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Preface

This thesis consists of three chapters on unethical behavior and experimental economics. While all chapters focus on unethical behavior such as corruption and cheating, each chapter answers distinct research questions. Chapter 1 investigates how corruption in government hiring affects individuals' selection into the public sector and their subsequent behavior on the job. Chapter 2 studies how reactions of third party beneficiaries affect unethical pro-group behavior of actors. Chapter 3 focuses on corrupt behavior of individuals in symmetric and asymmetric contests.

Apart from the common focus on unethical behavior, all chapters employ experimental methods. Experiments have been widely used over the last decades as they are a useful tool for behavioral and economic studies and provide many advantages such as inference about causal relationships between changes in variables of interests and their effects on individuals' behavior. Due to hygiene regulations during the Corona Pandemic, all experiments are conducted online. Chapter 1 and Chapter 3 use the subject pool from the University of Mannheim (Mlab), while Chapter 2 employs the subject pool from Amazon Mechanical Turk with participants located in the USA. In the following, I summarize each chapter.

Chapter 1 is joint work with Henrik Orzen and Franziska Heinicke. This chapter focuses on the role of recruitment processes in individuals' job selection and their subsequent behavior on the job. We ask two fundamental questions. First, how does corruption in government hiring affect individuals' selection into the private sector and the public sector? To be specific, we compare the types of individuals who choose the public sector with those who choose the private sector regarding their propensity for dishonesty, ability, prosocial preferences and risk preferences. The second research question concerns whether corrupt behavior of public officers who are recruited on the basis of merit differs from those who are selected through a corrupt hiring system.

To answer the above questions, we design two treatments which differ in recruitment processes between the public sector and the private sector. In the Meritocracy treatment, jobs in both sectors are distributed on the basis of merit, i.e. one gets a job based on their performance in a recruitment test. In the Bribery treatment, the recruitment process in the private sector is the same as in the Meritocracy treatment, whereas jobs in the public sector are distributed through a corrupt hiring system, i.e. one can pay a bribe to get a government job.

First, we find that on average individuals who select into the public sector cheat 19 percentage points less than those who choose the private sector. This indicates that *honest individuals* are more likely to choose the public sector, whereas *dishonest individuals* prefer the private sector. This pattern of job selection is observed in both treatments. Regarding other characteristics, we observe that self-selection into the public sector is not driven by ability, gender, risk preferences and pro-social preferences. Second, public officers who are recruited through a corrupt hiring system demand 20% higher bribes than those who are selected on the basis of merit. The higher bribe demand comes from both types of public officers, those who pay a bribe to get a government job and those who do not. This indicates the negative effect of corruption in government hiring on corrupt behavior in public sector jobs. Our finding provides a better understanding of high levels of corruption in countries where corruption in government hiring is prevalent.

Chapter 2, which is co-authored with Franziska Heinicke, focuses on cheating behavior in a group setting. Many forms of unethical behavior such as cheating, corruption, tax evasion benefit not only the self but also others, *third party beneficiaries*. This type of behavior is referred as *unethical pro-group behavior*. The main research question we answer in this study is what role beneficiaries play in preventing unethical pro-group behavior. Specifically, we investigate to what extent actors engage in unethical pro-group behavior when their behavior can be revealed, rewarded, punished or reported by third party beneficiaries and how reactions of beneficiaries in turn affect actors' subsequent behavior. We conduct four treatments in which we vary whether unethical behavior can be verified and how a third party beneficiary can react to such behavior.

We find that on average less than 20% of actors cheat and if they cheat, they tend to cheat to the full extent. This pattern of cheating behavior, however, does not differ significantly between treatments. The second finding is that around 70% of beneficiaries choose to verify actors' behavior, and they react more strongly (reward, punish) after they verify whether actors cheat or not. Finally, we observe that actors are more likely to be honest after their behavior is being verified or rewarded by beneficiaries, however, punishment does not have any significant effects on unethical pro-group behavior of actors.

Chapter 3 studies corrupt behavior in a contest setting. In this study, I investigate how corrupt behavior is affected by asymmetry in contests. In particular, I investigate whether corruption is more common in contests where players have the same or different abilities, and whether weak players or strong players are more likely to engage in corruption. Furthermore, I ask how corruption affects effort provision and contest outcomes. To be specific, I measure how corruption changes effort choices as compared to contests with no possibility for corruption. I employ a between- and within-subject design with four treatments which differ in two dimensions. The symmetry/asymmetry change is implemented as a between-subject design, whereas the corruption possibility is implemented as a within-subject variation.

First, I find that more groups in the symmetric contest engage in corruption than in the asymmetric contest. Looking further into the latter, I observe strong players are more likely to offer bribes than their weak opponents. Second, corruption induces lower effort provision. Efforts in a contest with corruption are significantly lower than those in a contest with no corruption. This holds for both the symmetric contest and the asymmetric one. To further isolate the effect of corruption opportunity on effort choices, I compare efforts of groups where corruption does not occur with groups in contests without corruption. Interestingly, efforts of the former are significantly lower than those of the latter. This indicates that the presence of corruption possibility induces lower efforts even when players do not utilize this possibility.

Chapter 1.

Corruption in government hiring and job selection *

with Henrik Orzen and Franziska Heinicke

1.1. Introduction

Corruption is one of the pressing issues across the globe. Scholars in different fields such as behavioral economics, politics and laws have extensively investigated causes of corruption (La Porta et al. (1999), Rothstein and Uslaner (2005), Dahlström, Lapuente, and Teorell (2012), etc.). Among these studies, Banerjee, Baul, and Rosenblat (2015), Hanna and Wang (2017), Barfort et al. (2019), Gans-Morse, Kalgin, et al. (2020) show that there is a strong correlation between individuals' selection into government jobs and levels of corruption in the public sector.[1] This study contributes to the literature on self-selection into the public sector by investigating how corruption in government hiring draws different types of individuals into the public sector as compared to the private sector and how this in turn affects their subsequent behavior on the job.

*We would like to thank participants in Joint Initiative for Latin American Experimental Economics Conference, audiences at Frankfurt Mannheim Workshop in Frankfurt, 8th HeiKaMaxY Workshop in Mannheim and seminar participants at Leibniz Centre for European Economic Research in Mannheim for helpful comments and suggestions.

[1] Barfort et al. (2019) show that *honest* individuals prefer government jobs which may explain a low level of corruption in the public sector in Denmark. In contrast, Banerjee, Baul, and Rosenblat (2015) find that *dishonest* individuals are more likely to select into the public sector in India and they are more likely to engage in corruption.

Government hiring systems vary from country to country. A merit-based recruitment system has been commonly used as an efficient mechanism to attract qualified people in many less corrupt countries (e.g. Denmark, Germany, Sweden[2]) and this is considered as an ethical and fair process to select the best candidates (Dahlström, Lapuente, and Teorell (2012), Setyowati (2016), Haider (2019), Brierley (2021), Oliveros and Schuster (2018), Jankowski, Prokop, and Tepe (2020), Meyer-Sahling, Mikkelsen, and Schuster (2020)). In other countries (e.g. Sudan, Indonesia, Pakistan and Vietnam[3]), however, many government jobs are distributed on a basis of corruption (Kristiansen and Ramli (2006), Y. Sun (2008), J. Weaver (2020)). In an interview with 60 Indonesian civil servants, Kristiansen and Ramli (2006) discover that all had to pay bribes to become public servants. The former President of Russia, Dmitry Medvedev, publicly admitted that money can buy many government jobs in Russia (News (2008)). The aviation minister in Pakistan revealed that nearly 1 in 3 pilots in Pakistan have paid bribes in pilots' exams (Saifi and Gan (2020)). In a study on corruption in government hiring, J. Weaver (2020) shows that one has to pay averaging 17 months of salary to get a job in the public health sector.

Corruption in government hiring deserves particular attention for two reasons. First, widespread corruption and bribery scandals among public officers raise the question of how many dishonest individuals have managed to get recruited in the first place. Second, corruption in government hiring may lead to a misallocation of government jobs to less qualified individuals which is likely to adversely affect public service delivery.

In this study we ask two fundamental questions. First, how does corruption in government hiring affect individuals' selection into the public sector? To be specific, we compare the types of individuals who choose the public sector with those who choose the private sector in terms of their propensity for dishonesty, ability, prosocial preferences and risk preferences. Second, we ask how the self-selection in turn affects behavior on the job. In particular, we investigate if there is any differences in corrupt behavior between public officers who are recruited through a corrupt hiring system and those who are selected through a merit-based process. We also compare performance on public service delivery between individuals who are recruited under different hiring processes.

[2]According to Transparency International (2022), Denmark, Sweden and Germany are ranked among the least corrupt countries.

[3]These nations are ranked among the most corrupt countries according to Corruption Perceptions Index in 2022.

To answer the above questions, we conduct an experiment for several reasons. First, doing empirical research on corruption in recruitment is challenging since corruption activities are mainly hidden and difficult to observe in the field. An experiment allows us to design a setting which captures important aspects of corruption and differences between the public sector and the private sector. Second, an experimental study enables us to vary dimensions of interests, while controlling for other factors, thus we can build causal relationships between changes in recruitment systems and individuals' job selection as well as their subsequent behavior on the job.

In addition to the difference in hiring, the public sector may differ from the private sector in other aspects. First, jobs in the public sector provide many chances for petty corruption, that is public officers demand bribes from citizens in exchange for public services (Foltz and Opoku-Agyemang (2015)). Second, as compared to the public sector, there is more competition in the work environment in the private sector.[4] Third, job stability is one of the distinct features of public sector jobs (Lewis and Frank (2002)). Furthermore, public services are mainly aimed to benefit people in the society, whereas private sector jobs are more profit-oriented. We integrate these fundamental differences between two sectors in our experimental design.

Our experiment consists of two parts. In the first part of the experiment, we measure individuals' dishonesty and other characteristics such as risk preferences, pro-social preferences and ability. To measure propensity for dishonesty, we employ a *dice-guess* game adapted by Barfort et al. (2019) and Gans-Morse, Kalgin, et al. (2020). This game consists of 30 rounds. In each round, participants are asked to guess a number between 1 and 6 of a die roll. Subsequently, they roll a digital die and report their guess, while the outcome of the die roll is still being displayed on screen. Therefore, participants can dishonestly increase their earnings by misreporting their guess, while their cheating behavior is not being observed. By comparing an expected distribution of correct guesses under full honesty with a distribution of observed number of correct guesses reported by participants, we can infer to what extent they cheat.

In the second part of the experiment, participants are asked to choose between the private sector or the public sector which, depending on treatments, may differ in hiring systems. In the Meritocracy treatment, the recruitment process in both sectors is merit-based, i.e. jobs are allocated based on performance in a test. In the Bribery

[4] Dixit (2002) argues that public officers encounter limited competition in their work environment as compared to workers in the private sector.

treatment, the recruitment process in the private sector is the same as in the Meritocracy treatment, while jobs in the public sector are distributed through a corrupt hiring system, i.e. participants who choose the public sector are asked if they want to apply for a free pass. This free pass secures them a government job without considering their performance in the recruitment test. Subsequently, in both treatments participants who get recruited into the public sector play a *petty-corruption* game. By comparing bribe demands of the public officers in two treatments, we can measure how corruption in government hiring affects corruption levels in the public sector. Finally, we include a competition game in the private sector to capture the intensity of competition in a work environment in the private sector and a contribution task in the public sector to capture the society-oriented feature of public sector jobs.[5]

Our design attempts to capture a fundamental aspect of corruption in hiring, i.e. a concern about a misallocation of government jobs to less qualified and less motivated individuals which might lead to poor public service delivery. We investigate this effect by asking individuals who choose the public sector to perform a contribution task which benefits everyone in the experiment. By comparing performances on this task of individuals who pay for a free pass with those who do not, we can test whether corruption in government hiring has any negative effects on behavior on the job.

Our results are as follows. First, there is a clear pattern of self-selection of more honest individuals into the public sector in both treatments. We employ a cheat rate to measure the propensity for dishonesty of an individual.[6] In the Meritocracy treatment the mean cheat rate is 0.51 for individuals who choose the private sector and 0.31 for those who choose the public sector, whereas in the Bribery treatment the cheat rate is 0.49 and 0.36, respectively. The selection pattern that more honest individuals choose the public sector is consistent with findings in previous studies on dishonesty and job selection (Barfort et al. (2019), Gans-Morse, Kalgin, et al. (2020)). Second, we investigate how individuals' job selections are linked to other characteristics. We find no evidence that decisions to choose the public sector are driven by risk preferences, pro-social preferences, ability or gender in both treatments.

[5]In the experimental instructions, we use neutral framing such as "Option 1" to represent the private sector and "Option 2" to represent the public sector. Participants are fully informed about the features of both options before they decide which option to choose.

[6]A cheat rate is calculated as the probability that an individual reports a correct guess when his/her actual guess is incorrect. A higher cheat rate indicates that an individual is more likely to be dishonest. Further details are provided in Section 1.3.1.

Third, we observe that public officers who are recruited through a corrupt hiring system demand 20% higher bribes than those who are recruited based on a merit hiring system. The design in our treatments allows us to test whether the difference in bribe demands comes from a wealth effect, e.g. free pass holders demand higher bribes to recover the cost of paying for a government job. We find that both free pass holders and individuals who do not pay for a free pass in the Bribery treatment demand considerably higher bribes than public officers in the Meritocracy treatment. This indicates that the higher bribe demand observed in the Bribery treatment is unlikely to come from the wealth effect. Instead, a possible reason is that individuals, who do not pay to obtain the government job but experience a corrupt hiring system, still perceive the public sector as corrupt, therefore, it might be appropriate for them to demand more bribes when delivering public services. This finding can, to some extent, explain high levels of corruption in the public sector in countries where corruption in government hiring is prevalent. Thus, policy makers in these countries should pay particular attention to corruption in government hiring when aiming to mitigate petty corruption in the public sector.

Fourth, we test the effect of a corrupt hiring system on job performance in the public sector. We observe in the Bribery treatment that individuals who are willing to pay for a free pass have a significantly lower performance on the contribution task than those are not. This indicates that individuals who want to pay a bribe in exchange for a government job are less motivated to work for the society than those who want to get a government job by their ability. This finding has an implication that corruption in hiring may lead to a misallocation of government jobs to low motivated individuals who have poor performance on public service delivery.

The remainder of this chapter is organized as follows. The second section reviews related literature. The third section describes experimental design and treatments. The fourth section provides experimental results and the last section discusses as well as concludes the paper.

1.2. Literature review

1.2.1. Dishonesty and job preferences

Our study first contributes to the experimental literature on the relationship between dishonesty and job preferences (Banerjee, Baul, and Rosenblat (2015), Hanna and Wang (2017), Barfort et al. (2019), Gans-Morse, Kalgin, et al. (2020), Brassiolo et al. (2021)). These studies on how the propensity for dishonesty is correlated with selection into government jobs provide mixed evidence. Using a survey experiment, Barfort et al. (2019) examine the role of job preferences in maintaining a low level of corruption in the public sector in Denmark which is classified as the world least corrupt country (Transparency International (2022)). They find that individuals with a higher propensity for honesty are more likely to prefer public sector employment, while jobs in the private sector are more attractive to dishonest individuals. The clear observed selection pattern of honest individuals may explain why some countries like Denmark and Sweden are able to sustain low levels of corruption in the public sector.

In contrast to the framework and findings by Barfort et al. (2019), Hanna and Wang (2017) investigate self-selection into the public sector in a high-corruption framework, India. Hanna and Wang show that individuals with a higher propensity for cheating and low pro-social preferences are more likely to choose public sector employment. This may explain high corruption levels in developing countries where government jobs are strongly preferred by dishonest individuals.

However, the selection of more dishonest individuals into the public sector has not always been observed in countries which are known as highly corrupt. Gans-Morse, Kalgin, et al. (2020) conduct a survey experiment with students in Russia, which is classified among the high corrupt countries according to Transparency International (2022). Surprisingly, this study shows that individuals who prefer to work in the public sector are less likely to engage in corrupt behavior such as cheating or bribing than those who choose the private sector.

Unlike previous studies which mainly use survey experiments to elicit individuals' job preferences, we develop a novel design for a laboratory experiment which captures fundamental features of the public sector and the private sector. Jobs in the private sector may differ to those in the public sector in several aspects. For example, the scope of corruption is high in the public sector and public sector employment is more secured and stable. Jobs in the private sector, on the other hand, may offer higher salaries and are more competitive (Lewis and Frank (2002), Bandiera, Khan, and Tobias (2017)). We contribute to this line of the literature by exploring the role of recruitment in self-selection and how this in turn affects job performance.

1.2.2. Intrinsic motivation and job preferences

The link between job selection and intrinsic motivation has been well-established in the existing literature (Perry and Wise (1990), Alonso and Lewis (2001), Leisink and Steijn (2008), Georgellis, Iossa, and Tabvuma (2011), Serra, Serneels, and Barr (2011), Kolstad and Lindkvist (2013)). Perry and Wise (1990) argue that individuals with high public service motivations are more likely to select government jobs and have better performance at work. Similarly, Georgellis, Iossa, and Tabvuma (2011) employ data in the US's public sector to show that individuals' selection into government jobs is driven by intrinsic motivations rather than financial rewards that the jobs offer. Using surveys of federal employees in the US, Alonso and Lewis (2001), however, find no evidence that employees who highly value public services have better work performance.

Serra, Serneels, and Barr (2011) combine both experimental economic and questionnaire data to study how pro-social motivations link to preferences for working in the non-profit health sector in Ethiopia. They find that pro-socially motivated individuals are more likely to work in the non-profit sector rather than in the profit sector. Similarly, Kolstad and Lindkvist (2013) explore that Tanzania students who prefer to work in the private health sector have lower pro-social preferences than those who want to work in the public health sector. We add to this strand of the literature by examining intrinsic motivations of individuals who select into the public sector under different recruitment schemes. We also test if there is any effects of corruption in hiring on individuals' performance on public service delivery.

1.2.3. Petty corruption

Our study is also related to the literature on petty corruption (Abbink, Irlenbusch, and Renner (2002), Barr and Serra (2009), Foltz and Opoku-Agyemang (2015), Abbink, Ryvkin, and Serra (2020)). These studies provide substantial evidence that public officials exploit their power to demand or receive bribes from citizens when delivering public services. Foltz and Opoku-Agyemang (2015) conduct a field experiment on police officers in Ghana and they show a positive relationship between public officers' salaries and their bribe demand. Using a laboratory experiment, Abbink, Ryvkin, and Serra (2020) find that police officers demand bribes from law-breakers to cover their misbehavior. Abbink, Irlenbusch, and Renner (2002) find that corruption levels are not affected by a negative externality which is in contrast to a finding by Barr and

Serra (2009). Among many forms of corruption, we focus on petty corruption as it is one of the most widespread forms in many countries and it has detrimental impacts on the society, e.g. losses of public trust in governments. We contribute to this line of the literature by examining petty corruption in the public sector where there is a possibility for paying a bribe in exchange for a government job.

1.3. Experiment

Our experiment consists of two parts and each part is explained as follows.

1.3.1. Part 1: Individuals' characteristics

In this part, we obtain experimental measures of individuals' attributes such as their propensity for dishonesty, ability, risk preferences and pro-social preferences. Each attribute is measured as follows.

Propensity for dishonesty: The dice-guess game

To measure dishonesty, we adopt an experimental task established by Barfort et al. (2019).[7] The task consists of 30 rounds and each round proceeds as follows. On a first screen, participants are asked to guess a number between 1 and 6 that a die shows up later and then click on a next button. On a second screen, they are asked to roll a digital fair six-sided die and report their guess, while the outcome of the die roll is still shown on the screen. On a third screen, they receive feedback about their guess. Participants earn 9 points for a correct guess and 3 points for an incorrect guess. The points are chosen such that in every round participants can dishonestly earn higher points by reporting the actual outcome of the die roll irrespective of their guess. Even though there is no way for us to directly observe cheating in this task, a fair six-sided die indicates that the chance that an honest participant correctly guesses an outcome of a die roll is only 1/6. Therefore, by comparing the distribution of correct guesses reported by participants with the expected distribution of correct guesses under full honesty, we can make inferences about the extent of cheating at the individual level.

[7] This method of measuring dishonesty is suitable for online experiments since participants do not need a physical die to perform this task. It has been used by other studies on cheating such as Gans-Morse, Kalgin, et al. (2020).

Note that there is no motivation for participants to dishonestly report without ensuring a correct guess. Therefore, we assume that if participants report dishonestly, they report a correct guess even when their actual guess is incorrect. If their reported guess is incorrect, we assume that they report honestly. Hence, we measure cheating in observations where participants make correct guesses. In each round, the probability of honestly making a correct guess is $\pi = \frac{1}{6}$. Let θ_i denote the participant i's cheat rate. The cheat rate is the probability that the participant reports "correct" when his/her guess is in fact incorrect. We estimate the cheat rate as follows.

$$X_i = (\pi + (1-\pi)\theta_i)T \Rightarrow \widehat{\theta}_i = \frac{6}{5}\left(\frac{X_i}{T} - \frac{1}{6}\right)$$

where X_i is the expected number of correct guesses given the number of trials T and the cheat rate θ_i.

Ability: The find-the-numbers game

In this task, participants are given a series of 3 by 3 matrices with 9 random numbers in each matrix. Their task is to find two numbers in each matrix which add up to ten.[8] If an answer is incorrect, an error message is displayed and participants have to try again. Participants can only move to the next matrix if the answer to the current matrix is correct. The task lasts three minutes and participants can solve as many matrices as they wish. The variable of interest is the number of matrices that participants correctly solve. A measure of ability in this task can be viewed as performance in a real effort task that represents the actual performance of an individual at work.

Risk preferences: The lottery game

To elicit risk preferences, we adopt a method introduced by Eckel and Grossman (2002). Participants are asked to choose one out of six options, each of which has a 50% chance of yielding a low payoff and a 50% chance of yielding a high payoff.[9] Option 1 ensures

[8]This task is widely used to measure ability in many experimental studies such as Mazar and Ariely (2006), Ariely et al. (2009) and Hanna and Wang (2017). In these studies, they use a 3 by 4 matrix with 12 random numbers and participants are allowed to solve up to 20 matrices. We employ, however, only 3 by 3 matrix to allow more variations in performance of participants.

[9]We increase the payoff of each option by 1.5 times relative to the original task to make payoffs across tasks in Part 1 comparable without changing the structure of these options.

a certain payoff, while Option 2 to Option 6 involve risk. There are two differences between these options. First, the standard deviation increases linearly from Option 1 to Option 5 but non-linearly from Option 5 to Option 6. Second, the expected values increase linearly from Option 1 to Option 5 but remain the same in Option 6 (see Eckel and Grossmann for details). The design of payoffs in each option allows us to make inferences about risk preferences of participants based on their choices.

Social preferences: The social-value-orientation game

To measure social preferences, we employ a social value orientation approach introduced by Murphy, Ackermann, and Handgraaf (2011). Participants make six decisions about how to allocate points between themselves and a recipient. In each decision, they are asked to choose one of nine options. This approach has an advantage that it enables us to obtain rich data on decision making under different distributions of joint payoffs. Based on their choices across six decisions, we can compute scores that allow us to classify participants into four types, including altruistic, prosocial, individualistic and competitive (see Murphy and Handgraaf for details).

1.3.2. Part 2: Selection into the private sector and the public sector

The main purpose of this study is to investigate how corruption in government hiring affects individuals' self-selection into the public sector and their subsequent behavior on the job. With this in mind, we design two treatments, Meritocracy and Bribery, which differ only in how personnel in the public sector is recruited. To control for an equal chance of getting a job in each sector, we fix the total number of job vacancies, i.e. in each sector 75% of candidates are recruited regardless of job applicants.[10] In the experimental instructions, we use neutral framing to describe each sector. To be specific, we use Option 1 to represent the private sector and Option 2 to represent the public sector. Individuals who get a job belong to the GREEN group, otherwise they belong to the RED group.

[10] The uncertainty in the number of participants who choose the public sector and the private sector makes it impossible to ex-ante determine how many people should be recruited. Therefore, by fixing the equal chance of getting a job in each sector, we can have more control over the probability of obtaining the job even if there are different distributions of the number of participants in each sector.

Treatments

In the Meritocracy treatment, the recruitment process is a merit-based competition in both sectors. Participants choose between the private sector and the public sector. In both sectors, they have to do the *find-the-numbers game* as in part 1.3.1.[11] Those who choose the same sector are ranked based on their relative performance. 75% best performers in each sector are recruited and the remaining 25% are not selected.

In the Bribery treatment, the recruitment process in the private sector is the same as in the Meritocracy treatment. The recruitment process in the public sector is, however, different and proceeds as follows. Unlike the private sector, the public sector offers participants a possibility to buy a free pass. A free pass means that a participant is recruited even if he/she is not among 75% best performers. In this case he/she would simply replace an actual top 75% performer.[12] Participants are informed that if they apply for the free pass and they are hired through the free pass, this piece of information is not visible to other participants.[13] 50% of participants who select the public sector are randomly chosen to be eligible for a free pass.[14] For a chance to buy the free pass a participant must click "Apply for a free pass" button. If one does that and it turns out that he/she is eligible, he/she is now guaranteed a government job. However, in this case a free pass's fee of 50 points is deducted from his/her balance points. If it turns out that he/she is not eligible, or if a participant does not apply for

[11] Similar to part 1.3.1, participants have 3 minutes to solve as many matrices as they wish, however, we use different series of matrices for this section.

[12] In some countries such as the USA and Germany, government officers are often recruited through state exams where the best performers are selected. In a corrupt hiring system, however, people can pay bribes to get government jobs, thus their performance in such exams becomes less relevant. In this case they take away the jobs from those who have better performance. This not only captures the immoral aspect of corruption in recruitment but also has other adverse consequences. For example, recruiting less qualified public officers may lead to a poor public service delivery.

