least 30 participants per treatment. Furthermore, the experiment was not conducted in the laboratory as intended due to Covid-19 situation. Instead, it was sent via link to friends, and friends of friends. I tried to be as partial as possible by sending it to people from different backgrounds, I share the raw data in the appendix. In addition, the payoffs were not offered for real. We asked the participants to imagine as if they would earn these payoffs. Therefore, there are unfortunately numerous reasons to doubt the results of the experiment.

External validation acknowledgements

Assuming we conducted the experiment in laboratory set-up, with real payoffs including many student participants, we cannot yet assume external validity. Decision and policy makers are arguably not university students, they do not face coin tosses and report their values in real life. By trying to infer causality we simplify, and with that we partially lose realism. To infer robust conclusions about human behavior we should implement different experiments and on larger samples. We discuss some experimental ideas under outlook.

Further Hypotheses

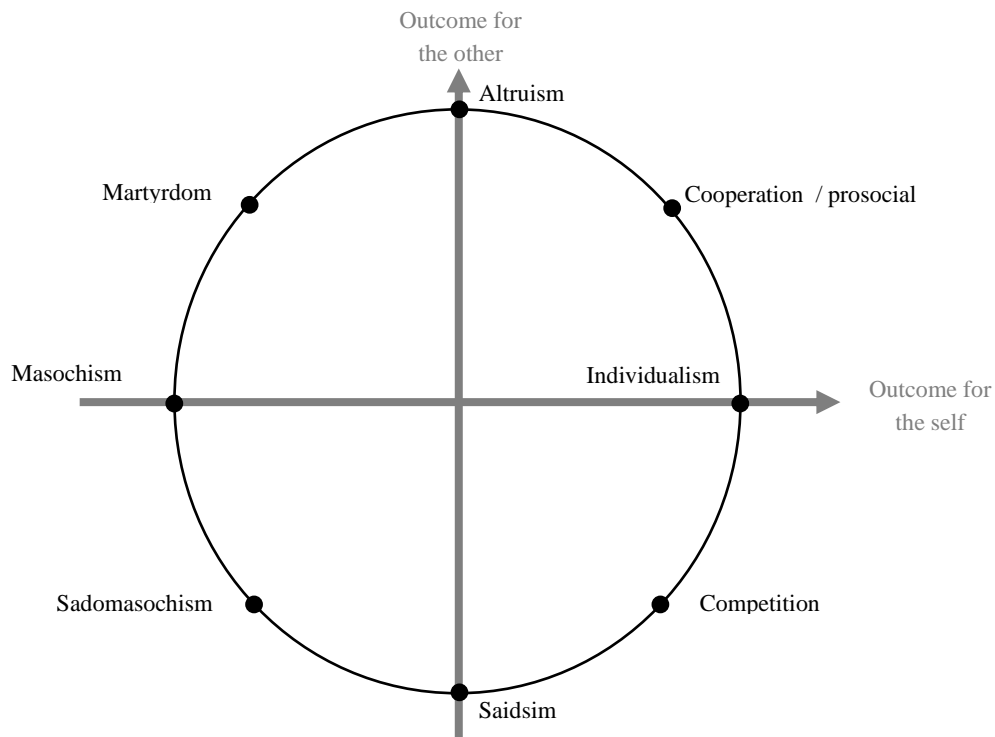


Figure 11: SVO ring- Categorisation of social value orientations based on allocation of resources between oneself and others (8 Categories). (WIM B. G. LIEBRAND, 1988)

We could introduce a social value orientation test (SVO) test in our experiment such that it precedes the cheating game. SVO is a person's preference about how to allocate resources i.e. money, between themselves and another person. It has been common to have 8 different Social Value orientations based on person's resource allocation presented in **Figure 11**. Akin to **Figure 2** we *could* adapt **The Ring measure** framework to our experimental setup. Under the control treatment (T0) there is no supervision. All lies promote pro-social behaviour, whereas in the punishment treatments subjects face different dilemmas, on one hand if they do not get caught, they increase their payoffs as well their partners whereas if they get caught, they either get penalised and their partner benefits (T1) or they get penalised and cause their “innocent” partner to get penalised as well (T2). It could be of interest to analyse the results and investigate whether different punishment mechanisms elicit different types of lies.