[13] We do not provide this piece of information to participants because in reality recruiters rarely reveal actual reasons for not selecting a candidate.

[14] We limit a chance for getting a free pass to 50% to capture the idea that people would need to have money, social power or connection in order to obtain a government job, thus this option is not available for everyone. Additionally, the number of job vacancies (75% of participants) are higher than the number of free passes (50% of participants). This allows some participants to get recruited by their ability. This reflects a real life scenario where excellent people can get government positions without having to pay bribes.

a free pass in the first place, there is no fee to pay.[15]

Subsequently, all participants who choose the public sector play *the find-the-numbers game* as in part 1.3.1. For those who hold the free pass, their performance in this task becomes irrelevant. All others are ranked behind the free pass holders according to their actual performance. The top 75% performers in this modified ranking list are recruited. This includes all free pass holders and the best performers without a free pass. The remaining 25% are not selected.

Compensation: Individuals who are successfully recruited receive 550 points in the private sector and 500 points in the public sector.[16] Individuals who are not hired obtain 200 points in both sectors.

Private sector: Additional aspects

Competition game: Dixit (2002) and Finan, Olken, and Pande (2015) show that one of fundamental differences between the private sector and the public sector is competition. They argue that public sector workers often encounter limited competition in their work environment as compared to those who work in the private sector. To capture this aspect, participants who are recruited in the private sector in both treatments compete with another person who is randomly chosen in the beginning of Part 2 and who is not asked to choose between the private sector and the public sector. Participants play the *find-the-numbers game* as in part 1.3.1 and who has a better performance gets a bonus of 50 points.[17]

A bad luck draw: Bandiera, Khan, and Tobias (2017) point out that governments often have stringent rules that limit firing of public servants. Additionally, Oliveros and Schuster (2018), Lewis and Frank (2002) argue that job stability is one of the distinct features of public sector employment as compared to jobs in the private sector.

[15] J. Weaver (2020) shows that if people pay an amount for buying a job but it turns out that they are not recruited, they get back that amount.

[16] Keefe (2016) points out that private sector workers earn, on average, 14% more in wages than public sector workers.

[17] We choose only one person, who we label as "Person X", to compete with all participants who are hired in the private sector. The performances of those in the private sector are compared with the performance of Person X. Person X receives a lump sum of 200 points. Additionally, to determine Person X's payoff, one participant in the private sector is randomly selected and his/her performance is used to compare with Person X's performance.

To integrate this feature in our experimental design, we introduce a small risk in the private sector that with a probability of 1% earnings of a participant are deducted to a lump sum payment of 150 points irrespective of whether the participant are recruited or not. That risk, however, does not exist in the public sector.

Public sector: A petty-corruption game

Note that the *petty-corruption* game differs from the *dice-guess* game in Part 1 in several dimensions. In the *dice-guess* game, participants cheat to increase their own payoff and their cheating behavior is not explicitly observed by someone, whereas the *petty-corruption* game captures different aspects of corruption. One aspect is that this type of corruption potentially causes harm to citizens and to the society. Another is a question of whether or not demands for bribes are fulfilled by citizens.

This *petty-corruption* game captures an interaction between a citizen and a public officer.[18] At the beginning of this game, the citizen receives a lump sum payment of 200 points. Additionally, he/she is eligible to receive an amount of 200 points. However, the amount is paid out to him/her only if it is authorized by the public officer. The public officer can ask the citizen for a transfer of b for the authorization ($b \in [0, 200]$). The citizen has to indicate the maximum number of points he/she is willing to pay for the authorization before he/she learns how much the public officer actually demands.[19] If the demand of the public officer is not more than the willingness to pay of the citizen, the transfer is authorized and the public officer obtains b additional points, while the citizen receives $200 - b$ extra points. Otherwise, the transfer is not authorized. In this case, the public officer does not receive b and the citizen does not receive the additional 200 points.

[18] Note that only those who successfully obtain government jobs are allowed to play this game. In the experimental instructions, we denote Player A as a public officer and Player B as a citizen. The role of Player B is taken by another participant who is randomly chosen in the beginning of Part 2 and who is not asked to choose between the private sector and the public sector. Note that Player B and Person X are not the same person.

[19] Banerjee (2016) shows that using loaded languages such as "public officer" and "citizen" instead of "Player A" and "Player B" and "bribe" instead of "transfer" may affect participants' behavior. To eliminate any experimenter demand effects, we use neutral terms to describe the *petty-corruption* game.

Public sector: Externality

One of the concerns about corruption is negative effects on the society such as losses of public trust in government which is likely to affect people in that society. To capture a negative externality of petty corruption, we compute the average bribe demand of public officers and multiply it with 0.1. This amount is deducted from a common pool points that each participant receives at the beginning of Part 2.[20]

Contribution task: Another aspect of public sector jobs is that they serve societal needs which positively affect the society. To capture such a positive externality, all participants, who choose the public sector, do the *find-the-numbers game* as in part 1.3.1.[21] The average points scored by these participants are multiplied by 2. This amount is added to the common pool of every participant, including those in the private sector. This task aims to test behavior on the job under different recruitment processes. By comparing performance between individuals who apply for a free pass with those who do not in the Bribery treatment, we can make inferences about the effect of corruption in hiring on public service delivery.

1.3.3. Hypotheses

In this study we investigate whether corruption in the public sector affects individuals' job selection. We compare the types of individuals who choose the public sector with those who choose the private sector. In the Meritocracy treatment, participants in both sectors are recruited based on merit, while in the Bribery treatment, participants in the public sector have a chance to pay a bribe in exchange for a government job. Corruption in government hiring may affect decisions to join the public sector of potential candidates through several channels. First, corruption in hiring may encourage dishonest individuals to obtain a government job. Second, it may attract low ability individuals to join this sector since it allows them to get a job without having a good

[20] A common pool can be considered a common good that a public officer benefits people in the society. In our setting, each participant who chooses the public sector is given a common pool of 10 points for two purposes. First, whenever the public officer engages in corruption, this has a negative effect on the society, thus points from the common pool are deducted. Second, one of the aspects of public sector jobs is to help the society. Therefore, we design a contribution task such that participants can work on a real effort task to increase the common pool.

[21] Participants have 3 minutes to solve as many matrices as they wish. We use different series of matrices as compared to previous parts.

performance in a recruitment test. Additionally, the public sector offers public officers a chance to demand bribes from citizens which may be attractive to more dishonest individuals. Therefore, we form the following hypotheses.

Hypothesis 1a: Individuals who choose the public sector cheat more as measured by the *dice-guess game* in part 1 than those who choose the private sector.

Hypothesis 1b: Individuals who choose the public sector in the Bribery treatment cheat more than those in the Meritocracy treatment.

Furthermore, individuals with low ability are unlikely to win the competition game in the private sector, thus in the Meritocracy treatment they might opt for the public sector to avoid competition. In addition to that, low ability individuals in the Bribery treatment can bypass competition to get a government job, thus the public sector appears to be more attractive to low ability individuals.

Hypothesis 2a: Individuals who choose the public sector have lower ability than those who choose the private sector.

Hypothesis 2b: Individuals who choose the public sector in the Bribery treatment have lower ability than those in the Meritocracy treatment.

Additionally, we investigate the links between job selection and prosocial preferences as well as risk preferences. The fact that government sectors serve societal needs may attract individuals who are strongly motivated to work for the society. Previous studies provide evidence that individuals with strong pro-social preferences are more likely to prefer public sector employment (Barfort et al. (2019), Gans-Morse, Kalgin, et al. (2020)). Furthermore, job stability and limited competition in the public sector may be more attractive to risk averse individuals.

Hypothesis 3: Individuals with high pro-social preferences are more likely to choose the public sector.

Hypothesis 4: Risk averse individuals are more likely to choose the public sector.

We argue that going through a corrupt hiring system makes individuals perceive the work environment in the public sector as more corrupt, thus they may consider demanding bribes from citizens as appropriate.[22] Additionally, payment for a government job may be considered as an investment in which the briber can extract rent when being in

[22]Serra and Barr (2010) employ an experimental study to show that corrupt behavior of individuals is strongly affected by social norms and cultures of places where they live and work.

office. Therefore, we expect that public officers recruited through corruption are more likely to demand higher bribes to cover the cost of obtaining their jobs.

Hypothesis 5a: Public officers in the Bribery treatment demand higher bribes than those in the Meritocracy treatment.

Hypothesis 5b: Public officers who pay for the free pass demand more bribes than those who do not.

1.3.4. Participants

In October, November 2021 and in July, November 2022 we conducted an online experiment with students from the subject pool of the University of Mannheim Laboratory (mLab). Students were recruited through ORSEE (Greiner (2004)). The experiment was programmed on Otree (D. L. Chen, Schonger, and Wickens (2016)). We run an online experiment instead of a laboratory experiment to increase participation rates and avoid physical contacts during the Corona Pandemic. In total, there were 249 participants with 9 sessions in the Bribery treatment and 7 sessions in the Meritocracy treatment. Of these participants, 96 took part in the Meritocracy treatment and 153 participated in the Bribery treatment. The following process was common in all sessions. At the beginning of each session, there was a short introduction about the rule of the experiment. After reading the instructions, participants were asked to answer a couple of comprehension questions to check their understanding of the instructions. Participants received points as experimental currency units and points were converted to Euros at an exchange rate of €0.03 per point. On average, the experiment lasted 63 minutes and the average payment was €14.83.

1.4. Results

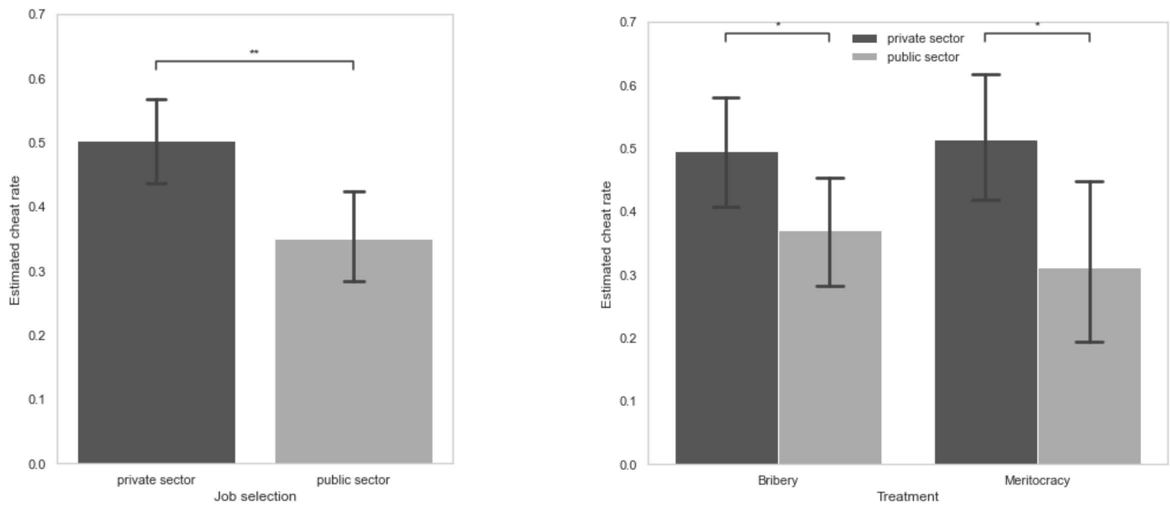
1.4.1. Job selection

Table A.1 in the Appendix A provides an overview of the relevant variables. As can be observed from this table that participants on average prefer the private sector over the public sector. In the following we take a closer look at the job selection process and analyse which types of participants select into which sector and whether this depends on treatment.

Job selection and dishonesty

We first consider the relation between dishonesty and job selection since we hypothesize that dishonest individuals are more attracted to the public sector and that this is even more pronounced in the Bribery treatment. When pooling both treatments, Figure 1.1 shows a significant difference in individuals' cheat rates between the private sector (M=0.50, SD=0.38) and the public sector (M=0.35, SD=0.35) (MW, p=0.002). Figure 1.2 and 1.3 display the distribution of observed correct guesses of individuals who choose the private sector and the public sector, respectively. Approximately 20% of individuals who choose the private sector cheat with the full extent (see Figure 1.2), whereas this share is only 8% for those who choose the public sector (see Figure 1.3). On average,

Figure 1.1.: Mean cheat rate by sectors



(a) Pooled data

(b) Bribery and Meritocracy treatment

individuals who choose the private sector make 16.68 (SD=9.60) correct guesses, while those who choose the public sector make only 13.02 (SD=8.74) correct guesses. The result indicates that individuals with a higher propensity for dishonesty are more likely to choose the private sector which does not support Hypothesis 1a. This finding, however, is consistent with previous studies on the relationship between dishonesty and job preferences. Using a survey experiment with students in Denmark, Barfort et al. (2019) show that *honest* students are more likely to prefer public sector employment. Gans-Morse, Kalgin, et al. (2020) conduct two survey experiments with students in Russia where corruption in the public sector is widespread. They show that *honest* students systematically prefer public sector jobs to private sector ones.

Figure 1.2.: Distribution of the observed number correct guesses and the expected distribution under full honesty in the private sector

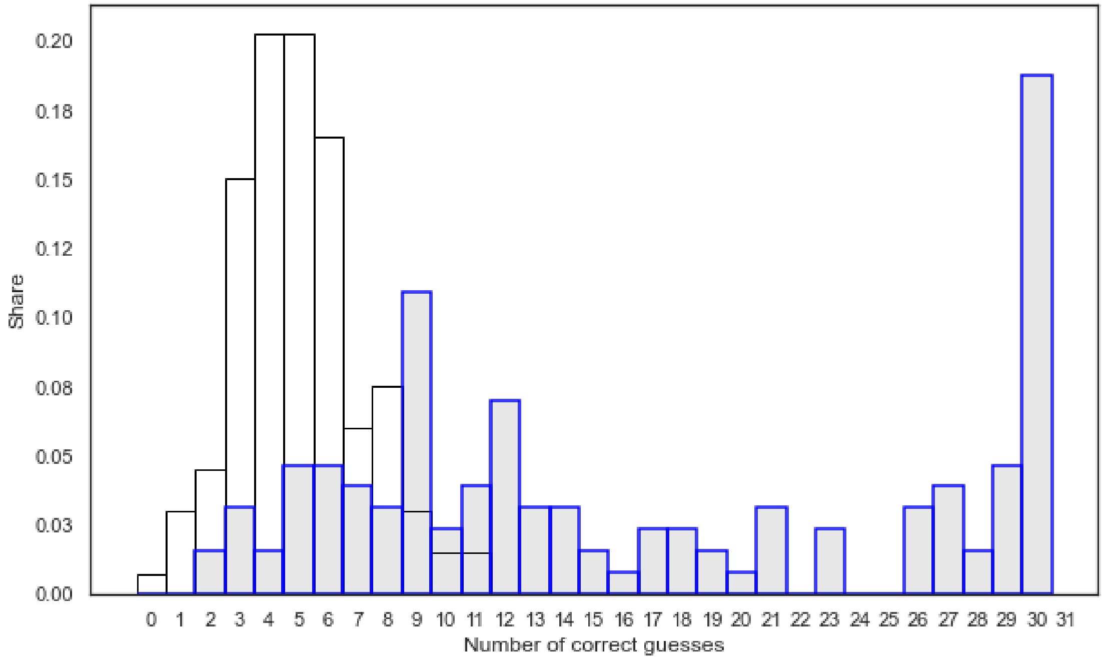
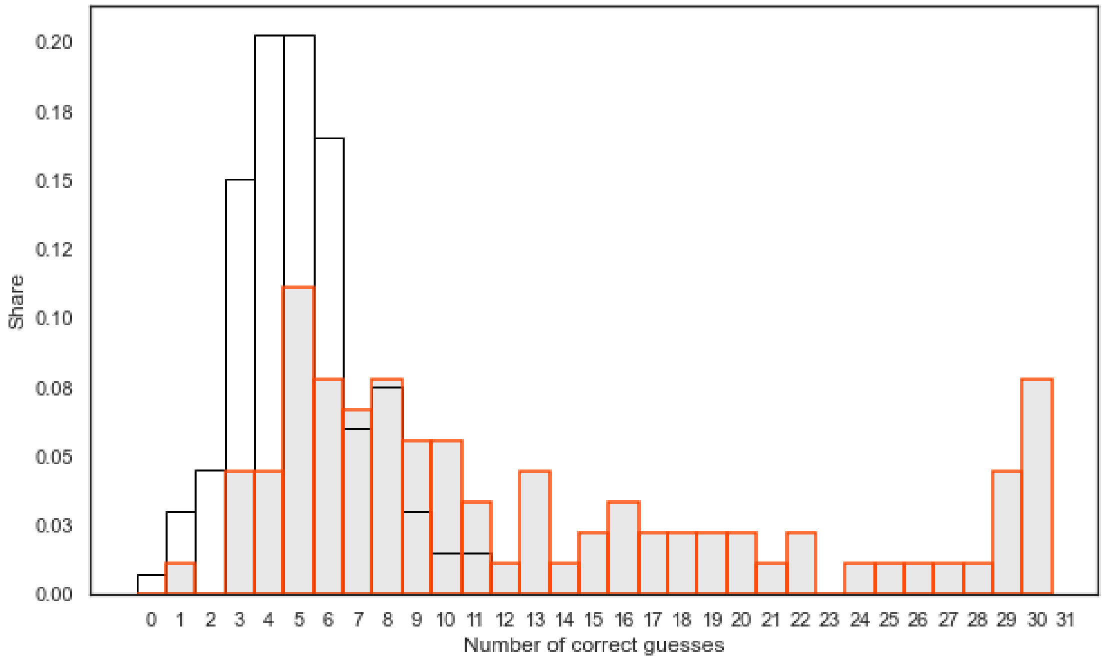


Figure 1.3.: Distribution of the observed number correct guesses and the expected distribution under full honesty in the public sector



Looking further into the observed number of correct guesses, we classify individuals into three groups. *Honest* individuals are those who make less than or equal to the expected number of correct guesses under full honesty. *Payoff maximizers* are those who maximize their payoff by making correct guesses in all rounds and the remaining are classified as *partially dishonest*. Figure A.5 in the Appendix A displays job selection by dishonesty types. It can be observed from the figure that *honest* individuals are more likely to choose the public sector, while 60% of *partially dishonest* individuals prefer the private sector and this ratio is around 80% for *payoff maximizers*. One possible explanation for the observed pattern of selection is that *dishonest* individuals are more monetarily incentivized, thus by choosing the private sector they are more likely to get a higher payoff than by choosing the public sector.[23]

Next, we consider each treatment separately to test whether selection was affected by the recruitment process. We find that the previous result, that honest individuals tend to prefer the public sector, holds for both treatments (MW, $p<0.05$ for all tests). If we focus on only those participants who are willing to buy a free pass, i.e. to participate in corruption in the recruitment process, we find that they have on average 13.19 correct guesses which are still lower than 15.85 correct guesses of the participants who chose the private sector in the Bribery treatment. Looking further into the participants who choose the public sector, we observe that the mean cheat rate is 0.37 for participants in the Bribery treatment and 0.31 for those in the Meritocracy treatment. The difference is statistically insignificant (MW, $p=0.530$). Thus, corruption during the selection process does not qualitatively affect the relationship between dishonesty and job selection. Table 1.1 depicts the results of regression analysis on the cheat rate. This analysis confirms the negative relation between dishonesty and choosing the public sector but shows no effect of the treatment on this relationship. Therefore, we find no support for Hypothesis 1b.

Finding: Honest individuals are more likely to choose the public sector in both the Meritocracy treatment and the Bribery treatment.

[23] A Mann Whitney test indicates that the average earning of individuals who choose the private sector is significantly higher than the earning of those who choose the public sector ($p<0.001$).

Table 1.1.: Regressions on a binary measure of job selection

	Public sector		
	(1)	(2)	(3)
Treatment	0.255	0.128	0.151
	(0.180)	(0.271)	(0.279)
Cheat rate	-0.701***	-0.893**	-0.997**
	(0.235)	(0.402)	(0.414)
Treatment*Cheat rate		0.306	0.337
		(0.497)	(0.506)
Ability			-0.021
			(0.028)
Risk preferences			-0.080*
			(0.048)
Prosocial preferences			-0.154
			(0.194)
Male			-0.027
			(0.185)
Intercept	-0.081	-0.004	0.568
	(0.173)	(0.214)	(0.380)
Observations	218	218	218
Pseudo R^2	0.037	0.038	0.055

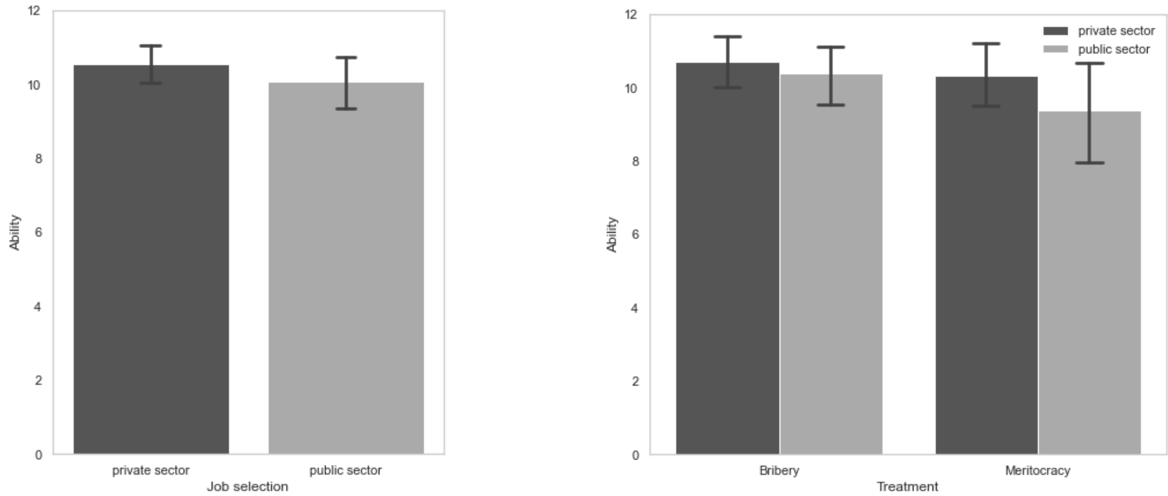
Notes: This table shows Logistic regressions of factors that determine individuals' selection into the public sector. The dependent variable is public sector which takes a value of 1 if a participant chooses Option 2 and 0 otherwise. Treatment is a binary variable which takes a value of 1 if this is the Bribery treatment and 0 otherwise. Standard errors are in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Job selection and ability

In our hypothesis we formulate the expectation that low ability individuals prefer the public sector where they can avoid competition and that this is more pronounced in the Bribery treatment where they can also avoid competition in recruitment. Figure

1.4 shows the ability composition by job choice and for each treatment separately. Considering the pooled data, we find that average ability, as measured by correct matrices in the first part of the experiment, is 10.54 for the private sector and 10.07 for the public sector. The difference is not statistically significant (MW, p=0.598).

Figure 1.4.: Ability by sectors



(a) Pooled data (b) Bribery and Meritocracy treatment

This also holds when analyzing each treatment separately (MW, p>0.10 for both tests).[24] Thus, there is no evidence to support Hypothesis 2a. Furthermore, we find that the difference in abilities between individuals who choose the public sector and those who choose the private sector is larger in the Meritocracy treatment than in the Bribery treatment which is not in line with Hypothesis 2b. The regression analysis in Table A.2 in the Appendix A confirms this impression. Ability plays no significant role in the job selection and this is independent of whether the selection process is corrupt.

Participants at the selection stage are not aware of their relative standing in the group. Thus, in addition to the actual performance, we consider the subjective rating of their relative performance. Participants are asked to indicate in which quartile they expect to be. Indicating that they are in the first quartile (top 25%), therefore means that they expect to have high relative performance.[25] We observe only 28% of participants make a correct guess. Among those who make incorrect guesses, 23% hold biased and

[24]In an experimental study, Hanna and Wang (2017) show that an individual's selection into the public sector or the private sector is not strongly driven by his/her ability.

[25]The correlation between performance in the ability task in Part 1 and the subjective rating is

over-confident beliefs about their ability, e.g. they state that they belong to the top 25% performers, whereas their actual performance is in the bottom 75%.

Next, we consider only individuals who believe that they belong to the top 25% performers and the bottom 25% performers. Table A.6 in the Appendix A reports the share of job selection based on their subjective performance ratings. We observe that 68% of individuals who believe to be the top performers choose the private sector in the Meritocracy treatment, whereas this figure is 58% in the Bribery treatment. In contrast, none of individuals whose subjective performance rating is in the bottom 25% performers selects the private sector in the Bribery treatment. This indicates that individuals who are highly confident about their ability are more likely to choose the private sector in both treatments.

Job selection and other attributes

When it comes to pro-social preferences, the pooled data shows that 37% of those choosing the private sector express pro-social preferences in the first part. This share is 39% in the public sector but the difference is not statistically significant (PT, p=0.730). In the Meritocracy treatment, the private sector has 30% pro-social individuals and the public sector has 38% (PT, p=0.480). In the Bribery treatment, the private sector has 42% and the public sector has 40% pro-social individuals (PT, p=0.821). This finding is in contrast to findings by Hanna and Wang (2017), Barfort et al. (2019) and Gans-Morse, Kalgin, et al. (2020). These studies show that there is a positive relationship between self-selection into the public sector and pro-social preferences. Our finding, therefore, does not support Hypothesis 3.