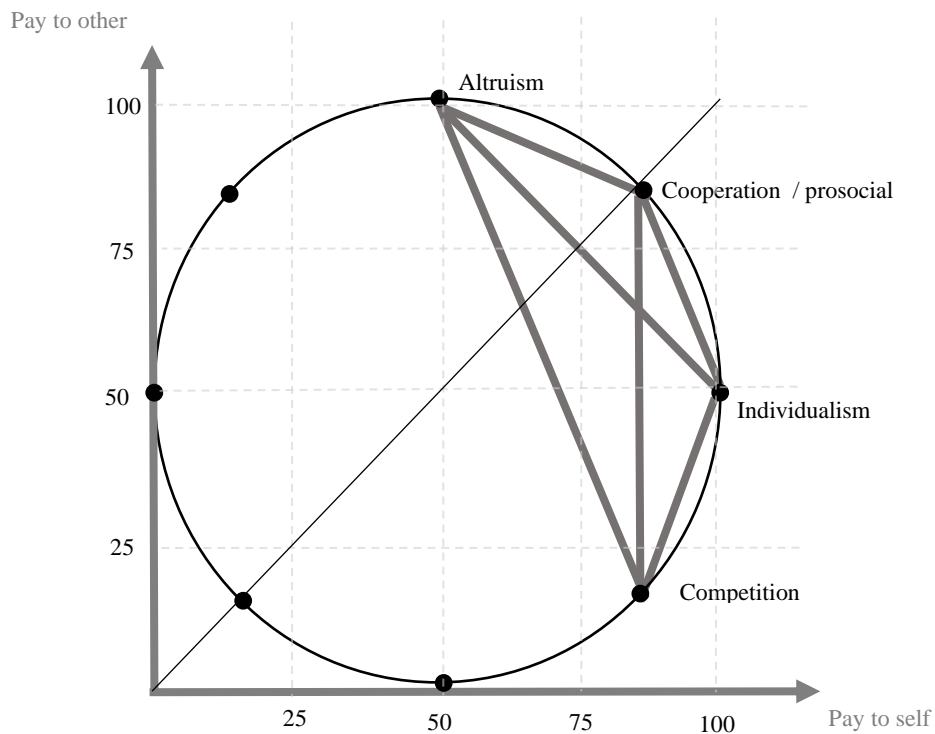


Figure 12: Murphy's framework (Ryan O. Murphy K. A., 2011)

Similar to (WIM B. G. LIEBRAND, 1988) framework Murphy proposed another framework that benefits our experimental design namely, the *slider measure*. Murphy argued that there is no significant evidence for the presence of second, third and fourth quadrants as social value orientations and only focused on differentiating *altruistic, prosocial, individualistic, and competitive behaviour*. By dropping the remaining categories as illustrated in **Figure 12** Murphy achieved a continuous measure to represent person's SVO, (i.e. *different degrees of individualism- it allows for statements such as A is more individualistic than B*), rather than having a person allocated into categories. And although there have been continuous measures for person's SVO such as the ring measure (WIM B. G. LIEBRAND, 1988). They were only applied to achieve categorical categorisation of person's SVO due to the lack of statistical usage. Augmentations in angular degrees beyond plus and minus 90° imply decreasing concerns for the other, while the opposite is true for angles within this range. Hence, the angle must be translated into a corresponding particular motivational category to be readily interpretable, which was commonly used as in the ring measure (Ryan O. Murphy K. A., 2014).

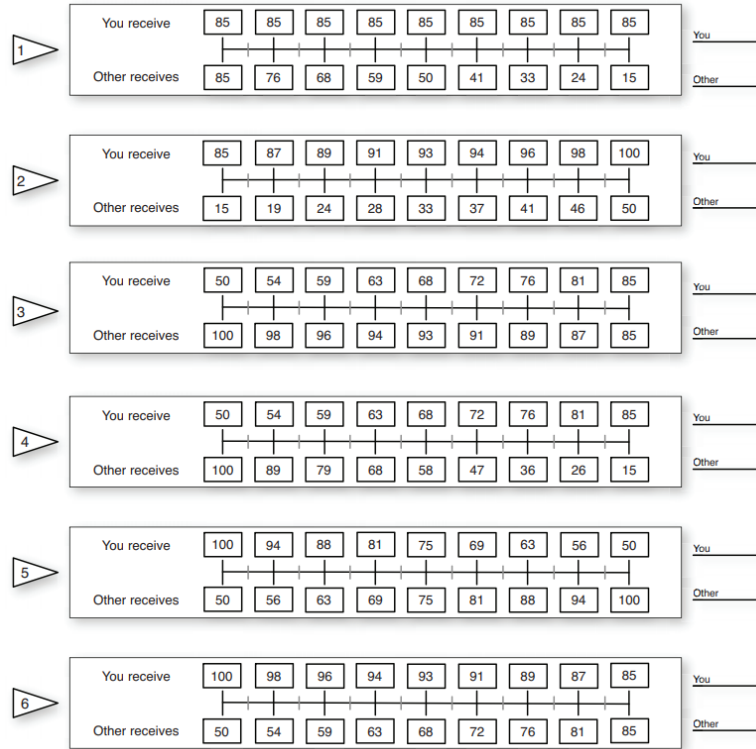


Figure 13- six primary items for the SVO slider measure (Ryan O. Murphy K. A., 2011)

Murphy's proposed SVO measure, the *Slider Measure* contains six primary items, each item is a resource allocation choice over a well-defined continuum of joint payoffs presented in **Figure 13**. Each item corresponds to an edge, a continuous scale joining different categories of SVO. By calculating the mean allocation for oneself and the mean allocation for others we can obtain a single index for a person's SVO. $SVO = \arctan \left(\frac{\bar{A}_o - 50}{\bar{A}_s - 50} \right)$. By subtracting 50 from each mean we shift the base of the result angle to the centre of the circle and achieve a continuous scale. Angles range between 61.39° and -16.26° where the former indicates perfectly consistent altruistic behaviour, and the latter indicates perfectly consistent competitive behaviour. Furthermore, Altruists would have an angle greater than 57.15° ; pro-socials would have angles between 22.45° and 57.15° ; individualists would have angles between -12.04° and 22.45° ; and competitive types would have an angle less than -12.04° .⁴

⁴ The angles do not correspond to figure 12 because the *Slider Measure* only uses a subset of possible items from the allocation plane and these items are not symmetrically distributed around the whole of the circle (Ryan O. Murphy K. A., 2014).

Hypothesis 3: For individualistic subjects, the share of dishonest reports in the individual punishment treatment is equal to the share of dishonest reports in the group punishment treatment:

$$\mathbf{H3:} \frac{\text{Nr.Dishonest Reports (T1)}|\text{Individualistic}}{N(\text{T1})} = \frac{\text{Nr.Dishonest Reports (T2)}|\text{Individualistic}}{N(\text{T2})}$$

By focusing on pro-social behaviour, Murphy went a step further and proposed 9 additional items that further disentangles prosocial behaviour from joint maximisation seeking behaviour and inequality aversion behaviour. A prosocial person with inequality aversion would yield an angle of 37.48° and a prosocial person who endeavoured to maximize joint gain (and is inequality tolerant) would yield an angle between 37.09° and 52.91°. In our experimental design there is a trade-off between joint gain maximisation behaviour (efficiency seeking behaviour) and inequality averse. According to expected payoffs presented in **Table 1** lying in the Individual punishment treatment (T1) generates higher joint payoff but at the same time generates inequality. Contrarily for the group punishment treatment lying does not generate inequality.

Hypothesis 4: For inequality averse subjects, the share of dishonest reports in the individual punishment treatment is lower than the share of dishonest reports in the group punishment treatment:

$$\mathbf{H4:} \frac{\text{Nr.Dishonest Reports (T1)}|\text{Ineq.Averse}}{N(\text{T1})} < \frac{\text{Nr.Dishonest Reports (T2)}|\text{Ineq.Averse}}{N(\text{T2})}$$

Hypothesis 5: For joint maximizing subjects, the share of dishonest reports in the individual punishment treatment is higher than the share of dishonest reports in the group punishment treatment:

$$\mathbf{H5:} \frac{\text{Nr.Dishonest Reports (T1)}|\text{Joint.Max}}{N(\text{T1})} > \frac{\text{Nr.Dishonest Reports (T2)}|\text{Joint.Max}}{N(\text{T2})}$$

Outlook

Addressing feedback

A picture of both sides of the €2 coin used is to be presented in the instructions to avoid confusion.

Proposed iterations

Similar to (Kocher, Schudy, & Spantig, 2020) experiment design. To increase group coherency a chat function is to be implemented that takes place before the cheating game. A window where participants exchange one out of 3 emojis, each emoji has different connotations, for example happiness, anger, and a no-emotion emoji.

Further Experiments

Implementing consensus between group members before reporting the coin toss result; Volkswagen has allegedly installed software in their diesel engines to improve their emission results that could detect when the cars were on the test stand and adjust the engine performance accordingly.

“VW must have had a chain of management command that approved fitting cheating devices to its engines” (Hotten, 2015).

Implementing a performance-based mechanism for the payoff; people cheat more and even cheat to the maximum extent possible when payoffs are based on performance rather than being randomly allocated (Gravert, 2013; Cadsby, 2010).

References

- Abeler, J., Nosenzo, D., & Raymond, C. (2016). Preferences for Truth-Telling. *IZA Discussion Papers*.
- Ariely, D. G.-R. (2014). The (True) Legacy of Two Really Existing Economic. *Munich Discussion Paper*.
- Becker, G. S. (1968). Crime and Punishment: An Economic Approach. *Journal of political economy*.
- Cadsby, C. B. (2010). Are You Paying Your Employees to Cheat? An Experimental Investigation. *The B.E. Journal of Economic Analysis & Policy*.
- Daniel L.Chena, M. S. (2016). oTree—An open-source platform for laboratory, online, and field experiments. *Journal of Behavioural and Experimental Finance*.
- Gächter, S. &. (2016). Intrinsic honesty and the prevalence of rule violations across societies. *Nature*.
- Gravert, C. (2013). How luck and performance affect stealing. *Journal of Economic Behavior and Organization*.
- Hotten, R. (2015). *The scandal explained*. BBC. BBC.
- Julian Conrads, B. I. (2011). Lying and Team Incentives. *IZA Discussion Papers*.
- Martin G. Kocher, S. S. (2020). I Lie? We Lie! Why? Experimental Evidence on a Dishonesty Shift in Groups. *Management Science*.
- Mas-Colell, A. M. (1995). Microeconomic Theory. In 1. Oxford University Press, *Microeconomic Theory*. Oxford University Press, 1995.
- Mazar, N. &. (2011). Greasing the palm: can collectivism promote bribery? . *Journal of the American Psychological Society*.
- Mazar, N. A. (2008). The Dishonesty of Honest People: A Theory of Self-Concept . *Journal of Marketing Research*.
- Ryan O. Murphy, K. A. (2011). Measuring Social Value Orientation. *Judgment and Decision Making*.

Ryan O. Murphy, K. A. (2014). Social Value Orientation: Theoretical and and Measurment issues in the study of social Preferences. *Personality and Social Psychology Review*.

Social Value Orientation: Theoretical and Measurement Issues in the Study of Social Preferences. (2014). *Personality and Social Psychology Review*, 18.

Uri Gneezy, S. E. (2011). White Lies. *Management Science*.

WIM B. G. LIEBRAND, C. G. (1988). The ring measure of social values: a computerized procedure for assessing individual differences in information processing and social value orientation. *European Journal of Personality*, 222.

Appendix

R Source Code

Below you can find the R source code for the analysis.