Our hypothesis on risk preferences points to the fact that the public sector is less risky than the private sector and should be preferred by risk averse individuals. We find in the pooled data that the average lottery choice is 3.45 (SD=1.99) for the private sector and 2.97 (SD=1.92) for the public sector. The difference is not statistically significant (MW, p=0.103). This also holds when we consider each treatment individually which indicates that job selection is not driven by risk preferences. Thus, we find no evidence to support Hypothesis 4.

-0.39 (Spearman's ρ, $p<0.001$) and indicates that participants on average are able to evaluate whether they perform very well or not.

1.4.2. Corruption in public sector recruitment

In the Bribery treatment there is an option to buy a free pass which captures corruption in government hiring, i.e. one can pay a bribe in exchange for a government job. Among participants who choose the public sector, over 80% of them apply for a free pass. A closer look at these participants reveals that their average cheat rate is 0.37, while this figure is 0.32 for those who do not apply for a free pass. The difference, however, is not statistically significant (MW, p=0.750).

A further investigation in these individuals shows that individuals who pay for a free pass are more risk averse than those who do not (MW, p=0.048). One of possible explanations for the high ratio of free pass applications is risk aversion. Holding a free pass secures a position in the public sector, therefore, risk averse individuals are more likely to apply for a free pass. We also find that average ability, as measured by correct matrices in the first part of the experiment, is 10.03 for individuals who apply for a free pass and 13.14 for those who do not. The difference is statistically significant (MW, p=0.043).

1.4.3. Performance in recruitment

Regarding performance in the recruitment test, we observe an interesting finding in the Bribery treatment that individuals in the private sector perform significantly better than those who apply for a free pass in the public sector (MW, p=0.026).[26] However, in the Meritocracy treatment, there is no differences in participants' performance across sectors (MW, p>0.10). One possible explanation for the lower performance in the recruitment test of individuals who apply for the free pass could be that the option to buy a free pass in the Bribery treatment allows individuals to get government jobs without having to exert a lot of effort, thus they are less motivated to perform as good as those in the private sector.

Finding: In the Bribery treatment, individuals who apply for a free pass perform in

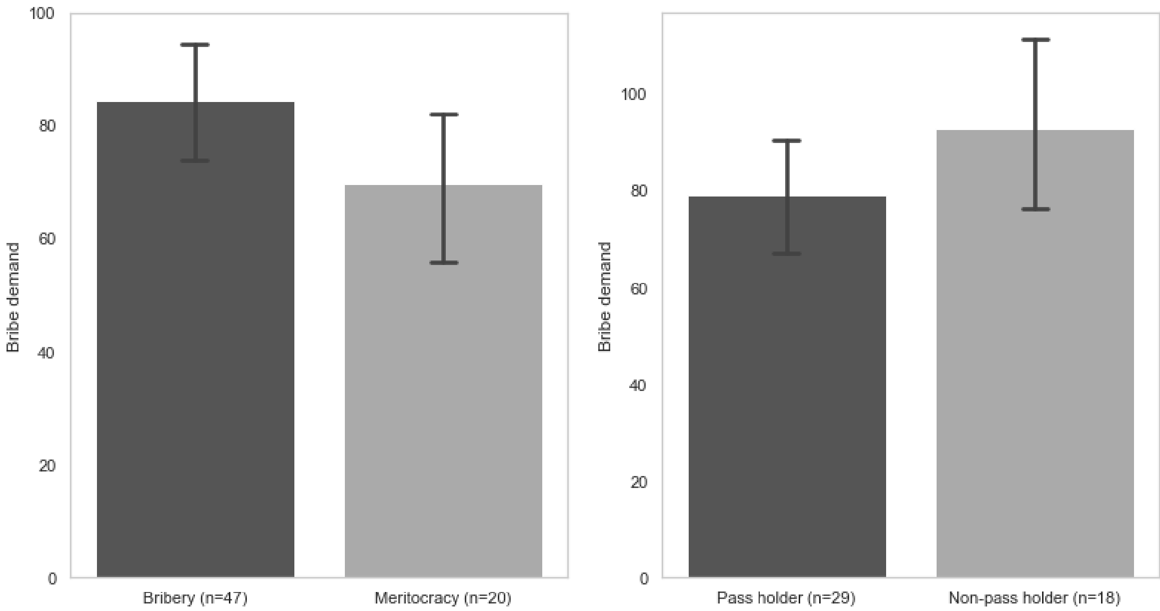
[26] In Part 1 we find no difference in ability between individuals who choose the public sector and those who choose the private sector in both treatments (MW, p>0.10 for all tests). A Spearman correlation shows a positive relationship between individuals' ability and their performance in the recruitment test (ρ=0.74, p<0.001). Therefore, ability can be considered a good predictor for performance in recruitment. Furthermore, we observe a negative correlation between individuals' performance in the recruitment test and their subjective ratings (Spearman's ρ=-0.24, p<0.001). This indicates that individuals are able to predict their performance in the test.

the recruitment test significantly worse than those who choose the private sector.

1.4.4. Bribe demand in the public sector

Figure 1.5 (left) shows average bribes demanded by public officers in both treatments. On average, public officers in the Bribery treatment demand 84.36 out of 200 points, whereas they demand 69.70 points in the Meritocracy treatment. The difference in bribe demands between two treatments is statistically weakly significant (MW, p=0.074). This finding provides evidence to support Hypothesis 5a which indicates that public officers recruited through a corrupt hiring system demand higher bribes than those recruited through a merit-based system.

Figure 1.5.: Bribe demand



(a) Treatment (b) Free pass holder

Looking further into public officers in the Bribery treatment, we classify them into two groups based on how they are recruited. In one group, they are selected based on their performance in the recruitment test and in another group, they are selected through corruption (free-pass holders). Surprisingly, we observe that public officers in the former group demand, on average, 92.94 points, while those in the latter group demand averaging 79.03 points (see Figure 1.5 (right)). This goes to the opposite direction as described in Hypothesis 5b, thus we find no evidence to support this hypothesis. Moreover, we observe the public officers who are not recruited through a free pass demand significantly more than those in the Meritocracy treatment (MW, p=0.045). Note that these two groups of public officers receive the same amount of wage which is 50 points higher than those who pay for the free pass. This indicates that the difference in bribe demands between two treatments is unlikely to come from a wealth effect. Instead, a possible reason is that going through a corrupt hiring system makes individuals to perceive the public sector as corrupt, thus they may consider corruption in the public sector as appropriate and therefore demand more bribes. Our finding provides, to some extent, a better understanding of why there are high levels of petty corruption in countries where corruption in government hiring is widespread.

Table A.8 in the Appendix A shows the effect of individuals' characteristics on bribe demand. In both treatments, more dishonest public officers demand higher bribes. We do not find any significant effects of risk preferences, prosocial preferences and gender on bribe demand in the Meritocracy treatment, whereas risk-taking individuals in the Bribery treatment are more likely to demand higher bribes.[27]

Finding: The public officers recruited through a corrupt hiring system demand 20% higher bribes than those selected through a merit-based hiring system. The higher bribe demand in the Bribery treatment comes from both public officers who pay for a free pass and who do not.

1.4.5. Performance in competition game and in contribution task

In the Meritocracy treatment there is a significant difference in performance of private workers in the competition for a bonus (M=15.23, SD=3.07) and performance of individuals in the contribution task (M=12.62, SD=3.80) (MW, p=0.007). A similar result can be observed in the Bribery treatment (MW, p=0.007). This indicates that individuals exert a higher level of effort when working for themselves than when working for everyone.

In the contribution task there is no significant difference in performance between participants in the Bribery treatment (M=12.85, SD=3.90) and those in the Meritocracy treatment (M=13.55, SD=3.80) (MW, p>0.10). However, we observe in the Bribery treatment that individuals who are willing to pay for a free pass have a significantly

[27] In a robustness check where the number of correct guesses are used as a measure for dishonesty, Table A.11 in the Appendix A shows similar results.

lower performance than those who are not (M=12.50 versus M=15.57) (MW, p=0.045). This indicates that in such a corrupt hiring system individuals who want to get a government job by their own ability are more motivated to work for the society than those who want to pay a bribe in exchange for a government job. Our finding implies that if these less motivated individuals are recruited in the public sector through a corrupt hiring system, they are unlikely to have good performance on public service delivery.

1.5. Conclusion

In this paper, we investigate the role of recruitment in job selection into the private sector and the public sector. The experimental variations in recruiting methods enable us to identify the effects of corruption in government hiring on individuals' job selection and how this in turn affects their subsequent behavior on the job. In our setting, corruption in recruitment is implemented by allowing individuals to pay a bribe in exchange for a government job without considering their performance in a recruitment test.

The treatment variations display some interesting results. First, there is a clear pattern of self-selection of *honest* individuals into the public sector in both treatments. This finding goes contrary to the simple intuition that a corrupt hiring system would attract more dishonest individuals. Rather, the result of our study is consistent with findings in Barfort et al. (2019) and Gans-Morse, Kalgin, et al. (2020), which show that *dishonest* individuals are more attracted to the private sector because they are more likely to get higher wages. In both treatments, we do not find evidence that individuals' self-selection into the public sector is strongly driven by gender, prosocial preferences or risk preferences.

We observe significantly higher bribe demand in the Bribery treatment than in the Meritocracy treatment. The difference, however, does not only stem from the bribe demand of the public officers who pay for their job in the public sector, but it also comes from the high demand of the public officers who go through a corrupt hiring system but do not pay for their job. This finding contributes to the literature on petty corruption by providing a better understanding of factors that determine high levels of corruption in the public sector in countries where corruption in hiring is prevalent. It is possible that going through a corrupt hiring system makes individuals perceive the public sector as corrupt and thus it may be acceptable to demand more bribes.

This has a policy implication that in countries where corruption in government hiring is widespread, policy markers should pay particular attention to recruitment processes if they aim to mitigate petty corruption in the public sector.

Finally, concerning the effect of self-selection on job performance we find that individuals who want to pay a bribe in exchange for a government job have lower performance than those who want to get a job by their own ability. This finding implies that corruption in government hiring may impose a risk of misallocating government jobs to less motivated individuals which is likely to adversely affect public service delivery.

This study is subject to some limitations. First, most of participants in our experiment come from Western countries which are classified as least corrupt countries (Transparency International (2022)) and where corruption in government hiring may not be common. Thus, the concept of "paying a bribe" to get a government job may not be widely known by these participants. Future research can investigate if a similar pattern of selection is observed with other subject pools in highly corrupt nations such as India, Pakistan or Indonesia. Second, in our setting the access to a free pass is rather easy and not correlated with individuals' characteristics. In real life scenarios, to get a government job individuals would need to be wealthy and/or have social power. Such conditions might be correlated with individuals' background and characteristics such as education levels, ability, and thus might have impacts on their behavior on the job.

Our findings open some avenues for future research. One possible direction is to investigate the interaction between corruption in hiring and differences in wages between the private sector and the public sector. Our result shows that *dishonest* individuals are more likely to choose the private sector in which they get higher compensation. It might be interesting to examine whether *dishonest* individuals are more likely to choose government jobs where they can get higher wages. Another feasible direction is to consider a possibility of detecting corruption in government hiring. Previous studies have shown that individuals are less likely to engage in corruption when their corrupt behavior can be detected and punished (Abbink, Irlenbusch, and Renner (2002), Gans-Morse, Borges, et al. (2018)). In our study, we observe a high share of individuals who are willing to pay a bribe in exchange for a government job. Future research can investigate the role auditing and punishment in mitigating corruption in government hiring.

Chapter 2.

How the reactions of third party beneficiaries affect unethical pro-group behavior of actors *

with Franziska Heinicke

2.1. Introduction

Unethical behavior such as cheating, bribery, and tax evasion, etc. often benefits not only actors but also others. For example, Diego Maradona took illegal drugs at FIFA World Cup 1994 and scored an important goal for his team to win against Greece team. Sale employees in Kobe Steel over-exaggerated their products' quality to customers in order to benefit their firm. Researchers found in a survey of over 2000 Canadian and American secretaries and executive assistants that 6.5% wrote documents with false or misleading information and about 10% eliminated damaging information. Such actions were taken by employees to benefit their groups or organizations (Kleiman 1996, Umphress, Ren, et al. (2009)). The in-group beneficiaries of such unethical behavior, as we understand them, are not involved in the behavior themselves but it is possible that they observe or are told about the unethical act. These in-group beneficiaries work closely with the transgressor and have frequent interactions. This does not only put them in a better position than authorities to observe unethical behavior but also

*We are grateful to Henrik Orzen, Wladislaw Mill and audiences at 2022 Virtual Asia Pacific Meeting, GESS Research Day in Mannheim and seminar participants from Leibniz Centre for European Economic Research in Mannheim for helpful comments and suggestions.

offers the opportunity to react in a favorable or disagreeing way. In this paper, we are interested in better understanding the role of third party beneficiaries in mitigating unethical behavior.

Unethical pro-group behavior has opposing features. On the one hand, it benefits not only actors, but also others in their group. The benefits for third parties allow actors to justify their unethical behavior as doing something good for others: "I do it for us" instead of "I do it for myself", thus their behavior appears to be less greedy and more moral than when they alone benefit from it. On the other hand, it is harmful for other groups or the society, so it may impose negative externalities. Additionally, it carries some risks for their own group once such unethical pro-group behavior is being detected. Because of such features, there are conflicting norms of whether one should help his/her own group or should not harm the society.

Unethical pro-group behavior has recently received great attention from the literature. Several studies show that individuals are more likely to engage in unethical behavior when it not only benefits the self and but also others as compared to when it only benefits the self (Wiltermuth (2011), Gino, Ayal, and Ariely (2013), Umphress and Bingham (2011)). Other studies investigate emotional aspects of individuals who engage in unethical pro-group behavior (Tang, Yam, and Koopman (2020)), short run benefits (Umphress and Bingham (2011)) and long run effects of unethical pro-group behavior (Zhang, He, and X. Sun (2018)). These studies mainly focus on actors, therefore, so far little is known about the role of third party beneficiaries in preventing unethical pro-group behavior. The present paper aims to fill this gap.

Reactions of third party beneficiaries are important for two reasons. A positive reaction of third party beneficiaries such as reward can be used to signal approval (Nikiforakis and Mitchell (2014)) and to reinforce preferred behavior. However, not all beneficiaries welcome benefits from unethical behavior. For example, many individuals and charity organizations refuse to take ill-gotten money from fraud activities (Schecter (2010)). A negative reaction such as punishment and whistle-blowing can be used to signal disapproval (Almenberg et al. (2010), Nikiforakis and Mitchell (2014)) and to encourage behavioral changes of actors.

The main research question we aim to answer in this study is what role beneficiaries play in mitigating unethical pro-group behavior. Specifically, we investigate to what extent actors engage in unethical pro-group behavior when their behavior can be revealed, rewarded, punished or reported by third party beneficiaries and how reactions of beneficiaries in turn affect actors' subsequent behavior.

To answer the above question, we design four treatments which differ in whether unethical behavior can be verified and what types of reactions are available. In this study, we focus on one specific aspect of unethical behavior – cheating. We focus on cheating as it is a prevalent problem in groups and organizations. In all treatments, actors first roll a fair six-sided die and then report a low, medium or high state of the die. A low state indicates that an outcome of the die roll is 1, 2 or 3. A medium state indicates an outcome of either 4 or 5 and a high state indicates an outcome of 6. Actors can earn higher payoffs for themselves and for third party beneficiaries by dishonestly over-reporting the state of the die roll. To capture a negative externality aspect of the unethical behavior, the benefit from cheating is transferred from a common pool of a charity organization, UNICEF, to actors and beneficiaries. With a 10% chance cheating is detected and actor's payoff is reduced by 40%.

The *Baseline* serves as a benchmark to measure the extent of cheating when no verification or reaction is possible. In the *Verification* treatment, beneficiaries have an option to verify the true state of the die roll, and thus compare to the state reported by actors. This treatment allows us to capture the effect of beneficiaries' scrutiny on cheating. Furthermore, to measure the effect of beneficiaries' reactions on cheating behavior of actors we employ the *Reaction* treatment where third party beneficiaries can first decide whether to verify die outcomes and then reward or punish actors. Note that these reaction options are available regardless of whether beneficiaries have verified or not. Unlike in the *Verification* treatment, these types of reactions in the *Reaction* treatment have monetary consequences on actors' payoffs. Finally, in the *Reporting* treatment, beneficiaries have an additional option to report actors which increases a probability of detecting cheating. If actors get caught for cheating, both actors and beneficiaries receive lower payoffs in the subsequent stage. This allows us to capture a detrimental effect of actors' unethical behavior on their group. The motivation to implement the *Reporting* treatment is to contrast the willingness of beneficiaries to intervene themselves with their willingness to make a proper report about the unethical behavior. Finally, we run a survey with different participants to measure norms on unethical pro-group behavior.

Our results are as follows. First, on average less than 20% of actors cheat and if they cheat, they tend to cheat to the full extent. This pattern of cheating behavior does not differ significantly across treatments. The second set of finding concerns behavior of beneficiaries. We observe that around 70% of beneficiaries choose to verify die outcomes. However, they tend to verify outcomes less often after observing a reported state of medium or high. Beneficiaries react more strongly after they verify the true state of the die roll as compared to when they do not verify. Overall, in the *Reaction* treatment 37% of beneficiaries reward actors, whereas 29% of them choose punishment. Surprisingly, introducing an option to report actors does not change the pattern of reactions in the *Reporting* treatment. Beneficiaries rarely report cheating behavior (only 2%), instead they prefer to reward and punish actors. Third, we find that actors are more likely to remain honest after their behavior is being verified in the *Reaction* treatment and after being rewarded in the *Reporting* treatment, whereas punishment does not affect their behavior.

Our survey on norm elicitation shows two conflicting norms. On the one hand, cheating benefits both actors and beneficiaries, thus is reported to be appropriate behavior. On the other hand, cheating imposes a negative externality (harming the charity), and is therefore reported to be inappropriate. It does not seem to be the case that one norm is considerably stronger than the other which could explain the results that we observe above. Taking all results together, this study shows that due to the conflicting norms, beneficiaries are unlikely to play an important role in preventing unethical behavior.

The remainder of the chapter is organized as follows. The second section reviews related literature. The third section describes experimental design and procedure. The fourth section shows results and the last section discusses as well as concludes the paper.

2.2. Literature review

There is small literature on unethical pro-group and pro-organizational behavior. Wiltermuth (2011), Gino, Ayal, and Ariely (2013) investigate unethical behavior of actors when such behavior benefits not only the self but also others. The possibility to benefit others allows actors to justify their self-interest behavior as morally acceptable, thus they can reduce the feeling of guilt and blame from others. Wiltermuth (2011) provides clear evidence that actors behave more dishonestly when such dishonest behavior benefits themselves and others. This finding is consistent with the results in an experimental study conducted by Gino, Ayal, and Ariely (2013). They point out that actors cheat to the full extent when cheating benefits both themselves and others. The above studies show that individuals are more willing to cheat if it benefits others, however, they do not take into account reactions of beneficiaries to such cheating behavior. We fill this gap by examining how beneficiaries react to cheating and how this in turn affects actors' subsequent behavior.

This study is also related to the literature on unethical behavior under public scrutiny. Greenberg, Smeets, and Zhurakhovska (2014) and Van de Ven and Villeval (2015) use a sender-receiver game to investigate lying under public scrutiny. In their setting, apart from sender and receiver, there is an observer whose payoff is aligned with the sender. The sender and the observer are informed about possible payoffs, but such information is hidden to the receiver. The observer can inform the receiver if the sender lies. They show that revealing the identity of the liar to others does not reduce dishonest behavior. A possible explanation is that many individuals perceive lying as justifiable, thus it affects their normative beliefs and lying behavior. Brocas, Carrillo, and Montgomery (2021) investigate effects of revealing the identity of thieves to others on stealing behavior. In their study, consumers have an opportunity to steal a good from producers. They show that stealing decreases significantly when pictures of those who get caught are shown publicly. This indicates that shaming is an effective mechanism to curb unethical behavior. Adding to this strand of the literature, we investigate the role of third party beneficiaries' scrutiny on cheating behavior by allowing them to verify whether actors cheat or not.

Our study also contributes to the literature on third party reward and punishment (e.g. Almenberg et al. (2010), Nikiforakis and Mitchell (2014)). Almenberg et al. (2010) and Nikiforakis and Mitchell (2014) exploit a dictator game to investigate demands for costly punishment and reward from unaffected third parties. In these studies, individuals use costly punishment or reward to signal disapproval or approval of dictators' transfers. In a treatment where both reward and punishment opportunities are available, many individuals indicate their approval of the behavior of dictators by withholding punishment, while they express their disapproval by refusing to reward dictators. Our study contributes to this line of the literature by investigating punishment and reward of third party beneficiaries who are indirectly affected by actors' behavior.

We are interested in how beneficiaries can mitigate cheating. Therefore, our study also adds to the whistle-blowing literature which is one important channel beneficiaries might use to prevent cheating (Waytz, Dungan, and L. Young (2013), Dungan, Waytz, and L. Young (2014)). These studies indicate that individuals encounter a trade-off between fairness and loyalty. Fairness requires that individuals across groups are equally treated, whereas loyalty requires that one's own group receives special treatment. C.-P.

Chen and Lai (2014) and Latan, Chiappetta Jabbour, and Lopes de Sousa Jabbour (2021) examine the impact of potential harm on whistle-blowing intention. The authors show that individuals are more willing to blow a whistle if unethical behavior causes more severe harm as compared to when it leads to mild damages. Overall, the literature on whistle-blowing shows that whistle-blowing can be a useful tool against misconduct but that the willingness to report is affected by many factors such as loyalty or potential harm. In our study, we design the *Reporting* treatment to measure the willingness of beneficiaries to report wrongdoing. We make explicit that beneficiaries might get lower payoffs if they report actors to capture a negative effect of unethical behavior on one's own group when it is detected.

Finally, the current study is relevant to another strand of research which examines emotions of individuals who engage in unethical pro-organizational behavior. Tang, Yam, and Koopman (2020) argue that individuals encounter an emotional dilemma between two opposing types of emotions. On the one hand, pro-organizational behavior triggers the feeling of pride and achievement because individuals behave in favor of their organization (Belschak and Den Hartog (2009), Tang, Yam, and Koopman (2020)). For instance, Belschak and Den Hartog (2009) show that employees feel proud after performing pro-group behavior that facilitates their organization's success. On the other hand, unethical behavior triggers the feeling of guilt when individuals behave unethically or violate normative standards. Eisenberg (2000), Treviño, G. R. Weaver, and Reynolds (2006) and Umphress and Bingham (2011) identify guilt and shame as emotional consequences of unethical behavior. They argue that guilt is likely to trigger changes in behavior, whereas shame is likely to evoke changes in self-image.

Coricelli, Joffily, et al. (2010) and Coricelli, Rusconi, and Villeval (2014) investigate effects of feedback of cheating behavior on emotions. They find that individuals encounter negative emotions, i.e. shame and regret, when their cheating behavior is detected and their picture is publicly revealed. In contrast, knowing that their cheating behavior is not being verified increases positive emotions such as relief and joy. They additionally find that the danger of being exposed to the public significantly reduces cheating. The previous literature shows that emotions are an important aspect to drive behavior. Therefore, in our study we capture emotions of both actors and beneficiaries by adopting emotion measurement in Tang, Yam, and Koopman (2020) and Tang, Yam, Koopman, and Ilies (2021).

2.3. Experiment

2.3.1. Experimental design

Participants form groups of two in which one participant takes the role of Person A and the other participant the role of Person B.[1] Roles remain unchanged throughout the experiment. Participants play a sequential game in which Person A is the first-mover and Person B is the follower. The game is repeated for two rounds and each round proceeds as follows.

Stage 1: Dishonesty Phase

In this stage, Person A rolls a digital six-sided die and reports the outcome of the die roll. This generates payoffs for Person A, Person B and a charity organization, UNICEF.[2] How much payoff is generated depends on the outcome of the die and the reported state. We define three states based on the outcome of the die: rolling 1, 2 or 3 is a low state, rolling 4 or 5 is a medium state, and rolling 6 is a high state. Reports are categorized in the same way.

Table 2.1.: Payoff table

True state	Reported state	Payoff to Person A	Payoff to Person B	UNICEF
low	low	10	5	50
	medium	20	10	35
	high	40	20	5
medium	low	10	5	50
	medium	20	10	50
	high	40	20	20
high	low	10	5	50
	medium	20	10	50
	high	40	20	50

[1] Person A takes the role of an actor and Person B takes the role of a third party beneficiary. We use neutral framing to avoid any experimenter demand effects.

[2] To capture an unethical aspect of cheating, we introduce a charity organization whose payoff is reduced if Person A over-reports the outcome of the die roll.

Table 2.1 displays the payoff distribution for each player and UNICEF. In each round, a fixed amount of 50 points is initially assigned to UNICEF regardless of the outcome of the die roll. If Person A reports the true state of the die roll, the payoff to UNICEF remains unchanged. Person A, however, can earn higher payoffs for himself/herself and for Person B by dishonestly reporting a higher state. This comes at the cost of UNICEF's payoff, i.e., increased payoffs resulting from such cheating behavior is transferred from UNICEF to Person A and Person B. Note that under-reporting the outcome of the die roll makes both Person A and Person B worse-off, while the payoff of UNICEF remains unchanged. Therefore, we assume that a rational individual either truthfully reports or over-reports the outcome of the die roll. For every reported outcome, the payoff to Person A is twice as high as that of Person B. For example, suppose that the true state of the die roll is a low state but Person A reports a high state. Then Person A receives 40 points and Person B obtains 20 points, while UNICEF receives only 5 points instead of 50 points.