Libraries

```
library(readxl)
library(ggplot2)

## Warning: package 'ggplot2' was built under R version 4.0.5

library(data.table)

## Warning: package 'data.table' was built under R version 4.0.5

library(magrittr)

## Warning: package 'magrittr' was built under R version 4.0.5

library(tidyr)

## Warning: package 'tidyr' was built under R version 4.0.5

##
## Attaching package: 'tidyr'

## The following object is masked from 'package:magrittr':
##
##   extract

library(dplyr)

## Warning: package 'dplyr' was built under R version 4.0.5
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:data.table':
##
##      between, first, last

## The following objects are masked from 'package:stats':
##
##      filter, lag

## The following objects are masked from 'package:base':
##
##      intersect, setdiff, setequal, union
```

Data

```
data <- read_excel("~/TUM Study Material/Thesis/Professorship of Economics
/Topics/Unethical behavior and optimal punishment mechanisms/Experiment Re
sults/01.03.21.xlsx") %>% as.data.table
```

Control questions summary

```
wrong_selections_per_treatment <- data %>%
  mutate(nr_total_wrong_answers = q1_wrongClicks+q2_wrongClicks+q3_wrongCl
icks) %>%
  mutate(nr_candidates_with_wrong_answers = ifelse(nr_total_wrong_answers
> 0 ,1,0))%>%
  gather(key = "question", value = "nr_wrong_answers", 6:8) %>%
  group_by(Experiment) %>% summarise(nr_wrong_answers = sum(nr_wrong_answe
rs, na.rm = T),
                                   nr_candidates_with_wrong_answers = su
m(nr_candidates_with_wrong_answers) / 3)
```

Confusion matrices

```
control_matrix <- table( data[Experiment == "Control",c(3,5)])
T1_matrix <- table( data[Experiment == "Treatment_1",c(3,5)])
T2_matrix <- table( data[Experiment == "Treatment_2",c(3,5)])
```

Lie summary per treatment

```
lie_summary_per_treatment <- data %>% group_by(Experiment) %>% count() %>%
  cbind(
    data[lie_dummy==1, .N, by = Experiment][,2]
  ) %>% mutate(proportion = N / n)
```

First hypothesis test

```
hypothesis_1_table <- data %>% as.data.table

for(i in 1:length(hypothesis_1_table$Experiment)){
  if(hypothesis_1_table[i,Experiment]=="Treatment_1" | hypothesis_1_table[
i,Experiment]=="Treatment_2"){
    hypothesis_1_table[i,Experiment:="Treatment"]
  }
}
```

```

}

matrix_of_expected_values_1 <- chisq.test(hypothesis_1_table$Experiment, hypothesis_1_table$lie_dummy)$expected

## Warning in chisq.test(hypothesis_1_table$Experiment,
## hypothesis_1_table$lie_dummy): Chi-squared approximation may be incorrect

hypothesis_1 <- fisher.test(table(hypothesis_1_table$Experiment, hypothesis_1_table$lie_dummy)[,c(2,1)], alternative = "g")

#Permutation testing
p_val_permutation_hypothesis_1 <- function(){
  T_ref <- nrow(hypothesis_1_table[Experiment == "Treatment" & lie_dummy==1]) / nrow(hypothesis_1_table[Experiment == "Treatment"])
  N_permu <- 1000
  T_star <- sapply(1:N_permu, function(x){
    hypothesis_1_table_randomised <- data.table(Experiment = sample(hypothesis_1_table$Experiment), lie_dummy = hypothesis_1_table$lie_dummy)

    hypothesis_1_table_randomised[Experiment == "Control" & lie_dummy==1, .N] / hypothesis_1_table_randomised[Experiment == "Control", .N]
  })
  p_value <- (sum(T_star > T_ref) + 1) / (N_permu + 1)
  return(p_value)
}

```

Second hypothesis test

```

hypothesis_2_table <- data %>% as.data.table %>%
  filter(Experiment != "Control")

matrix_of_expected_values_2 <- chisq.test(hypothesis_2_table$Experiment, hypothesis_2_table$lie_dummy)$expected

## Warning in chisq.test(hypothesis_2_table$Experiment,
## hypothesis_2_table$lie_dummy): Chi-squared approximation may be incorrect

hypothesis_2 <- fisher.test(table(hypothesis_2_table$Experiment, hypothesis_2_table$lie_dummy)[,c(2,1)], alternative = "g")

#Permutation testing
p_val_permutation_hypothesis_2 <- function(){
  T_ref <- nrow(hypothesis_2_table[Experiment == "Treatment_2" & lie_dummy==1]) / nrow(hypothesis_2_table[Experiment == "Treatment_2" & is.numeric(Index)])
  N_permu <- 1000
  T_star <- sapply(1:N_permu, function(x){
    hypothesis_2_table_randomised <- data.table(Experiment = sample(hypothesis_2_table$Experiment), lie_dummy = hypothesis_2_table$lie_dummy)

```

```

    hypothesis_2_table_randomised[Experiment == "Treatment_1" & lie_dummy==
1, .N] / hypothesis_2_table_randomised[Experiment == "Treatment_1", .N] #-
    #hypothesis_2_table_randomised[Experiment == "Treatment_2" & lie_dummy=
=1, .N] / hypothesis_2_table_randomised[Experiment == "Treatment_2", #.N]
    })
    p_value <- (sum(T_star > T_ref) +1) / (N_permu +1)
    return(p_value)
}

```

Python Source Code

As the experiment was deployed into 3 separate applications, to avoid repetitions I included the code for (T0) and supervision (video page in case of T1 or T2) which is only necessary for T1 and T2.

```

from otree.api import (
    models,
    widgets,
    BaseConstants,
    BaseSubsession,
    BaseGroup,
    BasePlayer,
    Currency as c,
    currency_range,
)
import random

author = 'Your name here'

doc = """
Your app description
"""

class Constants(BaseConstants):
    name_in_url = 'cheating_game'
    players_per_group = 2
    num_rounds = 1
    endowment = c(0)
    head_payoff = c(5)
    controlQuestion1 = "Q1) You witness 'tails' and report 'tails'. Your
teammate witnesses 'tails' and reports 'tails'. \n What is Your Individual
payoff?"
    controlQuestion2 = "Q2) You witness 'tails' and report 'tails'. Your
teammate witnesses 'tails' and reports 'heads'. \n What is Your Individual
payoff?"
    controlQuestion3 = "Q3) You witness 'tails' and report 'heads'. Your
teammate witnesses 'tails' and reports 'tails'. \n What is Your Individual
payoff?"

```

```

class Subsession(BaseSubsession):
    pass

class Group(BaseGroup):
    group_payoff = models.CurrencyField(label= "")

class Player(BasePlayer):
    player_report = models.IntegerField(
        choices = [[1, "Head"], [0, "Tail"]],
        label = "",
        widget = widgets.RadioSelect
    )
    report_value = models.CurrencyField(label= "")
    supervision = models.BooleanField(label = "")
    player_witness = models.IntegerField(label = "")
    wrong_clicksQ1 = models.IntegerField(label = "", initial=0)
    wrong_clicksQ2 = models.IntegerField(label = "", initial=0)
    wrong_clicksQ3 = models.IntegerField(label = "", initial=0)
    #ArrayClicks = [ wrong_clicksQ1, wrong_clicksQ2 ,wrong_clicksQ3]
    controlQuestionChoices1 = models.CurrencyField(label = "",
                                                    widget = widgets.RadioSelect,
                                                    choices = [c(2.5),
c(5.00),c(0.00)])

    controlQuestionChoices2 = models.CurrencyField(label = "",
                                                    widget = widgets.RadioSelect,
                                                    choices = [c(2.5),
c(5.00),c(0.00)])

    controlQuestionChoices3 = models.CurrencyField(label = "",
                                                    widget = widgets.RadioSelect,
                                                    choices = [c(2.5),
c(5.00),c(0.00)])
    #myArray = [controlQuestionChoices1, controlQuestionChoices2,
controlQuestionChoices3]

    age = models.IntegerField(
        label = "What is your age?",
        max = 100,
        min = 14
    )
    gender= models.IntegerField(

```

```

label = "What is your gender?",
choices= [
    [1,"Male"],[0, "Female"], [2,"Diverse"]

])
nationality = models.StringField(
    choices = ["Albania", "Algeria", "Andorra", "Angola", "Antigua
and Tuvalu", "Uganda", "Ukraine", "United Arab Emirates", "United
Kingdom", "United States of America",
"Uruguay", "Uzbekistan", "Vanuatu", "Venezuela", "Vietnam", "Yemen",
"Zambia", "Zimbabwe"], #<-- Removed many for space :).

    label = "What is your country of citizenship?"
)

#headsTailsDic = {"heads": 1, "tails" : 0}
intention = models.TextField(#We do not want to make it compulsory
    label = "", #print("You witnessed ", headsTailsDic[player_witness], "
but reported ", headsTailsDic[player_report], "please explain your
intention.")
    blank = "True" #This allows user to continue without filling up the
comment section
)

comment = models.TextField(#We do not want to make it compulsory
    label = "Were the instructions clear? If not, please explain why.",
    blank = "True" #This allows user to continue without filling up the
comment section
)
class game(Page):
    form_model = "player"
    form_fields = ["player_report"]

class video(Page):
    def vars_for_template(self):#We identify what we have in the html in the
return function in "" and the return brackets are curly unlike normal brackets
or dict() since the function returns a dictionary.
        if random.choice([1, 0]) == 1:
            self.player.player_witness = 1
            witness = 1
            video = 'global/giphy2.gif'
        else:
            self.player.player_witness = 0
            witness = 0
            video = 'global/giphy.gif'

    p1 = self.group.get_player_by_id(1)
    p2 = self.group.get_player_by_id(2)

```

```

isGroupSupervised = self.group.group_supervised
isP1Supervised= p1.supervision
isP2Supervised= p2.supervision

    return {"coin_toss": witness, "film": video,
"p1supervision":isP1Supervised, "p2supervision":isP2Supervised,
"groupsupervision": isGroupSupervised}
    timeout_seconds = 12.5

class ResultsWaitPage(WaitPage):← payoff calculation for T0
    def after_all_players_arrive(self):
        p1 = self.group.get_player_by_id(1)
        p2 = self.group.get_player_by_id(2)

##

        if p1.player_report == 1 and p2.player_report == 1:
            p1.report_value = c(5)
            p2.report_value = c(5)
            p1.payoff= c(5) + Constants.endowment #In case we decide upon
            p2.payoff= c(5) + Constants.endowment
            self.group.group_payoff = p1.payoff + p2.payoff

        if p1.player_report == 0 and p2.player_report == 0:
            p1.report_value = c(0)
            p2.report_value = c(0)
            p1.payoff= c(0) + Constants.endowment
            p2.payoff= c(0) + Constants.endowment
            self.group.group_payoff = p1.payoff + p2.payoff

        if p1.player_report == 1 and p2.player_report == 0:
            p1.report_value = c(2.5)
            p2.report_value = c(2.5)
            p1.payoff= c(2.5) + Constants.endowment
            p2.payoff= c(2.5) + Constants.endowment
            self.group.group_payoff = p1.payoff + p2.payoff

        if p1.player_report == 0 and p2.player_report == 1:
            p1.report_value = c(2.5)
            p2.report_value = c(2.5)
            p1.payoff= c(2.5) + Constants.endowment
            p2.payoff= c(2.5) + Constants.endowment
            self.group.group_payoff = p1.payoff + p2.payoff