We choose the payoff combinations in Table 2.1 for several reasons. First, the payoffs of actors are consistently higher than those of beneficiaries because we want actors to be mostly affected by their actions. Klein et al. (2017) show that individuals are more likely to engage in cheating when benefits are split more to the self than to others. Another reason is that it eliminates Person B's attempt to equalize his/her payoff with that of Person A for any reaction scheme (further details about reaction schemes are explained in Section 2.3.1). It is, of course, possible that Person B feels motivated to give up all of his or her payoff to decrease Person A's payoff to zero. However, previous literature on punishment has shown that participants spend on average less than half of their endowment on costly punishment (Fehr and Fischbacher (2004), Charness, Cobo-Reyes, and Jiménez (2008)). Finally, there are no efficiency gains from cheating since higher payoffs from over-reporting are taken from the charity organization.

To capture the risk of cheating, we introduce a 10% chance that cheating behavior is detected. In case of detection, Person A's payoff is reduced by 40% and points taken from Person A is transferred back to UNICEF. The transfer can be viewed as a compensation for a victim who suffers from cheating. We choose this punishment level that Person A's payoff is reduced by 40% because it ensures that Person A still earns higher than Person B even when he/she is being punished. This rules out a concern that Person B wants to report Person A to make his/her payoff equal to or more than payoff of Person A. Person B is excluded from punishment because he/she does not directly engage in cheating.[3] If Person A is detected for cheating in the first round, the payoffs for both Person A and Person B of every outcome in the second round are reduced by 20%. The reduction in the payoffs is motivated by a negative impact that cheating has on a group, once such cheating behavior is being caught. It is often observed that once employees get caught for wrongdoing, there is some loss of public trust in the organization. Cheating behavior contributes to losses, and thus everyone in the team or organization suffers from those damages. We capture this consequence in our setting by reducing available payoffs of every reported outcome, therefore, impose an overall reduction in social efficiency.[4]

Stage 2: Verification/Reaction Phase

We design four treatments which differ in the second stage. Each treatment is explained in the following.

Baseline: Person B does not have any option to verify the true state of the die roll or to react to Person A's behavior. After Person A reports the die roll, participants directly proceed to round 2. The *Baseline* serves as a benchmark to measure cheating behavior of Person A when no possibility for verification or reaction is available.

Verification treatment: Person B has the option to verify the true state of the die roll. This treatment is designed to measure how the threat of being verified affects actors' behavior in round 1 and how revealing Person A's cheating behavior to Person B affects behavior in round 2.

Reaction treatment: Person B can first verify the true state of the die roll as in the *Verification* treatment. Subsequently, Person B has three options to react to the behavior of Person A, including no reaction, take points, or give points.[5] To give points, Person B gives up his/her own points to increase the points of Person A. Giving up 1 point of the own payoff increases Person A's payoff by 2 points. To take points, Person B gives up his/her own points to decrease the points of Person A. Giving up 1 point

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[3] For an intuition, consider a college admission scandal in the US (Levenson (2019)) where a number of parents paid bribes to get college admissions for their children. After the illegal behavior was detected, the parents pledged guilty, while children were not punished for such behavior of their parents.

[4] The adverse impacts have been previously investigated in studies on unethical pro-organizational behavior (Umphress and Bingham (2011), Zhang, He, and X. Sun (2018)).

[5] We introduce a no reaction option to avoid any anchoring or experimenter demand effects.

of the own payoff decreases Person A's payoff by 2 points.[6]

Reporting treatment: In addition to all options in the *Reaction* treatment, there is a report option if Person B verifies the true state of the die roll and Person A dishonestly reports the outcome of the die.[7] Reporting increases the probability of detection by 4 times from 0.10 to 0.40.[8] Note that by reporting in the first round, Person B imposes a higher risk of getting lower payoffs for both Person A and Person B in the second round.[9]

In treatments with verification and reaction possibility, it is common knowledge for both persons that Person B can verify the true state of the die roll and/or react to Person A's behavior. Additionally, Person A is fully informed about Person B's reactions. After Person B's decision, cheating is investigated and is revealed to both players before they move to the next round. Our main variables of interest are cheating rates and behavioral changes of Person A from the first round to the second round. With the above-mentioned treatments we attempt to identify the following effects. First, the *Verification* treatment is intended to capture the effect of third party beneficiaries' scrutiny on decision making of actors. Second, the *Reaction* treatment is intended to capture the effect of internal reaction tools, i.e. reward and punishment, on actors' behavior. Third, the difference in chosen tools for reactions in the *Reporting* treatment should capture whether internal or external tools, i.e. reporting, are more often used by beneficiaries, and which tool is more effective in mitigating cheating behavior.

[6] A reward and punishment ratio of 1:2 has been used in previous studies on second-party or third party reward and punishment (Sutter, Haigner, and Kocher (2010), Nikiforakis and Mitchell (2014)).

[7] This is to ensure that reporting is only credible if Person B has reliable information about dishonest behavior of Person A.

[8] A probability of detection of 0.40 indicates that reporting still does not ensure a cheating detection. This captures many real life scenarios that authorities may lack evidence or not carry proper investigations to catch wrongdoers even after having received a report from beneficiaries.

[9] Rehg et al. (2008), Wainberg and Perreault (2016), and R. F. Young (2017) argue that whistleblowers are exposed to threat of ostracism, retaliation, harassment, or being fired. Additionally, organizations may suffer from losses of public trust which lead to losses in revenues and profits. In our design, we capture a short-term negative effect of detecting cheating behavior by reducing payoffs of both Person A and Person B. However, it is possible that in a long term, organizations may benefit when cheating behavior is detected and eliminated. This long term effect is outside of the scope of this study.

Emotion measurement

Measure emotions of actors: Previous studies have shown that emotions are drivers of behavioral changes (Coricelli, Joffily, et al. (2010), Brocas, Carrillo, and Montgomery (2021)). In this study, we measure emotional changes of actors after observing third party beneficiaries' reactions.[10] On the one hand, as actors' behavior does not only benefit themselves, but also third party beneficiaries, we predict that pro-group behavior stimulates the feeling of pride in actors. Therefore, we adopt two items for measurement of pride by Tracy and Robins (2007). An item can be viewed as a question in a survey. The items include *"accomplished"* and *"self-worthy"*. On the other hand, cheating behavior of actors is unethical because they take away payoffs from the charity. Furthermore, when cheating behavior is being exposed to others, it may trigger the feeling of shame and guilt in actors. We adopt some items to measure shame and guilt introduced by Gino, Ayal, and Ariely (2013). The items for guilt are *"guilty"* and *"blameworthy"*, and the items for shame are *"I felt like I am a bad person"* and *"I felt humiliated"*.

Measure emotions of third party beneficiaries: To understand motives behind reactions of third party beneficiaries, we measure their emotions in all treatments. Tang, Yam, Koopman, and Ilies (2021) argue that unethical pro-group behavior triggers complex emotions in third party beneficiaries. On the one hand, as they benefit from the pro-group behavior, we predict that the pro-group behavior elicits the feeling of admiration in third party beneficiaries. We use two items, *"admiring"* and *"grateful"*, to measure the feeling of admiration. On the other hand, the unethical behavior may lead to the feeling of disgust in third party beneficiaries. We use two items, *"disgust"* and *"disappointed"*, to measure this type of emotion. Each item of emotion in this study is assessed on a 7-point scale ranging from 1 = *not at all* to 7 = *very much.*

2.3.2. Hypotheses

Our goal is to investigate the effects of third party beneficiaries' reactions on unethical

[10] We elicit emotions of participants in the first round for two reasons. First, we want to capture instant emotions after actors engage in (dis)honest behavior and observe reactions of third party beneficiaries. Second, emotions in the second round might be affected by behavior or reactions in the first round, so it is not clear whether emotions measured in the second round is stimulated from this round or a previous round. Additionally, to avoid any experimenter demand effects, participants are asked to self-report their emotions only once.

pro-group behavior. First, we look at behavior of actors in the first round. It is possible that actors form norm perception towards cheating and beliefs about preferences of third party beneficiaries. Jordan (2001) states that attitudes towards cheating and social norms about cheating are significantly associated with cheating rates. Furthermore, Wiltermuth, Bennett, and Pierce (2013) show that actors consider beneficiaries' preferences when engaging in unethical behavior. Depending on whether the majority of actors expect beneficiaries to find lying for the mutual benefit desirable or undesirable, we expect them to more strongly act in accordance with this expectation in treatments that allow for a reaction of the beneficiary. Therefore, we form the following hypotheses.

Hypothesis 1a: There is more cheating in treatments where beneficiaries can react.

Hypothesis 1b: There is less cheating in treatments where beneficiaries can react.

Previous studies show that individuals act differently when their behavior cannot be verified as compared to when they are potentially observed by others (see Greenberg, Smeets, and Zhurakhovska (2014), Van de Ven and Villeval (2015), Brocas, Carrillo, and Montgomery (2021)). Therefore, if individuals are concerned about being scrutinized by others, they might cheat less when beneficiaries verify their behavior. We test the following hypothesis.

Hypothesis 2: Actors are less likely to cheat after their behavior has been verified by beneficiaries.

Next, we consider the effect of reward, punishment and report on cheating. Almenberg et al. (2010) and Nikiforakis and Mitchell (2014) show that reward can be perceived as a signal of approval or agreement with a certain type of behavior, therefore, we hypothesize that actors behave in the same manner in the second round after being rewarded. On the other hand, punishment and report are used to express one's disagreement with a certain pattern of behavior, thus, we predict that actors may change their behavior in the second round after being punished or reported. The design of the *Reaction* treatment and the *Reporting* treatment allows us to test the following hypotheses.

Hypothesis 3a: In the second round, reward reinforces actors' behavior in the first round.

Hypothesis 3b: In the second round, punishment and reporting stimulate behavioral changes of actors.

2.3.3. Participants

In January and February 2022 we conducted the main experiment with a subject pool on Amazon Mechanical Turk. In July 2022 we conducted a survey on norm elicitation with different participants. The experiment was programmed in Otree (D. L. Chen, Schonger, and Wickens (2016)). To be eligible for participating in our experiment, participants had to be located in the US and completed at least 500 tasks on Mturk with the approval rates of more than 95%. Participants were allowed to take part only once in our experiment.

There are some common features in the experiment across treatments. First, we used neutral framing for experimental instructions. We framed Person A for actor, Person B for third party beneficiary, "give points" for rewards, "take points" for punishments and "change the lottery" for reporting. After participants provided demographic information, they read the instructions and were asked to answer some comprehension questions related to the instructions. Participants were not allowed to continue with the experiment if they could not answer all questions correctly after two attempts. Excluding those who failed the quiz provided us with 216 participants in the *Baseline*, 190 participants in the *Verification* treatment, 190 participants in the *Reaction* treatment and 218 participants in the *Reporting* treatment. Each treatment consisted of 3 sessions. On average, the experiment lasted around 10 minutes. Participants received a show-up fee of $0.80 and earned, on average, an additional bonus of $0.90.

To investigate whether norm perceptions play a role in behavior of actors and beneficiaries, we elicit social norms from a new sample of participants who were also recruited via mTurk. Participants received the instructions of the main experiment and had to pass the same understanding questions as participants of the main experiment. Participants were informed from the beginning that they would not participate in the main experiment but that they had to answer questions about the behavior in that experiment. We elicit descriptive norms to measure the expectation of cheating rates and injunctive norms to evaluate appropriateness of actors' behavior and beneficiaries' reactions.[11] Of all the norms we elicited, one was randomly selected for the final payoff. We elicit norms for each treatment in a between-subject design. Participants could receive a bonus of $1.20 where the rule of receiving the bonus depended on the selected question.

[11]As observed in the main experiment, participants lie upward instead of downward, therefore, it would be interesting to elicit norms where the true state is low.

Descriptive norms: Participants had to predict the behavior of actors in round 1. Specifically, the questions are *"in your opinion, if the true state is low, what percentage of participants (on a scale from 0 to 100) reports a low (medium, high) state?"*. If participants guessed within ±10% of the true percentage in the main experiment, they would receive the bonus of $1.20.

Injunctive norms: We elicited injunctive norms for different stages of the main experiment. First, participants coordinated on injunctive norms in the dishonesty phase. To be specific, we asked *"suppose Person A observes a low state, how appropriate is it to report a low (medium, high) state?"*. Second, we elicited norms for the reaction phase. Here, we let participants coordinate on the most appropriate choice: *"suppose Person A reports a low (medium, high) state and Person B does not verify (Person B verifies and finds out that the true state is low). What is the most appropriate reaction?"*. For all injunctive norms, participants received the bonus if they gave the modal answer within their treatment.

In the survey on norm elicitation, there were 95 participants in the *Baseline*, 90 participants in the *Verification* treatment, 93 participants in the *Reaction* treatment and 93 participants in the *Reporting* treatment. They received a show-up fee of $1.00 and earned a bonus of $0.60. On average, the survey lasted approximately 10 minutes.

2.4. Results

In the following we discuss behavior in each stage and how it is affected by prior stages of the game.

2.4.1. Dishonesty phase – Round 1

We start our analysis by comparing cheating in the first round across treatments. Table 2.2 summarizes behavior in the dishonesty phase. We observe that only a minority of actors reports an outcome higher than the true state and no actor under-reports the outcome state of the die roll. In the first round, the share of cheaters varies from 15% in the *Reporting* treatment to 8% in the *Reaction* treatment. The distribution of honesty does not differ significantly between treatments (Chi2-test (CT), p=0.463). Pairwise comparisons between treatments are all not significant (Fisher's exact test

(FT), p>0.10).[12]

We classify actors into three groups based on their cheating behavior. We define actors who observed a low state but reported a medium state and those who observed a medium state but reported a high state as *partial liars*. Individuals who observed a low state but reported a high state are defined as *complete liars*. The shares of *partial liars* are 6.5% in the *Baseline*, 3% in the *Verification* treatment, 4% in the *Reaction* treatment and 6% in the *Reporting* treatment, while the shares of *complete liars* are 6.5%, 10%, 4% and 9%, respectively. The remaining individuals are *completely honest*.

Table 2.2.: Cheat rates and average reported dies by treatments

	Baseline	Verification	Reaction	Reporting
Report die	3.83	3.95	3.78	3.70
	(1.71)	(1.79)	(1.72)	(1.77)
True die	3.43	3.64	3.55	3.31
	(1.65)	(1.75)	(1.76)	(1.59)
Share of cheating	13%	13%	8%	15%
Observations	108	95	95	114

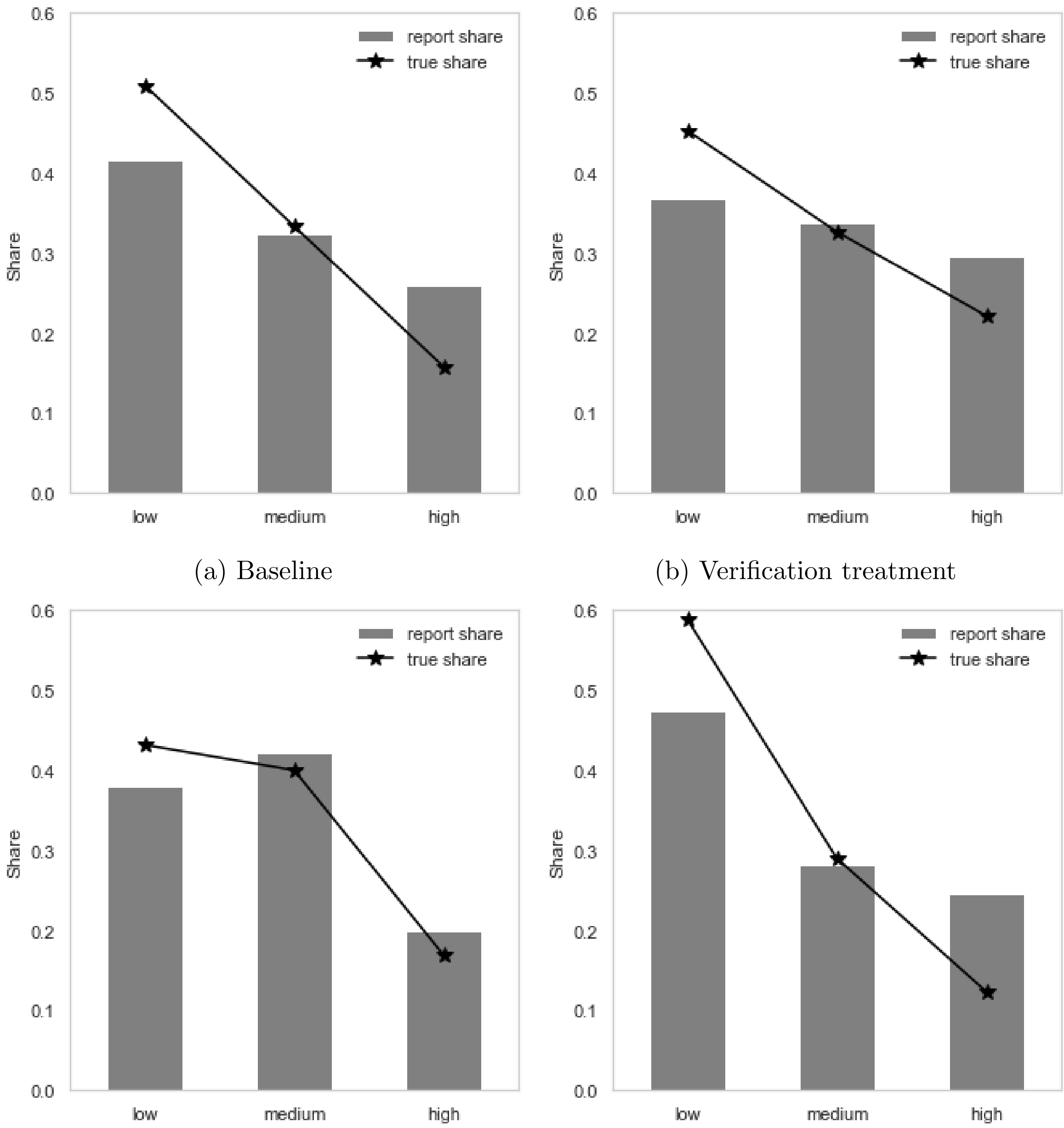
Notes: Standard deviations are in parentheses.

Next, we consider the distribution of reported outcomes. Figure 2.1 shows true states and reported states in each treatment. What stands out from this figure is that actors who cheat are more likely to cheat to the full extent. The medium state is only over-reported by a very low degree. Among those who observe a low state in the *Baseline*, 15% reported a high state, while only 5% reported a medium state. A similar pattern can be observed in the other treatments.

Finding: Less than 20% of actors lie. If they lie, they prefer to lie to the full extent. There are no differences in lying behavior between treatments.

[12]Previous studies on unethical pro-group behavior show that when the benefits of lying are split among cheaters and other participants, participants lie 20% more than when they only lie for themselves (Wiltermuth (2011), Gino, Ayal, and Ariely (2013)). Unlike our study, cheating behavior of participants in these experiments cannot be scrutinized by beneficiaries.

Figure 2.1.: Distribution of true states and reported states



(a) Baseline

(b) Verification treatment

(c) Reaction treatment

(d) Reporting treatment

2.4.2. Verification phase – Round 1

After observing the reported state, beneficiaries have the option to verify the true state of the die roll. In the *Verification* treatment 75% of beneficiaries make use of this option in the first round compared to 73% in the *Reaction* treatment and 67% in the *Reporting* treatment. While we observe a high share of verification, the differences across treatments are small. The distribution of verification behavior does not differ between treatments (CT, p=0.330) and pairwise comparisons are not significant (FT, p>0.10 for all tests).

Next, we explore when beneficiaries choose to verify the behavior of actors. Note that actors are unlikely to cheat downward since it makes both actors and beneficiaries worse-off, while it does not make the charity better-off, therefore, a low reported state strongly signals that actors are honest. However, we observe in Figure 2.2 that the proportion of verification in a low reported state is higher than in a medium state or a high state across treatments.

Figure 2.2.: Verification share based on reported states in Round 1 by treatments

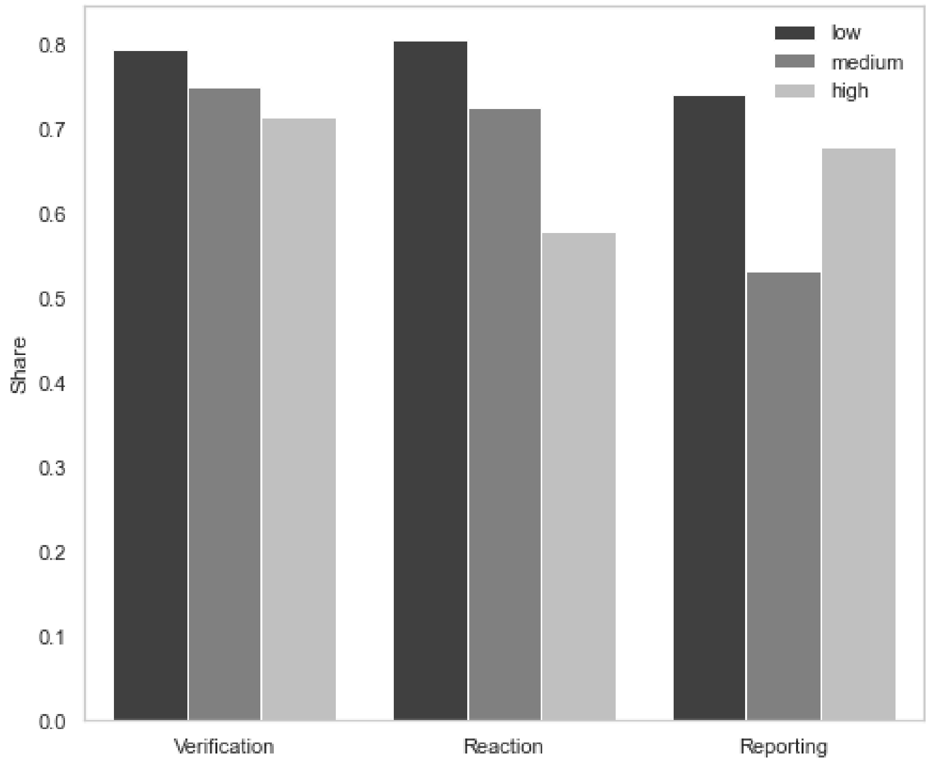


Table 2.3 shows Logistic estimates of the relationship between the decision to verify the true state of the die roll and the observed reported state. The regression analysis confirms that as compared to low reported states, beneficiaries in the *Reaction* treatment are less likely to verify high reported states and those in the *Reporting* treatment are less likely to verify medium reported states. A possible explanation for the lower share of verification in the medium and high reported states is that remaining ambigu-

ous about actors' behavior can help beneficiaries avoid moral costs when they might benefit from ill-gotten money.

Table 2.3.: Determinants of verification

	Verification		
	Verification	Reaction	Reporting
Medium	-0.269	-0.452	-0.924***
	(0.416)	(0.389)	(0.333)
High	-0.452	-1.102**	-0.302
	(0.210)	(0.443)	(0.361)
Intercept	1.368***	1.421***	1.049***
	(0.299)	(0.298)	(0.220)
Observations	95	95	114

Notes: This table shows the Logistic estimates of the relationship between the decision to verify the behavior of actors and the observed reported state. The dependent variable is a binary indicator which takes a value of 1 if a beneficiary chooses verification and 0 otherwise. Medium (High) is a binary variable which takes a value of 1 if the reported state is medium (high) and 0 otherwise. Standard errors are in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Finding: A high share of beneficiaries verifies the reported state in all treatments. There is a tendency to verify less for higher reported states.

2.4.3. Reaction phase – Round 1

Table 2.4.: Mean points of reward and punishment

	Reaction			Reporting			
	No reaction	Reward	Punishment	No reaction	Reward	Punishment	Report
Share	34%	37%	29%	44%	27%	27%	2%
Mean	–	5.08	5.21	–	4.48	4.61	–
		(4.05)	(3.34)		(4.07)	(4.82)	

Notes: Standard deviations are in parentheses.

Table 2.4 shows the average levels of reward or punishment in the *Reaction* treatment and in the *Reporting* treatment in round 1. In both treatments, the differences between

Table 2.5.: Multi-nominal regressions on beneficiary reaction

	Reaction			Reporting
No reaction	–	–	–	–
Reward				
Reported die	-0.192	-0.171	-0.089	-0.214
	(0.156)	(0.158)	(0.135)	(0.158)
Verification	1.678***	1.775***	1.650***	1.407**
	(0.607)	(0.616)	(0.608)	(0.627)
Verified dishonesty		-1.243		1.429
		(1.280)		(0.878)
Intercept	-0.367	-0.451	-1.372*	-0.924
	(0.817)	(0.827)	(0.736)	(0.775)
Punish				
Reported die	-0.015	-0.008	0.029	-0.022
	(0.165)	(0.167)	(0.131)	(0.144)
Verification	1.517**	1.563**	0.224	0.0819
	(0.615)	(0.628)	(0.467)	(0.493)
Verified dishonesty		-0.398		0.852
		(1.069)		(0.902)
Intercept	-1.096	-1.126	-0.720	-0.518
	(0.887)	(0.894)	(0.628)	(0.670)
Report				
Reported die			0.275	0.442
			(0.442)	(0.486)
Verification			13.62	14.25
			(710.5)	(828.9)
Verified dishonesty				-14.21
				(1639.8)
Intercept			-17.39	-18.52
			(710.5)	(828.9)
Observations	95	95	114	114
Log-Likelihood	-96.89	-96.36	-123.77	-121.56
LR χ^2	14.17	15.23	12.53	16.94

Notes: Standard errors are in parentheses. *p<0.10, **p<0.05, ***p<0.01.

average points for reward and punishment are small in magnitude and not statistically significant (MW, p>0.10).