```



```
##
```

```
class Results(Page):
```

```
    pass
```

```
class Welcome(Page):
```

```
    pass
```

```
class video(Page):
```

```
    def vars_for_template(self):#We identify what we have in the html in the  
    return function in "" and the return brackets are curly unlike normal brackets  
    or dict() since the function returns a dictionary.
```

```
        if random.choice([1, 0]) == 1:
```

```
            self.player.player_witness = 1
```

```
            witness = 1
```

```
            video = 'global/giphy2.gif'
```

```
        else:
```

```
            self.player.player_witness = 0
```

```
            witness = 0
```

```
            video = 'global/giphy.gif'
```

```
        return {"coin_toss": witness,"film": video}
```

```
    timeout_seconds = 12.5
```

```
class Questionnaire(Page):
```

```
    form_model = "player" #still do not understand, I know the class is  
    important for the logic of the html but..?
```

```
    form_fields = ["age", "gender","nationality", "comment", "intention"]
```

```
class ControlQuestions(Page):
```

```
    form_model = "player"
```

```
    form_fields = ["controlQuestionChoices1","controlQuestionChoices2",  
"controlQuestionChoices3"]
```

```
    def error_message(self, values):#Validation
```

```
        print('values is', values)
```

```
        solutions = [c(0),c(2.5),c(2.5)]
```

```
        if values['controlQuestionChoices1'] != solutions[0] and
```

```
values['controlQuestionChoices2'] == solutions[1] and
```

```
values['controlQuestionChoices3'] == solutions[2]:
```

```
            self.player.wrong_clicksQ1 = 1 + self.player.wrong_clicksQ1
```

```
            return 'Revise question 1, take another look at the cheat sheet!'
```

```

        if values['controlQuestionChoices1'] != solutions[0] and
values['controlQuestionChoices2'] != solutions[1] and
values['controlQuestionChoices3'] == solutions[2]:
            self.player.wrong_clicksQ1 = 1 + self.player.wrong_clicksQ1
            self.player.wrong_clicksQ2 = 1 + self.player.wrong_clicksQ2
            return 'Revise question 1 and question 2, take another look at the
cheat sheet!'
        if values['controlQuestionChoices1'] != solutions[0] and
values['controlQuestionChoices2'] != solutions[1] and
values['controlQuestionChoices3'] != solutions[2]:
            self.player.wrong_clicksQ1 = 1 + self.player.wrong_clicksQ1
            self.player.wrong_clicksQ2 = 1 + self.player.wrong_clicksQ2
            self.player.wrong_clicksQ3 = 1 + self.player.wrong_clicksQ3
            return 'Revise question 1, question 2 and question 3, take another
look at the cheat sheet!'
        if values['controlQuestionChoices1'] == solutions[0] and
values['controlQuestionChoices2'] != solutions[1] and
values['controlQuestionChoices3'] == solutions[2]:
            self.player.wrong_clicksQ2 = 1 + self.player.wrong_clicksQ2
            return 'Revise question 2, take another look at the cheat
sheet!'
        if values['controlQuestionChoices1'] == solutions[0] and
values['controlQuestionChoices2'] != solutions[1] and
values['controlQuestionChoices3'] != solutions[2]:
            self.player.wrong_clicksQ2 = 1 + self.player.wrong_clicksQ2
            self.player.wrong_clicksQ3 = 1 + self.player.wrong_clicksQ3
            return 'Revise question 2 and question 3 take another look at the
cheat sheet!'
        if values['controlQuestionChoices1'] == solutions[0] and
values['controlQuestionChoices2'] == solutions[1] and
values['controlQuestionChoices3'] != solutions[2]:
            self.player.wrong_clicksQ3 = 1 + self.player.wrong_clicksQ3
            return 'Revise question 3, take another look at the cheat sheet!'
        if values['controlQuestionChoices1'] != solutions[0] and
values['controlQuestionChoices2'] == solutions[1] and
values['controlQuestionChoices3'] != solutions[2]:
            self.player.wrong_clicksQ3 = 1 + self.player.wrong_clicksQ3
            return 'Revise question 1 and question 3, take another look at the
cheat sheet!'

```

```

page_sequence = [ControlQuestions, video ,game, Questionnaire,
ResultsWaitPage,Results]
supervision