Next, we compare the types of reactions chosen by beneficiaries. A first observation is that in the *Reporting* treatment, we find that only 2% of beneficiaries reports actors. This share is far lower than the 27% who choose to reward and the 27% who choose to punish. In the *Reaction* treatment, 37% of beneficiaries choose to reward, whereas 29% punish actors. Pairwise comparisons on reaction types between treatments are not statistically significant (proportion test (PT), p>0.10 for all tests).

Table 2.5 shows multinominal regressions of beneficiaries' reactions. We aim to see how reactions of beneficiaries depend on the earlier stages of the game. Thus, we regress the chosen reaction on the reported die, which is observed for sure, and on whether beneficiaries decide to verify. In a second regression we include the interaction between verification and whether actors are dishonest, i.e. we include whether beneficiaries observe a dishonest actor. We find that beneficiaries who verify are more likely to react. In the *Reaction* treatment this applies to reward and punishment, in the *Reporting* treatment only to reward. Most importantly, the reported die or discovered dishonesty has no effect on the reaction pattern.

Finding: Beneficiaries react more strongly after they verify the reported states. Around 30% of beneficiaries choose reward and punishment, while only a small share reports actors.

2.4.4. Dishonesty phase – Round 2

We now turn our analysis to behavior of actors and beneficiaries in round 2. Table B.2 in the Appendix B summarizes behavior in the dishonesty phase. It can be observed that the shares of cheaters in round 2 are higher than those in round 1, varying from 15% in the *Verification* treatment to 18% in the *Reporting* treatment. However, the distribution of dishonesty does not differ significantly across treatment (CT, p=0.880) and pairwise comparisons between treatments are not statistically significant (FS, p>0.10). However, there are significant differences between reported outcomes and true outcomes in all treatments (MW, p<0.05).

In the following, we analyze behavioral change of actors from round 1 to round 2. Behavioral change is a binary variable which takes a value of 1 if an actor has been honest in round 1 but becomes dishonest in round 2 or vice versus and 0 otherwise.

The share of actors who remain to be honest is around 80% for the *Baseline*, the *Verification* treatment and the *Reaction* treatment, whereas this share is 73% for the *Reporting* treatment. Among those who change their behavior, the share of actors who become dishonest in round 2 is 7% in the *Baseline* and the *Verification* treatment, whereas this figure is 11% in the *Reaction* treatment and the *Reporting* treatment. Only a small share of actors becomes honest in round 2 after cheating in round 1.

Table 2.6.: Determinants of behavioral changes of actors

	Behavioral change			
	Baseline	Verification	Reaction	Reporting
Honesty	-1.472**	-1.806**	0.311	-2.400***
	(0.720)	(0.799)	(1.255)	(0.615)
Verification		-0.362	-1.528**	0.033
		(0.843)	(0.780)	(0.606)
Reward			-0.070	-1.599**
			(1.002)	(0.819)
Punish			1.086	-0.591
			(0.855)	(0.680)
Positive emotion	0.036	-0.695**	-0.056	-0.256
	(0.220)	(0.270)	(0.255)	(0.167)
Negative emotion	-0.265	-0.207	-0.283	-0.265
	(0.220)	(0.240)	(0.217)	(0.174)
Intercept	-0.474	3.313**	-0.721	2.525**
	(1.192)	(1.504)	(1.787)	(1.146)
Observations	108	95	95	114
Pseudo R^2	0.086	0.272	0.134	0.212

Notes: This table shows the Logistic estimates of factors that determine behavioral changes of the actor. The dependent variable is a binary indicator which takes a value of 1 if the actor changes from being honest to dishonest or vice versa and 0 otherwise. Independent variables are all behaviors in earlier stage of the game, including honesty, verification, reactions of the beneficiary and the actor's emotions. Verification is a binary variable which takes a value of 1 if the beneficiary verifies the reported state and 0 otherwise. Reward (Punish) is a binary indicator which takes a value of 1 if the beneficiary gives points (takes points from) to the actor. Report reaction is omitted. Standard errors are in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Table 2.6 shows Logistic estimates of behavioral changes of actors in round 2 as compared to round 1. As explanatory variables we include all earlier stages of the game: whether the actor makes an honest report in round 1, whether the beneficiary verifies the reported state in round 1 and whether the beneficiary chooses to reward or punish, and emotion measures.[13] In all models except for the *Reaction* treatment, we observe that honest individuals are less likely to change their behavior as compared to dishonest one. Moreover, actors are less likely to change their behavior after being verified by beneficiaries in the *Reaction* treatment and after being rewarded in the *Reporting* treatment. This finding is in favor of Hypothesis 3a and is consistent with the existing literature on reward which shows that reward is used to signal approval or support a certain type of behavior (Almenberg et al. (2010), Nikiforakis and Mitchell (2014)). However, there is no significant effects of punishment on behavioral changes in actors, hence, we do not find evidence to support Hypothesis 3b.

To investigate in which direction actors change their behavior, we look at cheating in round 2. Table 2.7 shows Logistic estimates of determinants of honest behavior in round 2. Similar to the findings in Table 2.6, honest actors are likely to remain honest across treatments. In the *Reaction* treatment, actors are less likely to cheat after being verified by beneficiaries. This provides evidence to support Hypothesis 2. Actors in the *Reporting* treatment are more likely to be honest after being rewarded. Regarding emotions, actors in all treatments are more likely to be honest after experiencing negative emotions.

Finding: Actors in the *Reaction* treatment are less likely to change their behavior after being verified, whereas those in the *Reporting* treatment are more likely to remain honest after being rewarded.

[13]We measure positive emotions as average points reported for two items including *"accomplished"* and *"self-worthy"*. Negative emotions are measured as average points of four items including *"guilty"*, *"blameworthy"*, *"I felt like I am a bad person"* and *"I felt humiliated"*.

Table 2.7.: Determinants of honesty in Round 2

	Honesty in Round 2			
	Baseline	Verification	Reaction	Reporting
Honesty in Round 1	3.722***	2.812***	4.677***	2.373***
	(0.838)	(0.810)	(1.306)	(0.657)
Verification		-0.464	1.970**	-0.554
		(0.843)	(0.840)	(0.614)
Reward			-0.194	1.769**
			(0.974)	(0.837)
Punish			-0.8033	0.516
			(0.932)	(0.657)
Positive emotion	-0.383	0.162	0.183	0.015
	(0.238)	(0.230)	(0.255)	(0.163)
Negative emotion	0.642**	0.513**	0.529**	0.300*
	(0.270)	(0.235)	(0.263)	(0.166)
Intercept	-0.908	-2.158	-5.575***	-1.278
	(1.322)	(1.471)	(1.897)	(1.091)
Observations	108	95	95	114
Pseudo R^2	0.388	0.293	0.405	0.192

Notes: This table displays the Logistic estimates of determinants of actors' behavior in Round 2. Standard errors are in parentheses. *p<0.10, **p<0.05, ***p<0.01.

2.4.5. Perceived social norms

We report the analysis of elicited norms regarding the case that a low state was observed. This case gives most room for cheating and provides the best chance to observe differences in norms between different decisions.

Descriptive norms

Recall that we ask participants in the survey *"in your opinion, if the true state is low, what percentage of participants (on a scale from 0 to 100) reports a low (medium, high) state?"*. Table 2.8 reports descriptive statistics of descriptive norms. A non-parametric Kruskal-Wallis test shows no significant differences in reported shares between treatments ($\chi^2(4)$=2.96, p=0.398 for *low/low*, $\chi^2(4)$=2.97, p=0.397 for *low/medium* and $\chi^2(4)$=2.49, p=0.477 for *low/high*). This indicates that verification/reaction options in the *Verification*, the *Reaction* and the *Reporting* treatment do not change perceptions of how actors actually behave. As compared to the actual behavior, descriptive norms suggest much higher levels of cheating.[14] At the aggregate level, participants state that actors would be equally likely to report a medium and high state when observing a low state, whereas actual behavior shows that a significantly higher share of actors lie to the full extent (report a high state rather than a medium state). At the individual level, we observe that 40% of participants believe that at least 50% of actors would be honest, whereas 20% believe that actors would cheat to the full extent. This indicates heterogeneity in perceptions whether actors would help their own group or would not harm the society.

Table 2.8.: Descriptive norms by treatments

	Baseline	Verification	Reaction	Reporting
low/low	34.59	36.27	31.92	30.03
	(19.22)	(20.27)	(20.05)	(18.37)
low/medium	33.00	33.86	31.89	30.54
	(13.83)	(15.95)	(18.55)	(14.06)
low/high	32.41	29.88	36.18	33.43
	(24.44)	(25.40)	(29.64)	(23.31)
Observations	95	90	93	93

Notes: The table reports descriptive norms across treatments. low/low (low/medium, low/high) indicates that the true state is low and the reported state is low (medium, high). Note that three numbers in each column of the table add up to 100. Standard deviations are in parentheses.

Injunctive norms

Table 2.9 shows the distribution of appropriateness ratings for observing a low state and reporting a low, medium and high state, respectively. The main insight from this table is that honest reporting as well as lying were rated rather appropriate. The modal

[14]The actual shares of cheating are less than 20% in all treatments, while the suggested level of cheating in norm elicitation is more than 60%.

Table 2.9.: Distribution of injunctive norms for observing a low state

		1	2	3	4
low/low					
	Baseline	0.02	0.18	0.42	0.38
	Verification	0.04	0.19	0.44	0.33
	Reaction	0.04	0.25	0.44	0.27
	Reporting	0.01	0.18	0.48	0.33
low/medium					
	Baseline	0.04	0.20	0.52	0.24
	Verification	0.08	0.25	0.39	0.28
	Reaction	0.09	0.26	0.37	0.28
	Reporting	0.05	0.27	0.34	0.34
low/high					
	Baseline	0.06	0.13	0.45	0.36
	Verification	0.14	0.29	0.32	0.25
	Reaction	0.11	0.28	0.33	0.28
	Reporting	0.15	0.18	0.38	0.29

Notes: This table reports the shares of injunctive norms for observing a low state in each treatment. 1 means "very inappropriate", 2 indicates "somewhat inappropriate", 3 indicates "somewhat appropriate" and 4 means "very appropriate".

answer is "somewhat appropriate" for all cases and all treatments. We find this to be a first indication that the two conflicting norms in this situation – helping the own group and helping the society – prevent one morally preferable act to emerge. Instead, different actions are equally appropriate but because of different moral motivations.

Finally, we ask participants in the norm elicitation what the most appropriate reaction is in different situations. Since the reaction stage takes place after the verification stage, we consider two sets of answers here. First, we analyze most appropriate reactions after observing a low, medium and high state without verifying it. Second, we again analyze the case that a low state is observed and a low, medium or high state is reported and verified. Thus, we consider most appropriate reactions after not verifying anything and after having verified honesty or dishonesty in case of a true low state.

Figure B.5 and Figure B.6 in the Appendix B show most appropriate reaction choices of participants in case of no verification in the *Reaction* treatment and the *Reporting* treatment, respectively. Considering the *Reaction* treatment, we observe that reward is the most frequently chosen option when observing a low state. Thus, honesty should be met with a positive reaction. Only a very small share of participants considers punishment to be appropriate in this case. The distribution of reward and punishment choices varies significantly (PT, p=0.001). This is different for medium and high states which are more likely the result of cheating. In the *Reaction* treatment, both of these reactions are chosen to a similar degree. In the *Reporting* treatment, punishment is chosen more frequently than reward for medium reports while the share of punishment is significantly higher than that of reward for high reports (PT, p=0.014). This shows some preference for lying to the full extent over partial lying. Overall, the reaction further highlights the ambivalence of the situation. There is no clear morally appropriate reaction if the actor is a likely liar.

Finally, we turn our analysis to reaction choices when the beneficiary verifies the actor's behavior. Figure 2.3 and Figure 2.4 display the distribution of appropriate reactions in case the true state is low and verified in the *Reaction* treatment and the *Reporting* treatment, respectively. In the *Reaction* treatment, reward is commonly chosen as the most appropriate reaction. Additionally, we observe a higher share of punishment choice in case of a high reported state than a medium reported state. It would indicate that participants are more likely to tolerate partial lying than full lying.

Figure 2.3.: Reaction in case of verification and low true state in the Reaction treatment

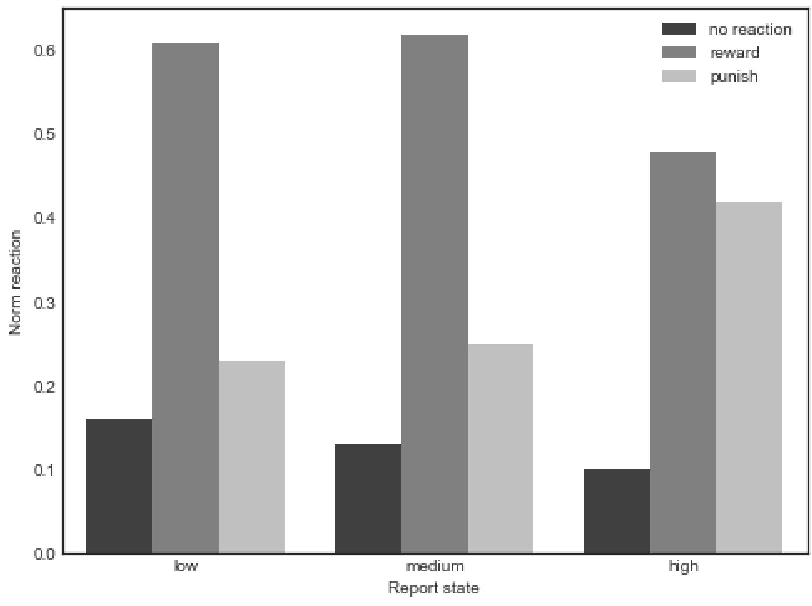
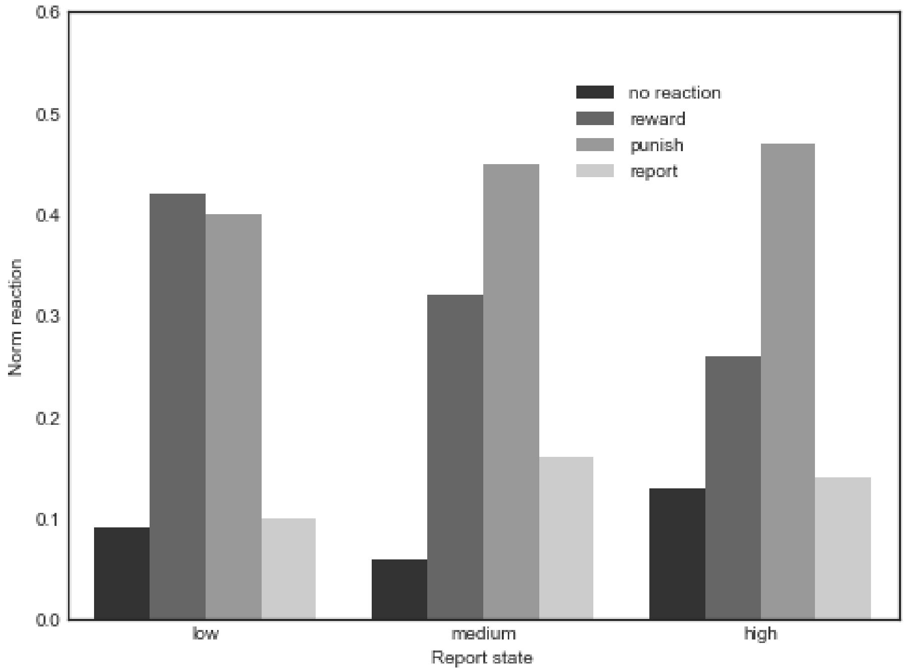


Figure 2.4.: Reaction in case of verification and low true state in the Reporting treatment



Interestingly, adding an option to report actors shifts reactions towards punishment. As compared to the *Reaction* treatment, more participants believe that punishment is the most appropriate reaction to lying. Consistent with the actual behavior, reporting is rarely stated to be an appropriate reaction to lying in norm elicitation. The distribution of reaction types in the *Reporting* treatment differ significantly (KW, $p<0.001$).

Overall, the norm elicitation reveals two conflicting norms in this situation. On the one hand, lying benefits both actor and beneficiary and is therefore reported to be appropriate behavior. On the other hand, lying harms the society, specifically UNICEF, and is thus reported to be not appropriate. It does not seem to be the case that one norm is considerably stronger than the other which could explain the results we observe above.

2.5. Conclusion

This paper investigates the effects of beneficiaries' reactions on actors' unethical pro-group behavior. We design four treatments which differ in verification/reaction possibilities. The result shows that less than 20% of actors cheat and there are no significant differences in cheating behavior across treatments. This indicates that the threat of being observed and being rewarded, punished or reported by beneficiaries does not affect actors' behavior. We further observe a significant share of beneficiaries choosing to verify the reported states but they tend to verify less after observing the medium or high states and they react more strongly after verification. It is possible that beneficiaries remain unclear about the origin of the benefit to avoid moral costs or the obligation for rewarding, punishing or reporting actors which are costly for them. Interestingly, adding an option to report actors does not change beneficiaries' preferences for reactions. Beneficiaries rarely report cheating behavior, instead they prefer to reward or punish actors. We find evidence that actors are more likely to be honest after their behavior is being verified and rewarded by beneficiaries, whereas punishment does not have any effects on actors.

We conduct an additional survey to elicit norms about unethical pro-group behavior. The result shows that because of conflicting norms, beneficiaries are unlikely to play an important role in mitigating unethical behavior. A limitation is that in our setting, the externality to UNICEF is comparable to the benefit to actor and beneficiary. If the consequences for the society are considerably larger, the norm of not harming the society might be stronger. Our results also carry an optimistic message. Earlier research on cheating usually does not include an externality but only costs to the experimenter. We capture a situation where cheating carries a negative externality to the society and we find much lower levels of cheating.

The current study is also subject to other limitations. We conduct online experiments which indicate that some aspects of unethical pro-group behavior are not represented. First, participants do not know each other and do not have long-term relationships like people working in the same group. Additionally, they interact with each other only a few times during the experiment, therefore, they might not be strongly influenced by others' reactions. In real life, however, employees interact with each other on a daily basis, thus, reactions of coworkers might be more important to them. Next, we observe that beneficiaries rarely use the reporting option. It might be possible that reporting does not guarantee a cheating detection, thus they are unlikely to perceive it as an effective tool to prevent cheating. Future study can investigate whether a higher probability of detection as a consequence of reporting will encourage more beneficiaries to report unethical behavior of actors.

The findings of our study open some avenues for future research. One feasible direction is to investigate the role of group or organizational cultures. Different organizations have different ways to handle unethical behavior of their employees. For example, if an organization has transparent guidance of how to deal with unethical behavior, e.g. a platform to report wrong-doings, while protecting whistle-blowers. Then people might be more willing to utilize this option. Another interesting possibility could be to implement a similar setting with different subject pools. For example, subjects can be friends, colleagues or couples who have more established relationships. It is possible that when people bond with each other, they might react differently to others' unethical behavior and their reactions might play a more significant role in other's behavior. Thus, we call for more investigations along these directions.

Chapter 3.

Corruption in symmetric and asymmetric contests: an experimental study *

3.1. Introduction

Contests are considered as a popular mechanism to allocate resources. They are often designed to motivate efforts of agents and reward those who have the best performance. In a standard Tullock contest (Tullock (1980)), contest outcomes depend on decisions made by agents and luck. In many other contests, however, outcomes do not only depend on performance of agents but also on decisions of referees who might be biased. In such scenarios, corruption might occur, i.e. agents bribe referees in exchange for illegal services. For example, in sport teams may compete for a championship not only by exerting efforts in the game but also by bribing referees to increase their chances of winning. In business firms compete for a government contract by bidding in procurement and may bribe public officials in exchange for being favored to obtain the contract (The Odebrecht case (2018)). In education students competing for an admission to elite universities may bribe admission testing officials (Garrison and Puente (2019)).

One of the interesting features of many contests is that agents are not necessarily ho-

*I would like to thank Henrik Orzen, Wladislaw Mill, Franziska Heinicke and participants at Center for Doctoral Studies in Economics seminar as well as seminar participants at Leibniz Centre for European Economic Research in Mannheim for useful comments and remarks.

mogeneous. Heterogeneity in contestants comes from various sources such as abilities, valuations of prizes and financial capacity. In this study, I focus on heterogeneity in abilities for several reasons. First, asymmetric abilities in contestants have been widely observed in many contests (e.g. football matches, national state exams). Second, differences in abilities cause undesirable outcomes such as wealth inequality or insufficient effort provision, as shown in previous studies (see Ryvkin (2007), March and Sahm (2017), Chowdhury, Esteve-González, and Mukherjee (2023)). To be specific, I investigate whether asymmetry in abilities between agents affects corrupt behavior in contests.

The reasons for engaging in corruption might vary among agents. In a rank-order tournament with homogeneous agents, if agents exert an equal level of effort, they have an equal probability of winning the contest. However, by gaining unfair advantages, they can substantially improve their payoffs if it helps them to win the contest. Corruption might be especially tempting in a contest where one agent is weaker than the other. The weak agent might not be able to win the contest by competing fairly, hence, corruption allows him/her to reduce the gap between him/her and the strong agent. The strong agent might, however, also have incentives for corruption in order to reinforce his/her advantageous position. Another possible incentive for engaging in corruption is strong desire to win the contest at any costs. The existing literature has shown that desire to win in a contest induces substantial unethical behavior (Kräkel (2007), Berentsen, Bruegger, and Loertscher (2008), Stowe and Gilpatric (2010)).

This paper aims to answer the following questions. First, how is corrupt behavior affected by asymmetry in contests? In particular, I investigate whether corruption is more common in a contest where players have the same or different abilities, and whether the weak players or the strong players are more likely to engage in corruption. Second, I ask how corruption in turn affects effort provision and contest outcomes. To be specific, I examine whether there are any differences in efforts between a contest with corruption and a contest without possibility for corruption.

I develop a theoretical model which employs the standard Tullock contest. In my baseline model, two players exert efforts to compete for a prize and contest outcomes are determined by efforts provided by these players as well as luck. In the extended model, there is an additional stage before players compete in the main contest. In this stage, players decide whether to pay a bribe in exchange for a favor that can increase their probability of winning the contest. The model predicts that players in a symmetric contest offer more bribes than those in an asymmetric contest and corruption induces lower efforts in the main contest.

To test the model's predictions, I conduct an experiment for several reasons. First, corruption in contests are difficult to observe in the field and empirical data on corruption is scarce. An experiment enables me to capture fundamental aspects of actual contests and simulate a setting where I can measure corrupt behavior of contestants. Furthermore, an experiment allows me to vary dimensions of interests while controlling for other factors, thus I can build causal relationships between changes and their effect on contestant-observable behavior.

I employ a between- and within-subject design with four treatments which differ in two dimensions. The symmetry/asymmetry change is implemented as a between-subject variation, whereas the corruption possibility is implemented as a within-subject variation. In the baseline treatment (SS-NC), players have the same marginal cost of efforts and they only make a decision on efforts which determine their probability of winning the contest. In the AS-NC treatment, one player has a higher marginal cost of effort than the other and they make the same decision as in the SS-NC treatment. In the symmetric treatment and the asymmetric treatment with corruption (SS-C and AS-C, respectively), players go through an additional stage before the main contest. In this first stage, players choose whether or not to offer a bribe in exchange for a favorable treatment in the subsequent contest stage. After learning whether their offer has been accepted, each player chooses efforts in the second stage. I assume that only one bribe offer is accepted[1] and bribers run the risk that their corrupt behavior can be detected. If corruption is detected, the non-briber wins the contest by default.[2]

My results are as follows. First, I find that a considerable share of players engage in corruption in both the SS-C treatment and the AS-C treatment. The share of groups in which at least one player offers a bribe in the symmetric contest is 10 percentage points higher than that in the asymmetric contest. Consistent with the model's predictions, bribe offers in the former are systematically higher than those in the latter. In the AS-C treatment, I find that 34% of strong players engage in corruption, whereas this share is 26% for weak players. Considering groups where both players offer bribes, I find no significant differences in bribe levels between weak players and strong players.

[1]It is possible that a greedy referee accepts offers of both players or an honest referee does not accept any offers. These scenarios, however, are outside of the scope of this study.

[2]This way of allocating prizes in contests has been employed in previous studies (see Kräkel (2007), Curry and Mongrain (2009) and Gilpatric (2011)).

Second, I observe that efforts in the symmetric contest are considerably higher than those in the asymmetric contest. This is consistent with the existing literature on effort provision in asymmetric contests (e.g. Ryvkin (2007), March and Sahm (2017), Chowdhury, Esteve-González, and Mukherjee (2023). This result holds for both contests with corruption and without corruption. In the asymmetric contests, strong players provide almost twice as much effort as weak players.

Third, corruption induces a significant reduction in efforts in both symmetric and asymmetric contests. To be specific, players in the SS-C treatment provide 32% less effort than those in the SS-NC treatment, while players in the AS-C treatment exert 35% less effort than those in the AS-NC treatment. To further isolate the effect of corruption possibility on effort choices, I compare efforts of groups in the SS-C treatment and the AS-C treatment where corruption does not occur with groups in the contests without corruption (SS-NC treatment and AS-NC treatment). Interestingly, efforts of the former are significantly lower than those of the latter. This indicates that the presence of corruption possibility induces lower efforts even when players do not utilize this possibility.

These findings have implications for contest organizers where corruption may occur. First, asymmetry in players' ability plays an important role in corrupt behavior, so contest organizers should pay particular attention not only to weak players but also to strong players when designing a contest in order to mitigate corruption. Second, corruption can severely distort competitive positions between players and affect their behavior in the contest. Thus, if efforts are desirable for the contest, corruption is problematic since it may reduce effort provision and impose adverse consequences on contest outcomes.

The remainder of the chapter is organized as follows. Section 2 summarizes related literature. Section 3 describes a theoretical model and section 4 presents experimental design. Section 5 analyses experimental results and the last section gives conclusion.

3.2. Literature review

The present study is closely related to the literature on contests with asymmetric players (Ryvkin (2007), Avrahami et al. (2014), Dari-Mattiacci et al. (2015), March and Sahm (2017), Chowdhury, Esteve-González, and Mukherjee (2023)). These studies show that as compared to symmetric contests where players have identical ability, heterogeneity in contests results in undesirable outcomes such as low effort provision, low competitiveness and wealth inequality. My contribution to this line of the literature is to examine whether asymmetry plays a role in corrupt behavior of contestants.

The second line of the literature focuses on rent-seeking contests in which asymmetric contestants have chances to commit into illegal activities. Berentsen (2002), Berentsen, Bruegger, and Loertscher (2008), Kräkel (2007) and Stowe and Gilpatric (2010) consider contest-like settings in which the probabilities of winning are determined by both training effort and doping. Berentsen (2002) and Berentsen, Bruegger, and Loertscher (2008) construct a model in which two asymmetric contestants simultaneously and independently make a discrete decision on whether or not to use performance-enhancing drugs. The authors show that the favorite contestants are more likely to engage in doping than the underdogs. While doping and corruption are both illegal activities in contests, there is a fundamental difference between them. Doping mainly involves players themselves in the illegal activity and may be hidden from referees in contests, whereas corruption in my setting involves collaboration between players and referees.[3]

Kräkel (2007) studies doping behavior in a contest setting. Players in his study decide between behaving honestly and doping. Kräkel assumes that once players dope, they always choose a fixed optimal level of doping. Therefore, the model does not consider how the optimal doping level responds to other parameters such as the probability of detection and a difference in abilities between the dopers and their opponents. There are three different effects of doping in Kräkel's model: a cost effect (taking drugs influences effort provision and thus, the cost), a likelihood effect (using drugs enhances players' winning probabilities if they are not being detected) and a windfall profit effect (if one player is disqualified for the contest, the other player wins a prize by default). While similar considerations of these three effects play a role in my setting, this paper differs from my approach in which I investigate how bribe levels respond to heterogeneity in abilities of players and how corruption in turn affects effort choices.

This paper is also related to a study by Stowe and Gilpatric (2010) which focuses on how cheating responds to probabilities of auditing. They consider asymmetric contests in which contestants decide whether to cheat or to behave honestly. They show that when the probabilities of detection are low (high), the favorite (underdogs)

[3]A similar argument can be also applied for sabotage. While corruption improves a player's own performance or probability of winning, sabotage reduces a rival's performance. Furthermore, corruption requires collaboration between bribers and referees, whereas sabotage mainly involves players.

are more likely to cheat. However, if the audit probability is sufficiently large, cheating is not a dominant strategy. Additionally, they argue that testing both players with an equal probability is more effective in reducing cheating than auditing them with different probabilities. Gilpatric (2011) investigates cheating in symmetric contests by constructing a theoretical model in which doping is a continuous variable added to players' effort choices. He finds that the extent of doping is reduced if a prize is allocated to non-doping players by default in case dopers are detected, which is consistent with the finding by Curry and Mongrain (2009) who emphasize the significant role of prize structures in deterring illegal activities. Following these studies, in my design I employ the winning-by-default mechanism when corruption is detected. I contribute to this line of the literature by examining whether there are any differences in corrupt behavior between symmetric contests and asymmetric contests under this punishment scheme.

3.3. Theoretical model

3.3.1. Contest without corruption

I first construct a contest model without corruption possibility to find the equilibrium effort of players. The result of this model serves as a benchmark to measure the effect of corruption on effort provision and contest outcomes.

Following the approach by Tullock (1980), I consider a contest between two risk-neutral players ($i = \{1, 2\}$) who compete for a prize V. Players are provided with an endowment E and choose an effort $e_i \in [0, E]$ with a linear cost function $c_i(e_i) = c_i e_i$. The marginal cost of effort c_i can be viewed as a measure of a player's ability, i.e. the higher the marginal cost of effort is, the lower is the player's ability. The contest success function can be written as

$$p_i = \frac{e_i}{e_i + e_j}$$

Each player chooses an effort level to maximize his/her expected payoff.

$$\max_{e_i} \pi_i(e_i, e_j) = \max_{e_i} \left(E - c_i e_i + V \frac{e_i}{e_i + e_j} \right)$$

Solving the maximization problem yields an equilibrium effort of $e_i^* = \frac{V c_j}{(c_i + c_j)^2}$. Player i's probability of winning is $p_i^* = \frac{c_j}{c_i + c_j}$ and his/her equilibrium payoff is $\pi_i^* = E + \frac{V c_j^2}{(c_i + c_j)^2}$.

Lemma 1: Effort provision decreases in asymmetry in abilities of players.[4]

3.3.2. Contest with corruption

Next, I modify the Tullock contest by introducing a corruption stage before the contest takes place. Consider a winner-take-all contest between two risk-neutral agents ($i = \{1, 2\}$) and a risk-neutral referee who has some influence on contest outcomes.[5] In the initial corruption stage players decide whether to offer a bribe to the referee and how much to offer ($b_i \geq 0$). I assume that the referee is ex-ante unbiased and accepts only one offer. It is possible that a greedy referee accepts offers from both players or an honest referee does not accept any offers. These scenarios, however, are outside of the scope of this study. Additionally, the idea that only one bribe offer being accepted ensures that bribing gives the briber advantages over the non-briber. If the offer is rejected, the briber does not pay the bribe. Otherwise, the briber receives a favor from the referee which gives him/her an advantage in the contest and pays the bribe in return. In the subsequent effort stage players choose an effort level (e_i). Then, corruption is investigated. There is a probability of detection ($p \in (0, 1)$) at which the briber loses the contest and the non-briber wins by default.[6] It is assumed that the investigation of corruption is conducted after the effort stage as this captures many real life scenarios when corruption is often detected after the contest.

First, I consider the referee's decision. Assume that the referee gets a flat wage W. If the referee accepts the bribe, he/she obtains the bribe b in case of no detection. If corruption is detected, the referee has to return the bribe.[7] The expected payoff of the referee can be written as

$$\pi^{\text{referee}}(\text{accept}) = W + (1 - p)b$$

In the absence of any punishment, the referee accepts any bribes. The main focus of

[4] A proof of Lemma 1 is shown in the Appendix C.

[5] I define a person who can influence contest outcomes as a referee. However, the setting can be generalized outside of the context of sport. For example, such a person could be a manager who can influence a decision to promote an employee or a judge who can affect a legal dispute.

[6] Apart from losing the contest, no further punishment is imposed on the briber as it does not qualitatively change the consequence of detection.

[7] I abstract any further punishment on the referee since it does not qualitatively change the structure of his/her payoff function.

this study is on corrupt behavior of players rather than that of the referee, therefore, in the following analysis of the model and later in the experiment I only focus on players' behavior.

Without loss of generality, assume that player i is the briber and player j is the non-briber. The contest success functions become

$$p_i = (1-p)\frac{(1+\lambda b_i)e_i}{(1+\lambda b_i)e_i + e_j} \text{ and } p_j = (1-p)\frac{e_j}{(1+\lambda b_i)e_i + e_j} + p$$

in which $\lambda > 0$ is an effectiveness factor of the bribe. There are several fundamental aspects of these contest success functions. First, if players do not bribe (b=0), the contest success functions are the same as in contests without corruption. Second, the effectiveness factor (λ) captures how effective a bribe is in increasing the chance of winning for the briber. Third, if a player's bribe is accepted (b>0) but he/she does not exert any effort (e=0), his/her chance of winning is zero. This indicates that a bribe cannot be effective without positive efforts. For the same effort level, the briber has a higher chance of winning the contest if he/she is not detected as compared to when he/she does not bribe.

Next, I turn the analysis to the effort stage. Each player chooses an effort level to maximize his/her expected payoff.

$$\max_{e_i}\left((1-p)\underbrace{\left(E - b_i - c_ie_i + V\frac{(1+\lambda b_i)e_i}{(1+\lambda b_i)e_i + e_j}\right)}_{\text{payoff if no detection}} + p\underbrace{(E - b_i - c_ie_i)}_{\text{payoff if detection}}\right)$$

$$\max_{e_j}\left((1-p)\underbrace{\left(E - c_je_j + V\frac{e_j}{(1+\lambda b_i)e_i + e_j}\right)}_{\text{payoff if no detection}} + p\underbrace{(E - c_je_j + V)}_{\text{payoff if detection}}\right)$$

The first order conditions are

$$(1-p)V\frac{(1+\lambda b_i)e_j}{((1+\lambda b_i)e_i + e_j)^2} = c_i \text{ and } (1-p)V\frac{(1+\lambda b_i)e_i}{((1+\lambda b_i)e_i + e_j)^2} = c_j$$

Solving the first order conditions yields the equilibrium effort levels of $e_i = (1-p)V\frac{(1+\lambda b_i)c_j}{((1+\lambda b_i)c_j+c_i)^2}$ and $e_j = (1-p)V\frac{(1+\lambda b_i)c_i}{((1+\lambda b_i)c_j+c_i)^2}$. In the symmetric contests the model predicts that effort provision of both players decreases in bribes. However, in the asymmetric contests effort provision depends on who obtains a favor through corruption. On the one hand, if strong players receive the favor, this increases the gap between strong players and their weak opponents. Therefore, effort provision is predicted to be lower as compared to contests without corruption. On the other hand, if weak players receive the favor, this may reduce the gap in abilities between weak players and their strong opponents. Thus, they may provide more efforts.

The general expected payoff function of each player can be written as

$$\pi_i = \begin{cases} E - b_i + (1-p)V\frac{(1+\lambda b_i)^2 c_j^2}{((1+\lambda b_i)c_j + c_i)^2} & \text{if } b_i > b_j \text{ and } b_i \geq b^{\min} \\ E + \frac{1}{2}(-b_i + (1-p)V(\frac{(1+\lambda b_i)^2 c_j^2}{((1+\lambda b_i)c_j + c_i)^2} & \\ + \frac{c_j^2}{((1+\lambda b_j)c_i + c_j)^2}) + pV) & \text{if } b_i = b_j \text{ and } b_i \geq b^{\min} \\ E + pV + (1-p)V\frac{c_j^2}{(1+\lambda b_j)c_i + c_j)^2} & \text{if } b_i < b_j \text{ and } b_j \geq b^{\min} \\ E + V\frac{c_j^2}{(c_i + c_j)^2} & \text{otherwise} \end{cases}$$

Table 3.1.: Parameters

Contest	Endowment	Marginal cost	Prize	Prob. of detection	Effectiveness factor
Sym.	$E_i = E_j = 100$	$c_i = c_j = 1$	$V_i = V_j = 100$	$p = \frac{1}{5}$	$\lambda = \frac{1}{9}$
Asym.	$E_i = E_j = 100$	$c_i = 1, c_j = 2$	$V_i = V_j = 100$	$p = \frac{1}{5}$	$\lambda = \frac{1}{9}$

To solve the model, I choose the combination of parameters shown in Table 3.1 for several reasons. First, there exists bribes and effort levels such that one player can be better off with bribing if the other player does not bribe. Second, the effectiveness factor is chosen in a way that even if a player obtains a favor by paying a bribe, there is no guarantee that his/her probability of winning the contest is increased unless he/she exerts enough effort.[8] For an intuition, consider a football match where one team is given an unfair penalty. Players of this team still need to show necessary skills or exert efforts to make it a goal. Without enough skills and efforts, they might not be able to utilize such a favor. Third, a detection probability is chosen to capture the risk inherent to corruption which has an impact on the briber's payoff when corruption is detected. However, it is not too extreme to make bribing or non-bribing a dominant strategy. Finally, the parameters are selected such that there is a distinct difference in predicted bribes and efforts between the symmetric and the asymmetric contests.

[8] To make sure that a bribe can increase the chance of winning, the briber needs to exert an effort level such that $(1 + \frac{1}{9}b)e \geq e + b$ which requires a minimum effort of 9.

Given the chosen parameters, the following lemmas describe the equilibrium bribes in the symmetric and asymmetric contests.[9]

Lemma 2: In the symmetric contest, there exists a unique symmetric equilibrium in which both players offer the same bribe level at which they are indifferent between bribing and not bribing ($b_i = b_j = 30$).

Lemma 3: In the asymmetric contest, there exists a unique asymmetric equilibrium in which the strong player offers a higher bribe than the weak player ($b_i = 10.7, b_j = 10.7 - \varepsilon, \varepsilon \in (0, 10.7)$).

Table 3.2 summarizes the equilibria.

Table 3.2.: Theoretical predictions

	Corruption (C)			No corruption (NC)	
	Bribe	Effort	Payoff	Effort	Payoff
Symmetry (SS)	$b_i = 30$	$e_i = 12.19$	$\pi_i = 122.81$	$e_i = 25$	$\pi_i = 125$
	$b_j = 30$	$e_j = 12.19$	$\pi_j = 122.81$	$e_j = 25$	$\pi_j = 125$
Asymmetry (AS)	$b_i = 10.71$	$e_i = 12.12$	$\pi_i = 142.31$	$e_i = 22.22$	$\pi_i = 144.44$
	$b_j = 10.71 - \varepsilon$	$e_j = 6.06$	$\pi_j = 122.74$	$e_j = 11.11$	$\pi_j = 111.11$

3.3.3. Hypotheses

The theoretical model suggests that players in the symmetric contest offer higher bribes than those in the asymmetric contest. If players in the symmetric contest exert the same level of effort, they have an equal probability of winning. Therefore, a favor can substantially improve their payoff if it increases their chance of winning. I hypothesize that as compared to the asymmetric contest, players in the symmetric contest compete more intensively in the corruption stage.

Hypothesis 1: There is a higher average bribe in the symmetric contest than in the asymmetric contest.

In a contest with asymmetric ability, both players have motivations to engage in corruption. On the one hand, weak players have a lower chance to win by competing fairly.[10] Thus, they might have incentives to offer bribes to improve their position in

[9]Proofs of these lemmas are explained in the Appendix C.

[10]Due to a higher marginal cost of effort, weak players have lower resources to exert the same level

the contest. Second, if weak players obtain unfair advantages, they can save efforts in the contest which are highly costly for them. On the other hand, strong players might, despite their initial advantage, bribe to reinforce their privileged position. Following the theoretical model, I form the below hypothesis.

Hypothesis 2: There is no differences in bribe levels between players in the asymmetric contest.

Next, I investigate the role of asymmetry in effort provision. Existing literature has widely established that players exert less effort when they compete with opponents of different ability levels (see Ryvkin (2007), Chowdhury, Esteve-González, and Mukherjee (2023)). In this study, I test whether the same pattern of behavior occurs in contests where players have a possibility to pay a bribe in exchange for a favorable treatment in the contest.

Hypothesis 3a: Efforts in the symmetric contest are higher than those in the asymmetric contest. This holds for both contests with corruption and without corruption.

Finally, I examine consequences of corruption on effort provision. It is predicted that efforts are lower in the contest with corruption as compared to the contest without corruption possibility. This comes from two sources. First, players choose how to allocate endowment between bribes and efforts, thus bribes and efforts can be substitutes. Once players pay for a bribe, they have lower endowment to invest in efforts. Second, once bribers gain a favor in the contest, they might not have much motivation to exert high efforts for winning. At the same time, other players might be discouraged to provide high efforts since they have a low chance of winning the contest. I formulate the following hypothesis.

Hypothesis 3b: Effort provision is lower in the contest with corruption than in the contest without corruption. This holds for both contests where players have similar or different abilities.

3.4. Experiment

3.4.1. Experimental design

To test the predictions of the model, I develop a between-subject and within-subject

of effort as compared to strong players.

design with four treatments which differ in two dimensions. Two treatments vary with respect to a corruption possibility, whereas the other two treatments differ with respect to the asymmetry in abilities which is measured by marginal costs of effort. The baseline treatment (SS-NC) uses the standard Tullock contest between two players with the same ability. In the AS-NC treatment, one player has a higher marginal cost of effort than the other. In the SS-C treatment and the AS-C treatment, there is an additional stage of corruption before the main contest takes place.

Participants form groups of two in which one participant takes the role of Player A and the other participant takes the role of Player B. Roles remain unchanged throughout the experiment. The experiment consists of two parts[11] and each part consists of twenty rounds. Each round has the same structure and proceeds as follows.

Part 1: SS-NC (AS-NC)

At the beginning of each round, players obtain an endowment of 100 points and compete for a prize of 100 points. Players independently and simultaneously decide how many "contest tokens" to buy. They can choose any number between 0 and 100 contest tokens. In the SS-NC treatment, one contest token costs each player one point, whereas in the AS-NC treatment, one contest token costs Player A one point and it costs Player B two points. Any points that have not been spent on the contest tokens are kept in the player's payoff. After players have made their decisions, the total number of contest tokens bought by both players are calculated and one contest token is drawn at random. Each contest token has an equal chance of being selected. The owner of the selected token is the winner of the prize.

Part 2: SS-C (AS-C)

The main difference between Part 1 and Part 2 is that in each round of Part 2, players are asked to make an additional decision (Decision 1) before moving to Decision 2 which is similar to Part 1.

Decision 1

At the beginning of each round, each player obtains an endowment of 100 points. Players are asked to decide whether to buy "lottery tokens" and how many lottery tokens they would like to buy.[12] Each lottery token costs a player one point and they

[11] I randomize the order of part 1 and part 2 between sessions to control for order effects.

[12] In the experimental instructions, I use neutral framing to avoid experimenter demand effects. "Lottery tokens" are used to indicate bribe offers. "A lottery is played at the end of the contest" can

can buy up to 100 lottery tokens. In line with the model, in each round only one player who would like to buy a higher number of lottery tokens is allowed to buy them. The player who is allowed to buy receives the lottery tokens and pays the cost. Any points that are not used to buy the lottery tokens are kept in the player's point balance. The player who is not allowed to buy receives no lottery token and does not have to pay. Lottery tokens bought in Decision 1 are used in Decision 2, as is explained below.

Decision 2

Decision 2 is similar to Part 1 of the experiment except the following differences. First, the endowment to buy contest tokens is the remaining point balance after Decision 1. Second, a player's total tokens are calculated as follows.

$$\text{total tokens} = \left(1 + \frac{1}{9} \cdot \text{lottery tokens}\right) \cdot \text{contest tokens}$$

If a player has acquired lottery tokens in Decision 1, a further lottery is played at the end of the contest. With a 20% chance the player who has owned lottery tokens in Decision 1 loses the prize and the other player wins it. Otherwise, the contest winner is determined as in Part 1.

Post-survey

At the end of the experiment, participants are asked a number of questions regarding their demographic information such as gender, age, education and nationality and prosocial preferences as well as risk preferences.[13]

3.4.2. Participants

The experiment was conducted in January and February 2023 with students from the subject pool of the University of Mannheim Laboratory (mLab). Students were recruited through ORSEE (Greiner (2004)). The experiment was programmed on Otree (D. L. Chen, Schonger, and Wickens (2016)). I conducted an online experiment instead of a laboratory one to increase participation rates and avoid physical contacts during

be viewed as an investigation of corruption after the contest.

[13]To measure risk preferences, participants are asked to self-assess "*how willing or unwilling you are to take risks?*" on an 11-point scale ranging from 0=completely unwilling to 10=completely willing. For prosocial preferences, participants answer a hypothetical question "*Imagine that you won €100 in a lottery. Considering your current situation, how much would you give to others (for example: family, friends, charity, etc.)?*"

the Corona Pandemic. A total of 172 participants took part in this experiment which consisted of 10 sessions and no participant played in more than one session. Of these participants, 86 took part in the symmetric treatments (SS-NC and SS-C) and 86 took part in the asymmetric treatments (AS-NC and AS-C).

The following process was common in all sessions. Each session consisted of an even number of participants. At the beginning of each session, there was a short introduction about the rule of the experiment. After reading the instructions, participants were asked to answer a couple of comprehension questions and to do several trial rounds to check their understanding of the instructions. At the beginning of the experiment, the computer randomly assigned each participant to the role of either Player A or Player B. Roles remained unchanged over the course of the session. At the beginning of each round, participants were randomly matched in pairs. Participants, however, did not know the identity of their opponents. Each session consisted of 2 parts and each part consisted of 20 rounds. At the end of the session, one round in each part was randomly selected and participants were paid based on their total earnings from these two selected rounds. Participants received points as experimental currency units and points were converted to Euros at an exchange rate of €0.06 per point. On average, participants earned €14.89 and each session lasted 80 minutes.

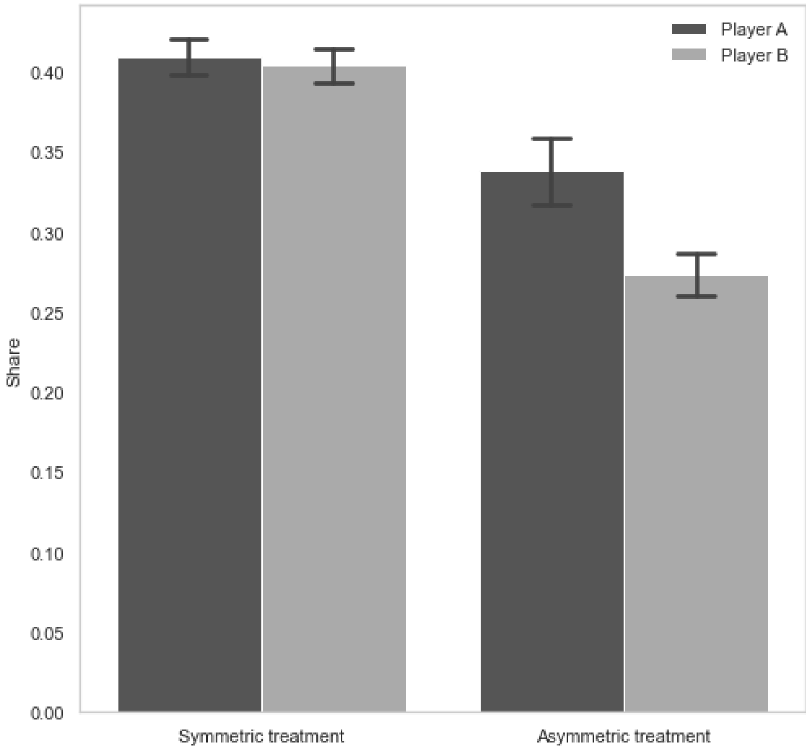
3.5. Results

Before analyzing experimental results, I first highlight a couple of points about the terminology used in this section. Unless stated otherwise, I use Wilcoxon signed-rank test (WSR) when testing differences within treatments and Mann Whitney U test (MW) when making comparisons between treatments. *Bribe decision* is constructed as a binary variable which takes a value of 1 if a player offers a positive bribe and 0 if the player does not bribe. In the asymmetric treatment, strong players (Player A) are referred to those who have the marginal cost of effort of 1 point per contest token, whereas weak players (Player B) are referred to those who have the marginal cost of effort of 2 points per contest token.

3.5.1. Bribe decision

I begin the analysis by investigating to what extent players engage in corruption and comparing differences in corrupt behavior between treatments. Figure 3.1 illustrates the share of bribe decision by player types in each treatment. I observe a significantly higher share of corruption in the SS-C treatment than in the AS-C treatment (Proportion test (PT), $p<0.001$). To be specific, the share of bribe decision in the SS-C treatment is 10 percentage points higher than that in the AS-C treatment. In the AS-C treatment, the share of bribe decision is 34% for the strong players and is 26% for the weak players. The difference is statistically significant (PT, $p<0.001$).

Figure 3.1.: Share of bribe decisions by treatments



Finding: The share of groups which engage in corruption in the symmetric treatment is 10 percentage points higher than that in the asymmetric treatment. Strong players are more likely to engage in corruption than weak players.

Second, I analyse the extent of corruption by examining the magnitudes of bribe offers. What stands out from Table 3.3 is that bribe offers in the SS-C treatment significantly differ from what was predicted in the theoretical model (MW, two-sided, $p<0.001$). Bribe offers in the SS-C treatment are significantly higher than those in the AS-C treatment (MW, $p<0.001$) and thus, this finding supports Hypothesis 1. In contrast, average bribe offers in the AS-C treatment are close to the predicted bribes shown in Table 3.2 (MW, two-sided, p=0.940). There is no significant differences in bribes between strong players and weak players (MW, p>0.10) which is in favor of Hypothesis 2. Combining the share of bribe decisions and bribe levels, it can be concluded that there is higher intensity of corruption in the symmetric contest than in the asymmetric contest, which indicates the role of asymmetry in corrupt behavior.