```

Raw Data

| | A | B | C | D | E | F | G | H | I | J | K | L | M | N | O | P | Q | R | S | T | U | V | W | X | Y | Z | AA | AB | AC | AD | AE | AF |
|----|-------|-------------|--------|------|--------|-------|--------|------|-------|-------------|-------|----------|---------|-----------|-----|----|-------|-----|--------|------|---|---|---|---|---|---|----|----|----|----|----|----|
| 1 | Index | Experiment | player | role | player | super | player | with | q1_wi | q2_wi | q3_wi | q3_wrong | gender | count | lie | du | nonbi | age | intent | comm | | | | | | | | | | | | |
| 2 | 1 | Control | 1 | 0 | 0 | 1 | 1 | 1 | 0 | Switzerland | 1 | 0 | 20 | | | | | | | | | | | | | | | | | | | |
| 3 | 2 | Control | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 23 | | | | | | | | | | | | | | | | | | | | |
| 4 | 3 | Control | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | Germany | 0 | 0 | | | | | | | | | | | | | | | | | |
| 5 | 4 | Treatment_1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | Egypt | 1 | 0 | | | | | | | | | | | | | | | | | |
| 6 | 5 | Treatment_2 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | | 1 | 0 | | | | | | | | | | | | | | | | | |
| 7 | 6 | Treatment_2 | 1 | 0 | 0 | 0 | 0 | 2 | 2 | 2 | 2 | | | 1 | 0 | | | | | | | | | | | | | | | | | |
| 8 | 7 | Treatment_2 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 2 | Egypt | 0 | 0 | | | | | | | | | | | | | | | | | |
| 9 | 8 | Treatment_2 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | | 0 | 0 | | | | | | | | | | | | | | | | | |
| 10 | 9 | Treatment_2 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | Egypt | 0 | 0 | | | | | | | | | | | | | | | | |
| 11 | 10 | Control | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | Germany | 0 | 0 | | | | | | | | | | | | | | | | |
| 12 | 11 | Control | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 2 | | 0 | 0 | | | | | | | | | | | | | | | | |
| 13 | 12 | Control | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | China | 0 | 0 | | | | | | | | | | | | | | | | |
| 14 | 13 | Control | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | China | 0 | 0 | | | | | | | | | | | | | | | | |
| 15 | 14 | Control | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | Egypt | 1 | 1 | | | | | | | | | | | | | | | | |
| 16 | 15 | Control | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | Egypt | 1 | 1 | | | | | | | | | | | | | | | | |
| 17 | 16 | Treatment_2 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | Germany | 0 | 0 | | | | | | | | | | | | | | | | |
| 18 | 17 | Treatment_2 | 1 | 0 | 0 | 0 | 0 | 3 | 1 | 1 | 1 | 1 | 1 | Germany | 1 | 0 | | | | | | | | | | | | | | | | |
| 19 | 18 | Treatment_2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | Germany | 0 | 0 | | | | | | | | | | | | | | | | |
| 20 | 19 | Treatment_2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | Germany | 0 | 0 | | | | | | | | | | | | | | | | |
| 21 | 20 | Treatment_2 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | Italy | 1 | 1 | | | | | | | | | | | | | | | | |
| 22 | 21 | Treatment_2 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | Finland | 1 | 0 | | | | | | | | | | | | | | | | |
| 23 | 22 | Treatment_2 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | Germany | 0 | 0 | | | | | | | | | | | | | | | | |
| 24 | 23 | Treatment_2 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | Finland | 1 | 1 | | | | | | | | | | | | | | | | |
| 25 | 24 | Treatment_2 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | Finland | 0 | 0 | | | | | | | | | | | | | | | | |
| 26 | 25 | Treatment_2 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | Romania | 1 | 0 | | | | | | | | | | | | | | | | |
| 27 | 26 | Treatment_2 | 1 | 1 | 0 | 0 | 6 | 3 | 0 | 0 | 0 | 0 | 1 | Hong Kong | 1 | 0 | | | | | | | | | | | | | | | | |
| 28 | 27 | Treatment_2 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | Germany | 0 | 0 | | | | | | | | | | | | | | | | |
| 29 | 28 | Treatment_2 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | Slovakia | 1 | 0 | | | | | | | | | | | | | | | | |
| 30 | 29 | Treatment_1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | Egypt | 0 | 0 | | | | | | | | | | | | | | | | |
| 31 | 30 | Treatment_1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | Germany | 0 | 0 | | | | | | | | | | | | | | | | |
| 32 | 31 | Treatment_1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | Germany | 1 | 0 | | | | | | | | | | | | | | | | |
| 33 | 32 | Treatment_1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | Germany | 0 | 0 | | | | | | | | | | | | | | | | |
| 34 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
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Experiment Pages

Below I share screenshots from the experiment webpage including the welcome page and the instruction for each treatment.

Welcome page



Welcome to the Experiment!

Thank you for participating in our experiment, if you participated in the experiment via link, we apologise for not being to offer real payments. For the purpose of our research we kindly ask you to engage in the experiments as if the payoffs were real. We highly appreciate your participation.

In this experiment you will be paired up with another player forming a team. You and your teammate will be presented with separate videos showing a series of coin tosses. You will be asked to report the outcome of the second coin toss, i.e 'heads' or 'tails'. What you earn during this experiment is based on the reports you and your teammate provide. We provide a more through explanation below.

Control Treatment Instructions (T0)

When reporting the coin toss it is important to acknowledge that:

- Reporting 'heads' contributes to the group payoff by €5.00
- Reporting 'tails' contributes to the group payoff by €0.00.

Do not confuse report contributions -*mentioned above* with your payoff and your teammate's payoff. Below we provide some mathematical formulas and further explanation.

The Payoff Mechanics:

Your individual payoff -*as participant i* is later calculated by equally splitting up the group payoff

$$\pi_i = \frac{\pi_g}{2}$$

Where

$$\pi_g = p_i + p_j$$

π_i : participant i's payoff.

π_g : group Payoff.

p_i (p_j): player's (teammate's) report contribution to the group payoff.

In this case your payoff is an equal split of the group payoff. Reporting heads generates a payoff of €5.00 while reporting tails generates a payoff of €0.00. For example, if your teammate reported heads and you reported tails, your group earns €5.00. Accordingly each of you would earn €2.50.