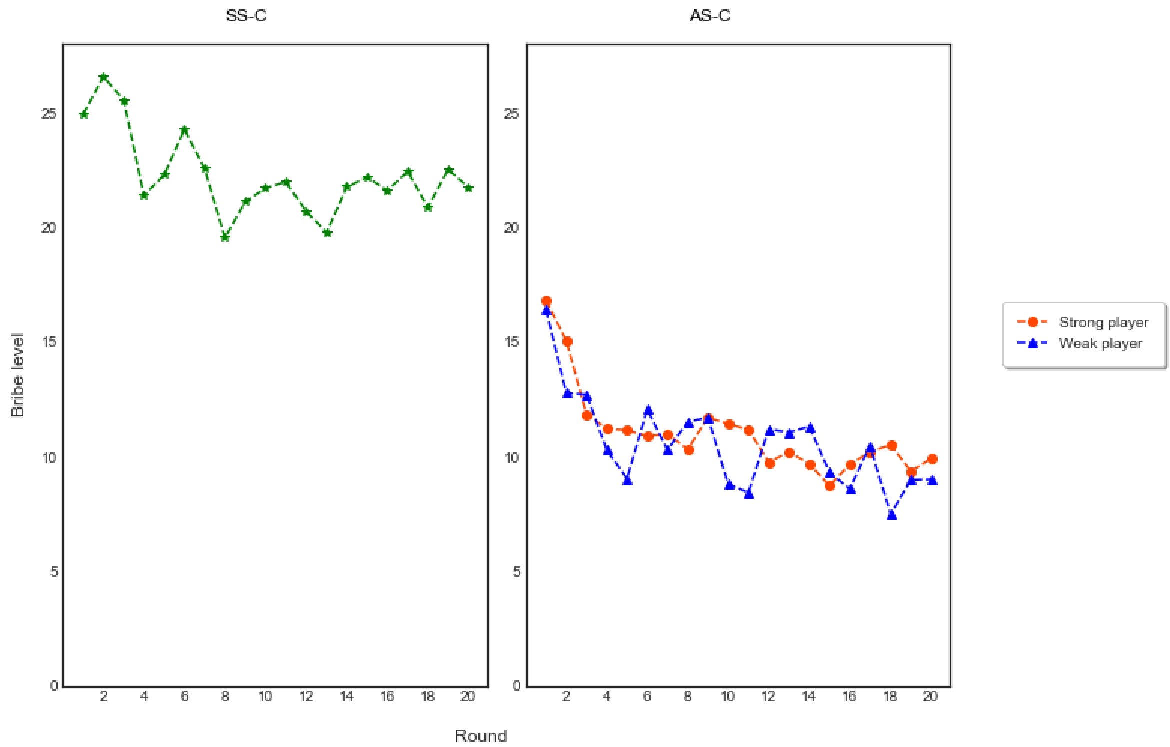
Table 3.3.: Mean bribe offers

Rounds	1-10	11-20	All	Theoretical prediction
SS-C	22.99	21.56	22.23	30.00
	(2.24)	(1.37)	(2.11)	–
Strong player	12.15	9.93	11.04	10.71
(AS-C)	(2.08)	(0.67)	(1.88)	–
Weak player	11.57	9.60	10.58	10.70
(AS-C)	(2.20)	(1.34)	(2.04)	–
Observations	86	86	86	–

Notes: Standard deviations are in parentheses.

Figure 3.2 illustrates average bribes over time by player types. In both treatments, bribe levels in the first 10 rounds are higher than in the last 10 rounds. Additionally, it is clear from this figure that bribes of both players in the AS-C treatment are systematically lower than those in the SS-C treatment over a course of 20 rounds. Looking further into the AS-C treatment, I find that in groups where both players offer bribes, the differences in bribes between these two players are small in magnitude and statistically insignificant (MW, p>0.10). A possible explanation for this observation is that when weak players bribe, even with a small amount, this induces strong players to offer bribes to secure their advantageous position. By doing this, weak players can exploit the winning-by-default outcome if corruption from strong players is detected. This is confirmed by evidence that weak players offer slightly smaller bribes than their strong opponents. Furthermore, the share of weak players who engage in corruption in the first 5 rounds is 7 percentage points higher than in the last 5 rounds. This indicates that toward the end of the game, weak players have lower motivation to engage in corruption.

Figure 3.2.: Bribe levels over time by treatments



Notes: The graph shows mean bribe offers per individual in the SS-C treatment (left) and the AS-C treatment (right) over the course of 20 rounds.

Finding: Bribe offers in the symmetric contest are almost twice as high as those in the asymmetric contest. There are no systematic differences in bribes between weak players and strong players.

3.5.2. Effort provision

In this section, I compare effort provision across treatments which vary by the level of asymmetry and the possibility for corruption. Figure 3.3 displays efforts over time and the corresponding equilibrium in each treatment. Efforts in the SS-NC treatment are highest over the period of 20 rounds, whereas efforts in the AS-C treatment are significantly lower than those in other treatments. Unlike findings in previous studies (see Abbink, Brandts, et al. (2010), Fallucchi et al. (2021)), I find no end game effects of effort investment, e.g. a significant reduction in efforts towards the last rounds of the experiment. In all treatments, efforts remain relatively stable over time.

Figure 3.3.: Mean total effort over time by treatments

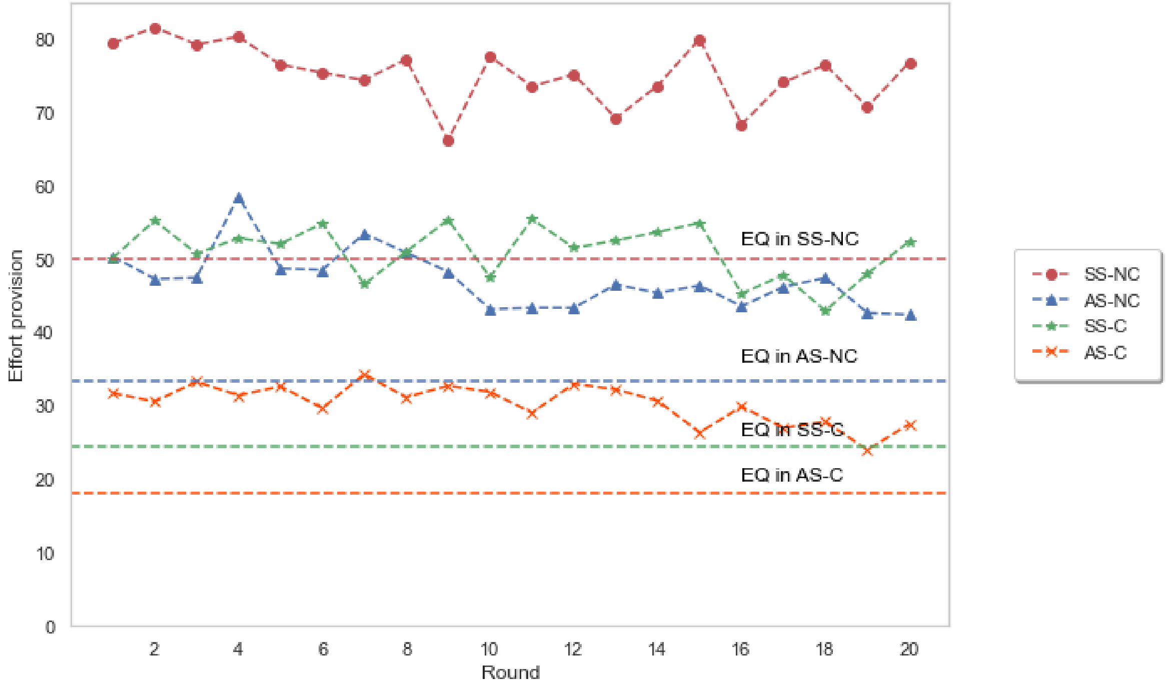


Table 3.4.: Mean total efforts per group

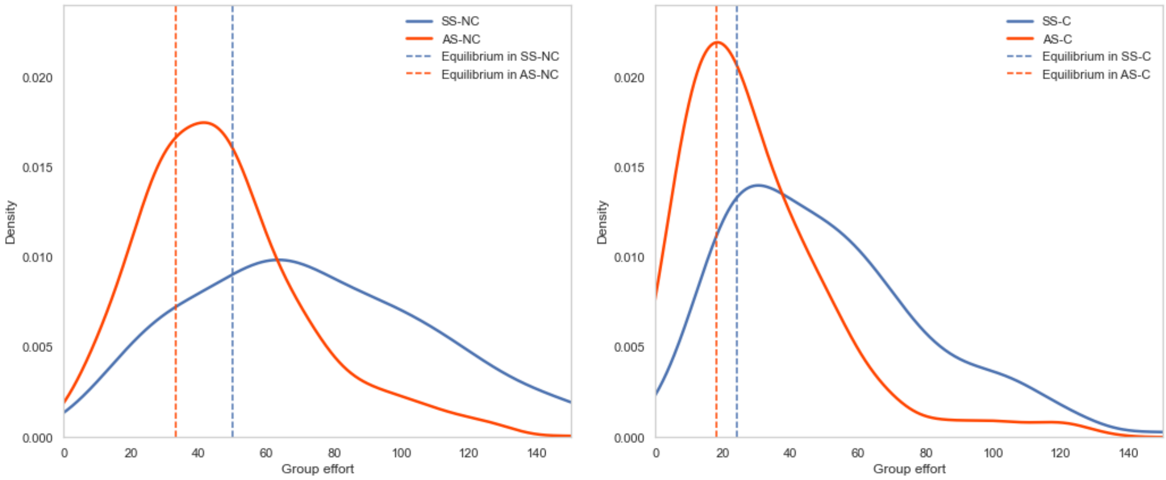
Rounds	1-10	11-20	All	Theoretical prediction
SS-NC	76.79	73.80	75.29	50.00
	(4.32)	(3.61)	(4.17)	–
SS-C	51.63	50.45	51.04	24.38
	(3.07)	(4.22)	(3.64)	–
AS-NC	49.67	44.73	47.20	33.33
	(4.11)	(1.85)	(4.01)	–
AS-C	31.94	28.75	30.35	18.18
	(1.35)	(2.77)	(2.68)	–
Observations	86	86	86	–

Notes: Standard deviations are in parentheses.

Table 3.4 summarizes mean total efforts per group in each treatment. Combining weak players and strong players, mean total efforts vary from 30.35 tokens (SD=2.68) in the

AS-C treatment to 47.20 tokens (SD=4.01) in the AS-NC treatment, while mean total efforts in the symmetric treatment range from 51.04 tokens (SD=3.64) in the contest with corruption to 75.29 tokens (SD=4.17) in the contest without corruption. The distributions of efforts differ significantly across treatments. Efforts in the symmetric treatment are considerably higher than those in the asymmetric one (MW, $p<0.001$). This holds for both treatments with corruption and without corruption. This finding provides evidence to support Hypothesis 3a. Aggregate efforts in the SS-NC treatment are significantly higher than those in the SS-C treatment (WRS, $p<0.001$). A similar pattern is also observed in the asymmetric treatment (WRS, $p<0.001$).[14] The result is thus in favor of Hypothesis 3b.

Figure 3.4.: Kernel density estimations of efforts



(a) Contest without corruption

(b) Contest with corruption

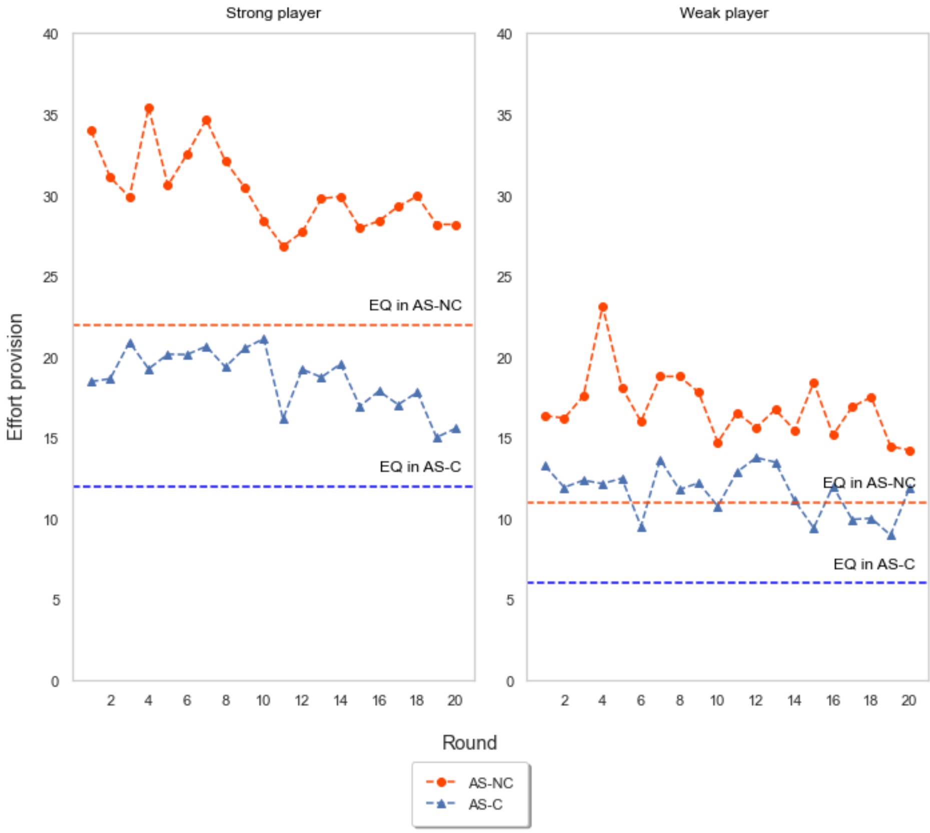
Figure 3.4 shows kernel density estimations of efforts per group in each treatment. What emerges from this figure is that the distributions of efforts in the symmetric treatment are flatter than those in the asymmetric treatment and have long tails which reconfirm that efforts in the former are considerably higher than the latter. Especially, I observe that 26.62% of groups in the SS-NC treatment spend more than 100 tokens

[14] As a robustness check, I consider subsets of data. As can be seen from Table 3.4 that efforts in the symmetric treatments (SS-NC and SS-C) are significantly higher than those in the asymmetric treatments (AS-NC and AS-C) both in the first 10 rounds and in the last 10 rounds. Furthermore, the difference in efforts between the contest without corruption and the contest with corruption is larger in the symmetric contest than in the asymmetric contest. To be specific, the difference is around 24 tokens in the former as compared to 17 tokens in the latter.

on efforts and this figure is 8.72% in the SS-C treatment. These shares are 4.65% and 2.67% in the AS-NC treatment and the AS-C treatment, respectively. The high levels of efforts imply over-dissipation of efforts in the symmetric contest.

Finding: Average efforts in the contest with corruption are significantly lower than those in the contest without corruption. This holds for both the symmetric contest and the asymmetric contest. There are distinct differences in the distributions of efforts between the symmetric contest and the asymmetric one.

Figure 3.5.: Efforts over time by player types in the asymmetric treatment



Notes: The graph shows mean effort of strong players (left) and weak players (right) over 20 rounds in the AS-NC treatment and in the AS-C treatment.

Next, I compare efforts between strong players and weak players in the asymmetric contest. Figure 3.5 shows mean efforts exerted by strong players (left hand side) and by weak players (right hand side) over the 20 rounds. The first observation is that strong players provide nearly twice as much effort as their weak opponents in both treatments with and without corruption (MW, $p<0.001$ for both tests). This disparity remains relatively stable across rounds. Considering the AS-NC treatment, efforts of strong players range from 35 tokens in the first round to 28 tokens in the last round, whereas efforts of weak players range from 24 tokens in the second round to 15 tokens in the last round. A possible explanation is that in the asymmetric contest, it is more expensive for weak players to exert the same amount of effort as compared to strong players, hence, they provide a low effort level. Anticipating this, strong players do not need to exert high efforts in order to win the contest. Therefore, total efforts in the asymmetric contest become lower than those in the symmetric one.

The second observation is that efforts provided in the treatment with corruption (AS-C) of both types of players are substantially lower than those in the treatment without corruption (AS-NC). The result is in line with the comparative-static predictions of the theoretical model (see Table 3.2). To be specific, strong players invest, on average, 19 tokens in the contest with corruption, whereas they spend 30 tokens in the contest without corruption. On average, weak players invest 17 tokens in the contest without corruption and 12 tokens in the contest with corruption.

Finding: Efforts of strong players are significantly higher than those of weak players in the asymmetric contest. This holds for both the AS-NC treatment and the AS-C treatment.

Table 3.5.: Actual efforts as compared to equilibrium predictions

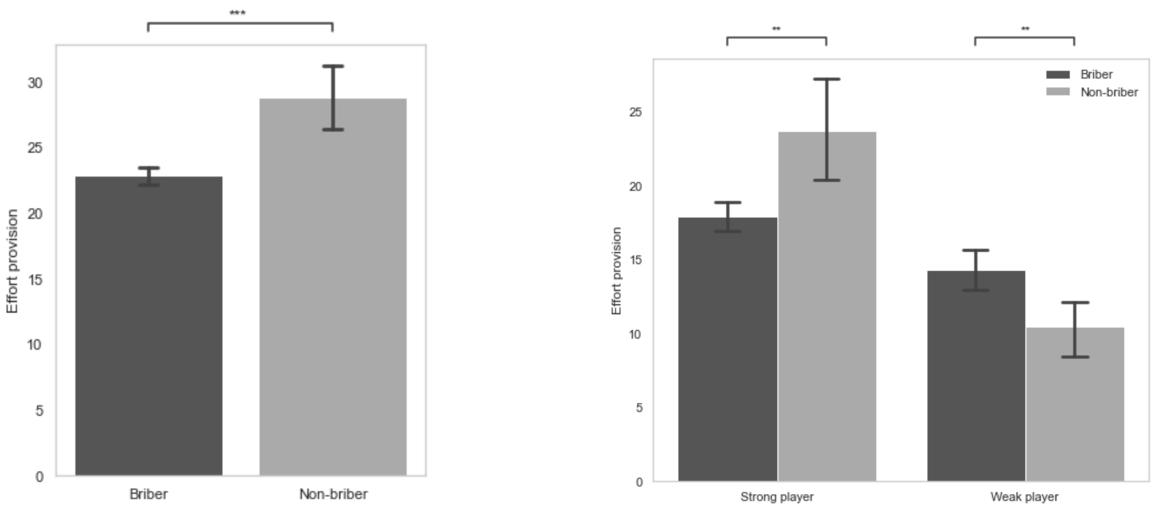
	Predicted effort		Actual effort		Effort as % of equilibrium prediction		
	Strong player	Weak player	Strong player	Weak player	Strong player	Weak player	Observations
SS-NC	25.00		37.50		150%		86
SS-C	12.19		25.72		209%		86
AS-NC	22.22	11.11	30.27	16.93	136%	154%	86
AS-C	12.12	6.06	18.66	11.69	158%	200%	86

Table 3.5 summarizes comparisons between actual efforts and the equilibra. What can be taken from this table is that the differences in efforts between the SS-NC and the SS-C treatment go in the same direction as predicted in the theoretical model shown in Table 3.2. However, actual efforts provided by players are substantially higher than predicted which indicates high dissipation of efforts. For example, participants in the

SS-C treatment provide twice as much effort as predicted. Similar patterns can also be observed in the AS-NC treatment and in the AS-C treatment.

Note that bribing does not secure bribers an advantageous position if they do not exert enough effort. If the bribers choose an effort level lower than 9 contest tokens, bribing does not increase the chance of winning as compared to exerting effort alone.[15] I observe that the shares of bribers who invest at least 9 contest tokens in effort are 93% in the symmetric contest and 81% in the asymmetric contest. Bribers choose mean efforts of 23 tokens in the former and 16 tokens in the latter. This ensures that the combination between bribes and efforts gives bribers advantages over their opponents as compared to when they spend the same amount of points on effort.

Figure 3.6.: Efforts of bribers and non-bribers in the contest where corruption occurs



(a) SS-C treatment (b) AS-C treatment

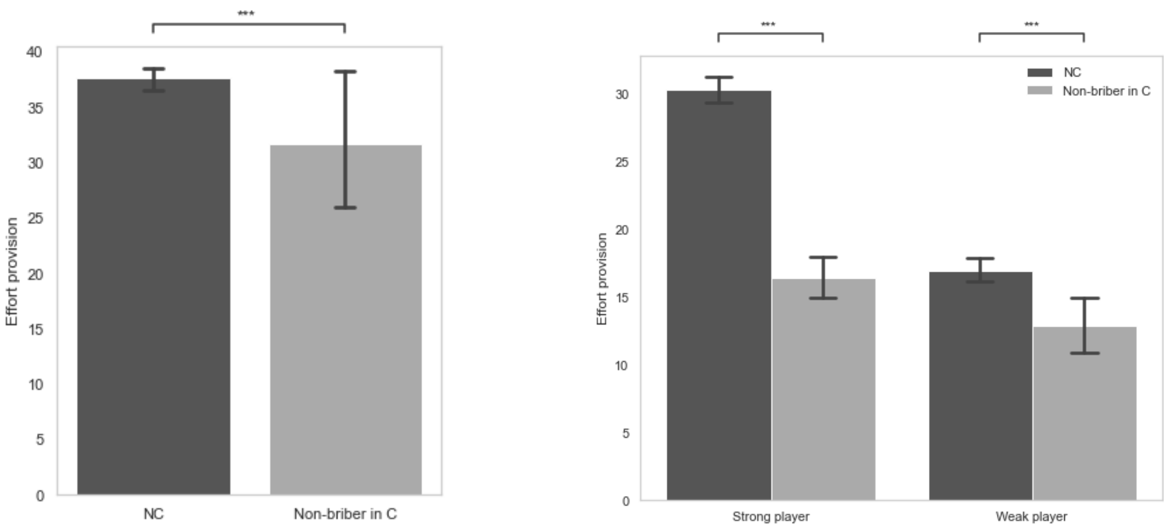
Notes: The graph shows mean efforts of bribers and non-bribers in the SS-C treatment (left) and the AS-C treatment (right). I further compare efforts provided by strong players and weak players in the AS-C treatment. Error bars display 95% confidence intervals. *p<0.10, **p<0.05, ***p<0.01.

Figure 3.6 displays efforts provided by bribers and non-bribers in the contest where corruption occurs. In this part, I define "non-bribers" as players who do not offer any bribes or whose bribe offers are not accepted. In the SS-C treatment mean efforts

[15] To make sure that a bribe can increase the chance of winning, the briber needs to exert an effort level such that $(1 + \frac{1}{9}b)e \geq e + b$ which requires a minimum effort of 9 contest tokens.

of the non-bribers are 28.79 (SD=7.66) which are higher than those of the bribers (M=22.85, SD=2.21). This difference is significant at the 1% level for the SS-C treatment. A similar pattern of effort differences is also observed for strong players in the AS-C treatment. Surprisingly, weak players in the AS-C treatment who offer bribes choose significantly higher efforts than the non-bribers (M=14.25 versus M=10.45, respectively) (MW, $p<0.05$). A possible explanation for this finding is that the bribers need to choose a high level of effort to secure the advantage of the bribe offer, whereas the weak non-bribers lose motivation to compete in the contest since the marginal net benefit of effort becomes small in this case.

Figure 3.7.: Efforts in groups without corruption



(a) SS treatment (b) AS treatment

Notes: The graph compares mean efforts between groups in the contest without corruption (SS-NC treatment and AS-NC treatment) and groups in the contest with corruption but no player offers any bribes (SS-C treatment and AS-C treatment). In the asymmetric treatment, I further compare efforts based on player types. Error bars display 95% confidence intervals. *p<0.10, **p<0.05, ***p<0.01.

In the contest with corruption a considerable share of groups choose not to engage in corruption (see Figure 3.1). In the following, I compare efforts of players in these groups with those in the contest without corruption. This gives an insight into how the presence of corruption possibility affects players' behavior. In this part, I denote "non-bribers" as players in groups where no corruption occurs in the SS-C treatment and in the AS-C treatment. As can be seen in Figure 3.7, efforts of players in the SS-NC treatment and the AS-NC treatment are significantly higher than those of non-bribers in the SS-C treatment and the AS-C treatment. The difference ranges from 6 tokens in the symmetric treatment to approximately 9 tokens in the asymmetric treatment. At the individual level the non-bribers in the SS-C treatment provide, on average, 31.64 tokens which are lower than those in the SS-NC treatment (M=37.64, SD=3.25). The difference is statistically significant (WSR, $p<0.001$). In the asymmetric contest, the strong players in the contest without corruption invest 30.27 tokens (SD=2.40) which are significantly higher than efforts provided by strong non-bribers in the contest with corruption (M=16.44, SD=3.76). A similar pattern of observation is also found for weak players (M=14.93 versus M=12.82). These differences are statistically significant at the 1% level. This indicates that the presence of corruption possibility induces lower efforts even when players do not use this option. A possible explanation is that when no player offers any bribes in the corruption stage, this signals cooperativeness between two players that they would not want to over-compete in the contest, thus both of them choose lower effort levels.

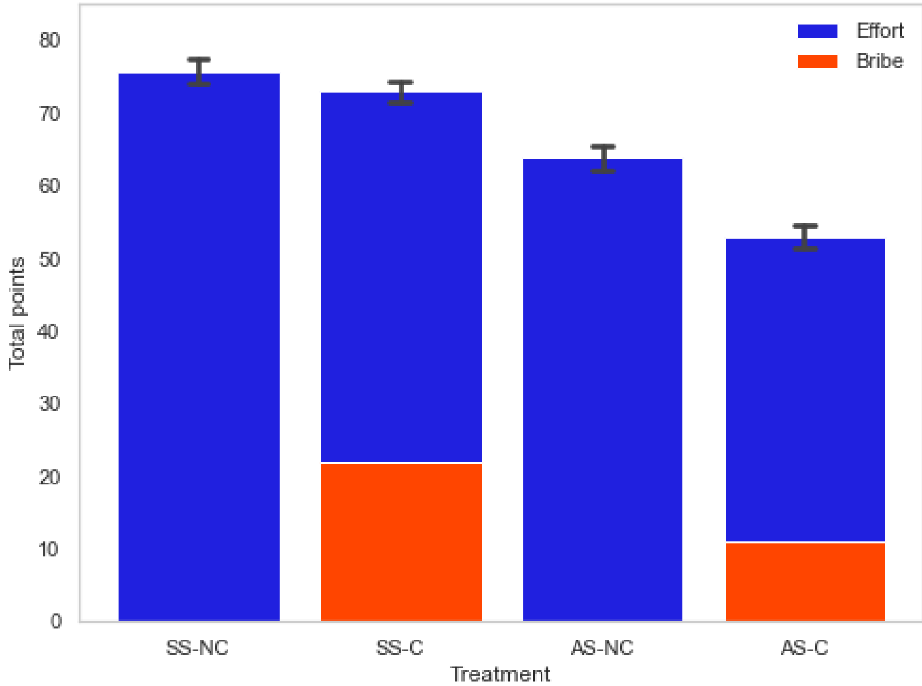
Finding: In the contest with corruption, average efforts of players in groups where no corruption occurs are significantly lower than those of groups in the contest without corruption.