Individual Punishment Treatment Instructions (T1)

When reporting the coin toss it is important to acknowledge that:

- Reporting 'heads' contributes to the group payoff by €5.00
- Reporting 'tails' contributes to the group payoff by €0.00.

Do not confuse report contributions -*mentioned above* with your payoff and your teammate's payoff. Below we provide some mathematical formulas and further explanation.

The Payoff Mechanics:

As shown above, reporting heads is associated with a positive payoff, which could serve as a motivation to misreport the coin flip outcome in case tails is shown. However, there is a 25% chance that you will be supervised.

To explain the payoff we start off with the simple scenario that neither you nor your team mate will be supervised. In this case the payoffs are determined as follows:

$$\pi_i = \pi_j = \frac{\pi_g}{2}$$

Put simply, your payoff is simply an equal split of the group payoff, and reporting heads generates a payoff of €5.00 while reporting tails generates €0.00. For example, if you teammate reported heads and you reported tails, your group earns €5.00 and each of you earns €2.50.

If one team member i is supervised and reported a false coin toss, it results in the following payoffs:

| Individual i | Individual j |
|------------------------------|---------------------------|
| $\pi_i = -1 + \frac{p_i}{2}$ | $\pi_j = \frac{\pi_g}{2}$ |

i.e. Individual j 's payoff will not be penalised by his teammate i 's lie

In this case your payoff is an equal split of the group payoff. Reporting heads generates a payoff of €5.00 while reporting tails generates a payoff of €0.00. For example, if your teammate reported heads and you reported tails, your group earns €5.00. Accordingly each of you would earn €2.50.

Where

$$\pi_g = p_i + p_j$$

π_i : participant i 's payoff.

π_g : group's Payoff.

p_i (p_j): player's (teammate's) report contribution to the group payoff.

Put simply, if you get caught misreporting the coin toss you will earn half the value associated with whichever your teammate reports (€5.00 in case of heads, €0.00 in case of tails) subtracting €1.00 (as a penalty). On the otherhand, your partner still earns an equal split of the values associated with the reports. They would benefit from your lie. Assuming your teammate reported tails, you would earn - €1.00 and they would earn €2.50.

Group Punishment Treatment Instructions (T2)

When reporting the coin toss it is important to acknowledge that:

- Reporting 'heads' contributes to the group payoff by €5.00
- Reporting 'tails' contributes to the group payoff by €0.00.

Do not confuse report contributions -*mentioned above* with your payoff and your teammate's payoff. Below we provide some mathematical formulas and further explanation.

The Payoff Mechanics:

As shown above, reporting heads is associated with a positive payoff, which could serve as a motivation to misreport the coin flip outcome in case tails is shown. However, there is a 25% chance that you will be supervised.

To explain the payoff we start off with the simple scenario that neither you nor your teammate will be supervised. In this case the payoffs are determined as follows:

$$\pi_i = \pi_j = \frac{\pi_g}{2}$$

Put simply, your payoff is simply an equal split of the group payoff, and reporting heads generates a payoff of €5.00 while reporting tails generates €0.00. For example, if you teammate reported heads and you reported tails, your group earns €5.00 and each of you earns €2.50.

If one team member i is supervised and reported a false coin toss, it results in the following payoffs:

$$\text{Individual } i \\ \pi_i = -1 + \frac{p_i}{2}$$

$$\text{Individual } j \\ \pi_j = -1 + \frac{p_j}{2}$$

Where

$$\pi_g = p_1 + p_2$$

π_i : participant i 's payoff.

π_g : group's Payoff.

$p_i(p_j)$: player's (teammate's) report contribution to the group payoff.

Put simply, if you got caught misreporting the coin toss you will earn half the value associated with whichever your teammate reports (€5.00 in case of heads, €0.00 in case of tails) subtracting €1.00 (as a penalty). Your teammate would in this case would earn the same payoff. They would suffer from your lie. Assuming your teammate reported tails, you would earn -€1.00 and they would earn similarly -€1.00.

Report page

Report

Please enter your report for the second coin toss!

☒ Head

☐ Tail

Next

Waiting page

Please wait

Waiting for the other participant.

Questionnaire

Questionnaire

What is your age?

What is your gender?

What is your country of citizenship?

You witnessed Tails but reported Heads . Please explain your intention.

Were the instructions clear? If not, please explain why.

Next

Experiment: Payoff Control Questions

Quiz!

Q1) You witness 'tails' and report 'tails'. Your teammate witnesses 'tails' and reports 'tails'. What is Your Individual payoff?

- ☐ €2.50
- ☐ €5.00
- ☐ €0.00

Q2) You witness 'tails' and report 'tails'. Your teammate witnesses 'tails' and reports 'heads'. Your teammate is supervised. What is Your Individual payoff?

- ☐ €2.50
- ☐ €5.00
- ☐ -€1.00

Q3) You witness 'tails' and report 'heads'. Your teammate witnesses 'tails' and reports 'tails'. you are supervised. What is Your Individual payoff?

- ☐ -€1.00
- ☐ €5.00
- ☐ €0.00

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Declaration of Authorship

I hereby declare that the thesis submitted is my own unaided work. All direct or indirect sources used are acknowledged as references.

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A handwritten signature in black ink, appearing to read 'Mohamed Hassan', with a horizontal line underneath.

Mohamed Hassan

Munich, 28.03.2021

DISCLAIMER:

This thesis is an improved version of the one submitted at the time. The reason is for that is, it contained some typos and structurally it was not organized. I decided to spend some time after finishing my bachelor to improve it.