To examine whether bribes are used as a substitute for efforts in the contest, I create Figure 3.8 which shows total expenditures spent by each group across treatments. Total expenditures are calculated as total points that players in each group spend on bribes and efforts.[16] On average, players in the SS-NC treatment spend 75 points, whereas those in the SS-C spend 73 points. This figure is 64 points for players in the AS-NC treatment and 53 points for the AS-C treatment. Bribes account for 30% of total expenditures in the SS-C treatment and approximately 20% in the AS-C treatment. What stands out from this figure is that players in the symmetric contest spend more points on both bribes and efforts than those in the asymmetric contest. Moreover, there is almost no difference in total expenditures between the SS-NC and the SS-C treatment, whereas the total amount spent in the AS-C treatment is 10 points lower than those in the AS-NC treatment. This comes from the fact that both weak players and strong players in the asymmetric contest offer lower bribes and provide lower efforts

[16]Players in the asymmetric contest have different marginal costs of effort, i.e. one player has a marginal cost of effort of one point per contest token, while the other player has a marginal cost of effort of two points per contest token. Therefore, to make total expenditures comparable across treatments points spent on efforts are multiplied with the marginal cost of effort.

than players in other treatments.

Figure 3.8.: Total expenditures by treatments



3.5.3. The effect of corruption on effort provision

As discussed above, there are distinct differences in effort provision between contests with corruption and without corruption possibility. To further understand the effects of corruption on efforts, I estimate the following regression:

$$\text{effort}_{i,t} = \beta_0 + \beta_1 \text{bribe decision}_{i,t} + \beta_2 \text{bribe level}_{i,t} + \varepsilon_{i,t}$$

where effort is total effort of group i, bribe decision is a binary variable which takes a value of 1 if at least one player in group i offers a bribe and 0 otherwise and bribe level is the accepted bribe offer.

Table 3.6 summarizes OLS estimates of determinants of efforts. The bribe decision has a negative effect on effort provision in both treatments. Model 1 shows that players in groups where corruption occurs provide 27.09 contest tokens less than groups where there is no corruption in the SS-C treatment, whereas model 3 indicates that groups with corruption provide 6.00 contest tokens less than groups where no corruption occurs in the AS-C treatment. This is consistent with Figure C.3 in the Appendix C which shows that efforts of groups where corruption occurs are significantly lower than those in groups where corruption does not occur.

Table 3.6.: The effect of corruption on efforts

	Effort			
	SS-C	SS-C	AS-C	AS-C
	(1)	(2)	(3)	(4)
Bribe decision	-27.090***	-30.248***	-6.002***	-8.243***
	(7.567)	(5.501)	(1.767)	(1.939)
Bribe level		0.048*		0.106***
		(0.040)		(0.040)
Intercept	77.028***	77.028***	35.200***	35.200***
	(7.498)	(5.302)	(1.675)	(1.675)
R^2	0.031	0.034	0.010	0.013
Observations	860	860	860	860

Notes: This table shows OLS regressions of factors that determine efforts in the contest with corruption. Model 1 and 2 consider the SS-C treatment, while model 3 and 4 analyse the AS-C treatment. The dependent variable is effort provided by both players in each group. Independent variables are bribe decision and bribe level. Bribe decision takes a value of 1 if at least one player offers a positive bribe and 0 otherwise. Bribe level is an accepted bribe. Robust standard errors are in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Considering contests where corruption occurs, I find efforts increase in bribe offers in both treatments. The effect is stronger in the asymmetric contest than in the symmetric one. The result holds when I control for other variables such as gender, prosocial preferences and risk preferences as shown in Table C.2 in the Appendix C. A possible explanation is that given one player bribes and obtains the favor, the non-bribers attempt to provide higher efforts because that is the only way for them to win the contest. This is consistent with what I have shown in Figure 3.6 that on average, the non-bribers exert higher efforts than the bribers in both the symmetric treatment and the asymmetric treatment. However, note that efforts in the contest with corruption are significantly lower than those in the contest without corruption opportunity as discussed in the previous section 3.5.2. This comes from the fact that the non-bribers in the contest with corruption provide considerably lower efforts than those in the contest without corruption possibility as illustrated in Figure 3.7.

3.6. Conclusion

This study investigates corruption in symmetric and asymmetric contests. I develop a theoretical model where a standard two-player Tullock contest is extended by introducing a corruption stage before the contest takes place. Consistent with the predictions of the model, findings in the experiment show that the level of asymmetry affects corrupt behavior. The share of groups which engage in corruption in the symmetric contest is 10 percentage points higher than that in the asymmetric contest. On the extensive margin, I find average bribes in the former are significantly higher than those in the latter. In the asymmetric contest, strong players are more likely to engage in corruption than their opponents.

Another important finding is that asymmetry in abilities has effects on effort provision, both in contests with corruption and without corruption. I find efforts in the symmetric contest are considerably higher than those in the asymmetric contests. Looking further into the latter, I observe that strong players exert more efforts than their weak opponents. These patterns of behavior are in line with the theoretical predictions and also with findings in previous studies (Abbink, Brandts, et al. (2010), Fallucchi et al. (2021)).

To investigate the effect of corruption possibility on effort provision, I further compare efforts in groups where no player engages in corruption with efforts of groups in the contest without corruption possibility. Interestingly, the result shows that effort provision of the former is significantly lower than that of the latter. This implies that the presence of corruption possibility induces lower efforts even when players do not exploit this option. This has an important implication for contest organizers that in an environment where corruption may occur, players might be discouraged to exert high efforts in the contest. In case efforts are desirable for the contest, corruption is problematic since it induces lower effort provision.

The findings in this study open some areas for future research. One possible direction is to consider public trust as a component in a player's utility function. When corruption is revealed to the public, it may lead to losses of public trust in a "good" player which damages the player's reputation. Second, one can consider corruption in contests where players have symmetry/asymmetry valuations of prizes. Previous studies show that the valuation of prizes plays an important role in players' behavior (see Fonseca (2009), Fallucchi et al. (2021)). It is possible that players who value higher prizes have more motivation to engage in corruption than others. Third, this study highlights that not only weak players engage in corruption to improve their position but strong players also bribe to reinforce their advantageous position. It would be interesting to see if different audit probabilities based on player types can mitigate corrupt behavior.

Appendices

A. Appendix to Chapter 1

A.1. Additional results

Table A.1.: Descriptive statistics

	Meritocracy			Bribery			P-value
	Mean	**SD**	**N**	**Mean**	**SD**	**N**	
Part 1							
Correct guesses	16.17	9.51	96	14.92	9.41	153	0.199
Cheat rate	0.44	0.37	96	0.44	0.37	153	0.937
Correct matrices	10.18	3.42	96	10.52	3.07	153	0.372
Lottery choice	3.42	1.99	96	3.30	2.01	153	0.646
Prosocial preferences	0.31	0.46	89	0.41	0.49	143	0.133
Ability guess	1.97	1.01	96	1.97	0.92	153	0.771
Part 2							
Public sector	0.35	0.48	82	0.44	0.49	136	0.168
Test scores	13.45	3.48	82	13.19	3.74	136	0.560
Bribe demand	69.70	29.97	20	84.36	35.35	47	0.074
Pass application	–	–	–	0.88	0.32	61	–
Demographic							
Male	0.54	0.50	96	0.45	0.49	153	0.163
Age	23.14	3.63	96	22.94	3.04	153	0.948

Notes: Correct guesses refer to the total number of observed correct guesses in the *dice-guess* game over 30 rounds. *Correct matrices* indicate the number of correct matrices in the *find-the-numbers* game. *Lottery choice* refers to Option 1 to Option 6 in the *lottery* game. *Pro-social preferences* take a value of 1 if a participant is classified as pro-social and 0 if he/she is categorized as individualistic. *Ability guess* indicates a participant's subjective performance rating in the *find-the-numbers* task. *Public sector* is a binary variable which takes a value of 1 if a participant chooses Option 2 and 0 otherwise. *Test scores* refer to the number of correct matrices that a participant solves in the recruitment test. *Bribe demand* is the amount that a participant demands in the *petty-corruption* game. *Pass application* is a binary variable which takes a value of 1 if a participant applies for a free pass and 0 otherwise.

Figure A.1.: Distribution of the observed number correct guesses and the expected distribution under full honesty in the Meritocracy treatment

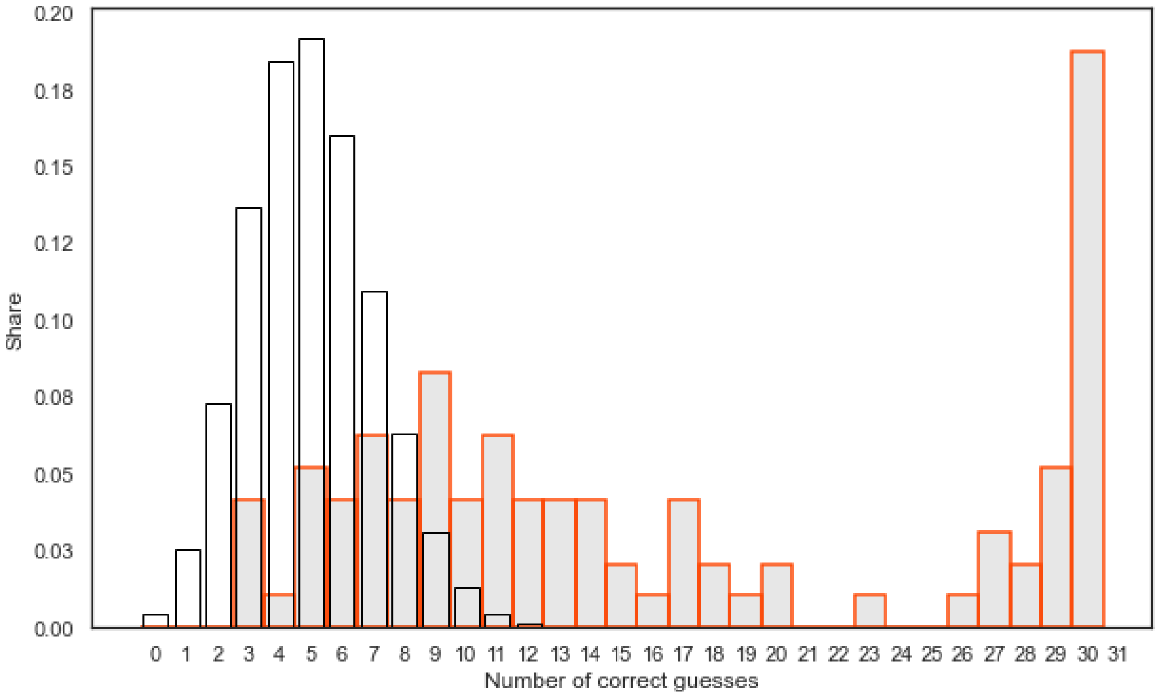


Figure A.2.: Distribution of the observed number correct guesses and the expected distribution under full honesty in the Bribery treatment

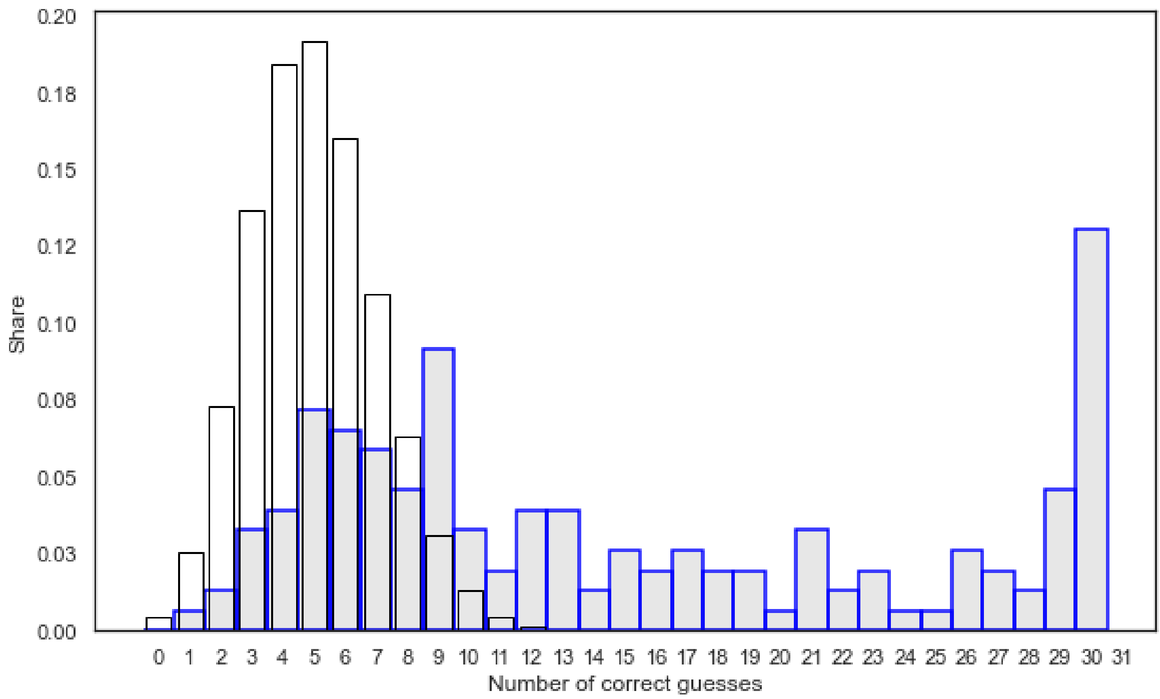
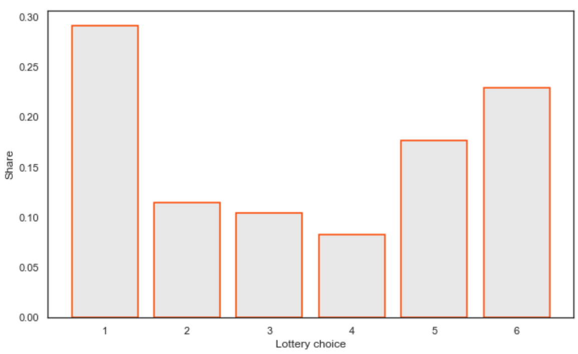
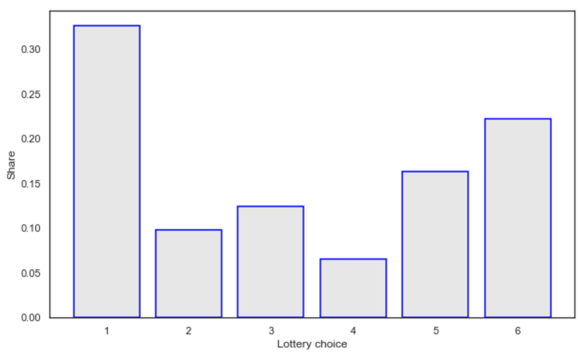


Figure A.3.: Distribution of lottery choices



(a) Meritocracy treatment



(b) Bribery treatment

Figure A.4.: Job selection by treatments

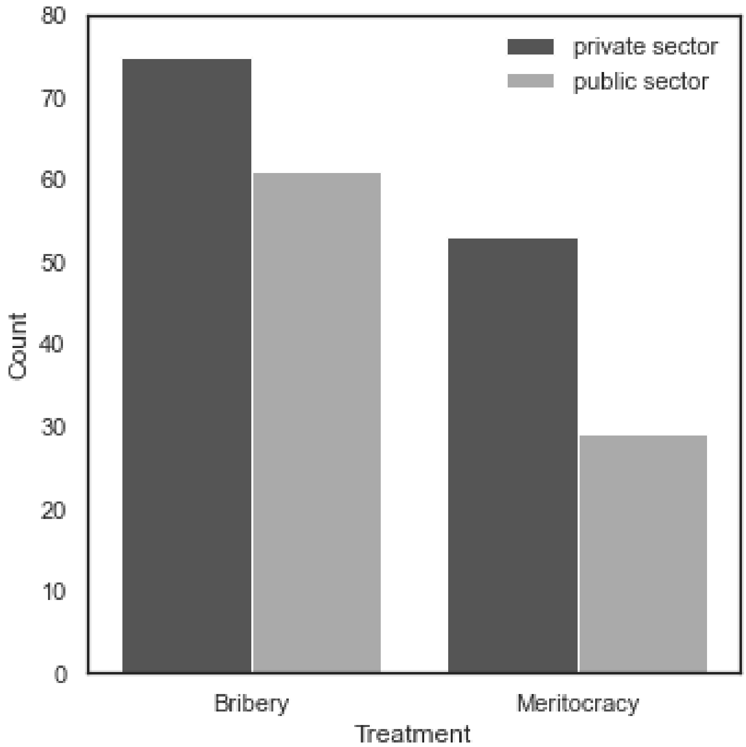


Figure A.5.: Job selection by dishonesty types

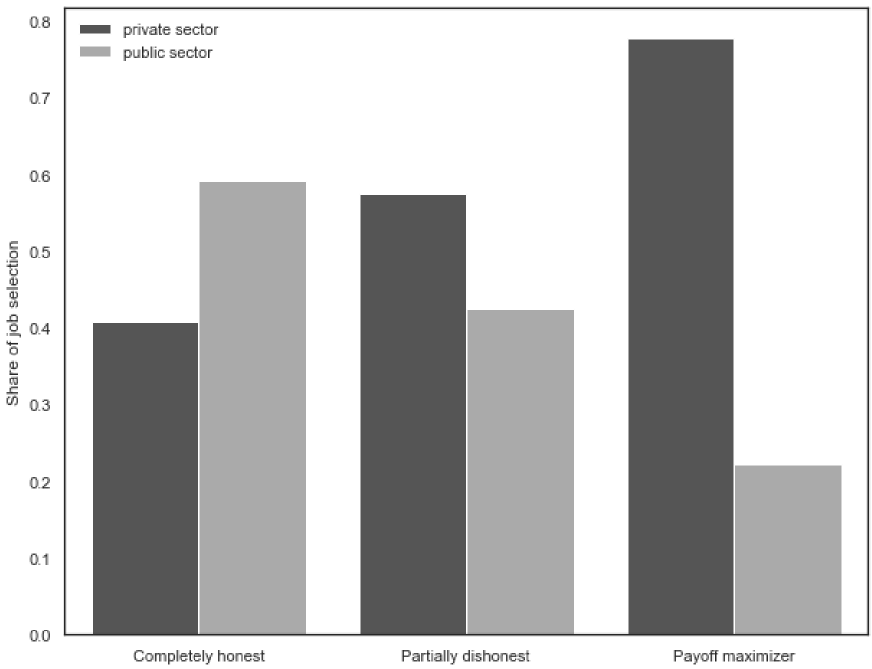
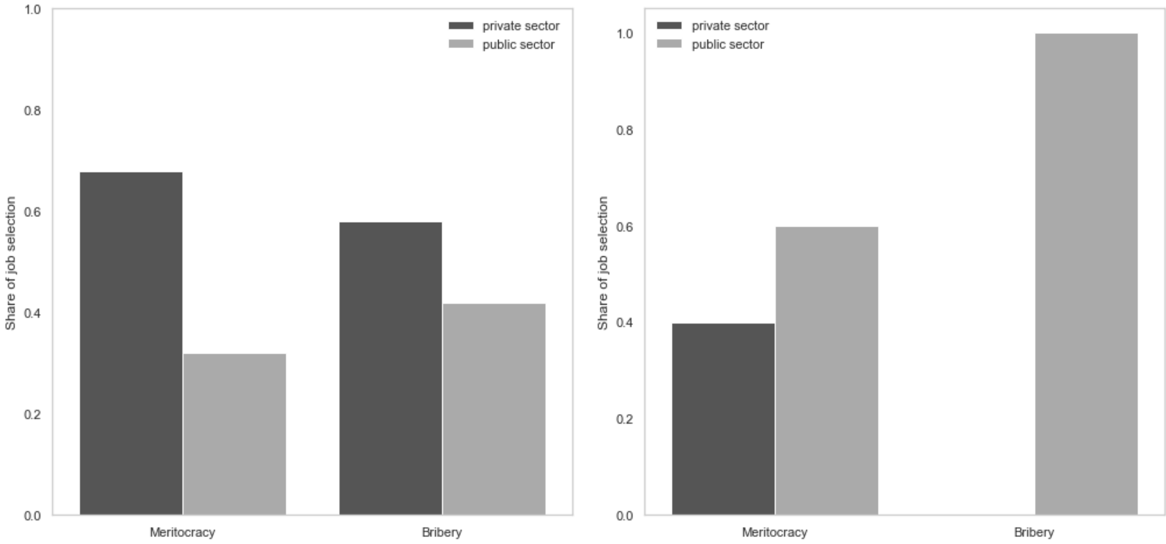
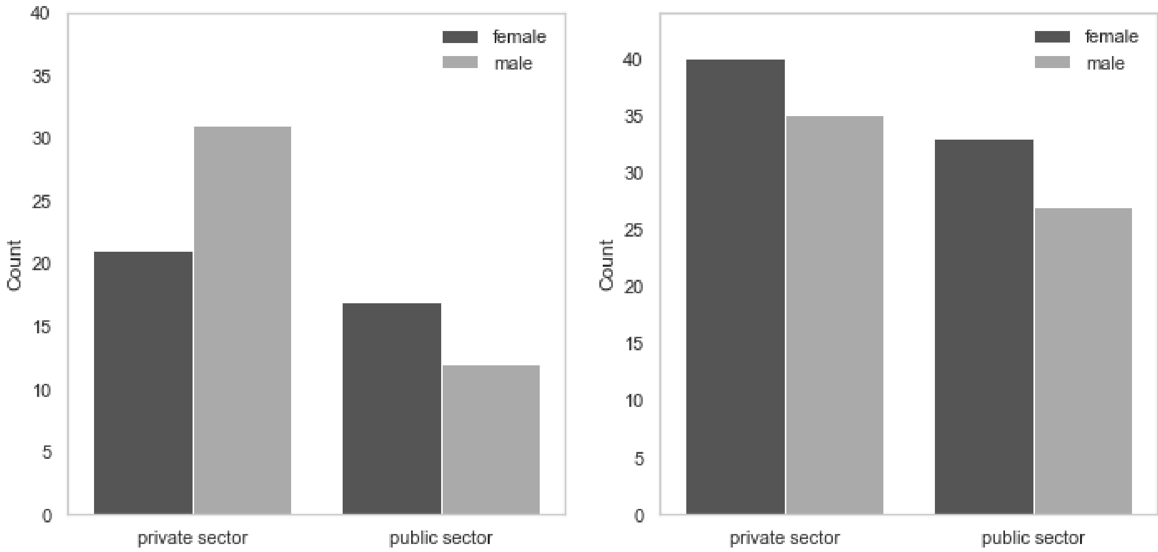


Figure A.6.: Job selection and subjective performance ratings



(a) Top 25% performers (b) Bottom 25% performers

Figure A.7.: Job selection by gender



(a) Meritocracy treatment (b) Bribery treatment

Figure A.8.: Cheat rates by pro-social preferences

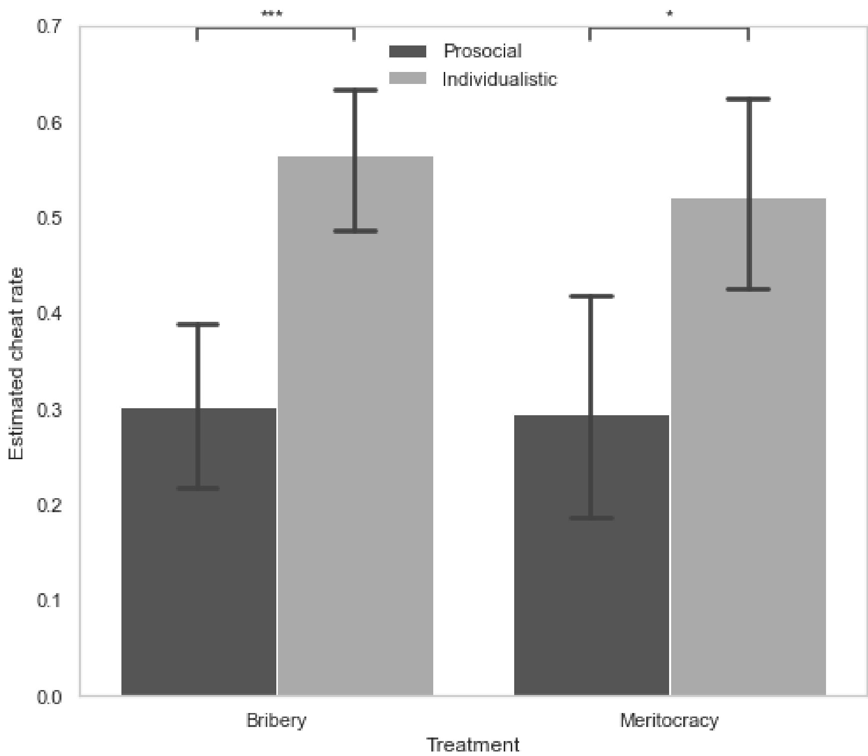


Figure A.9.: Cheat rates by gender

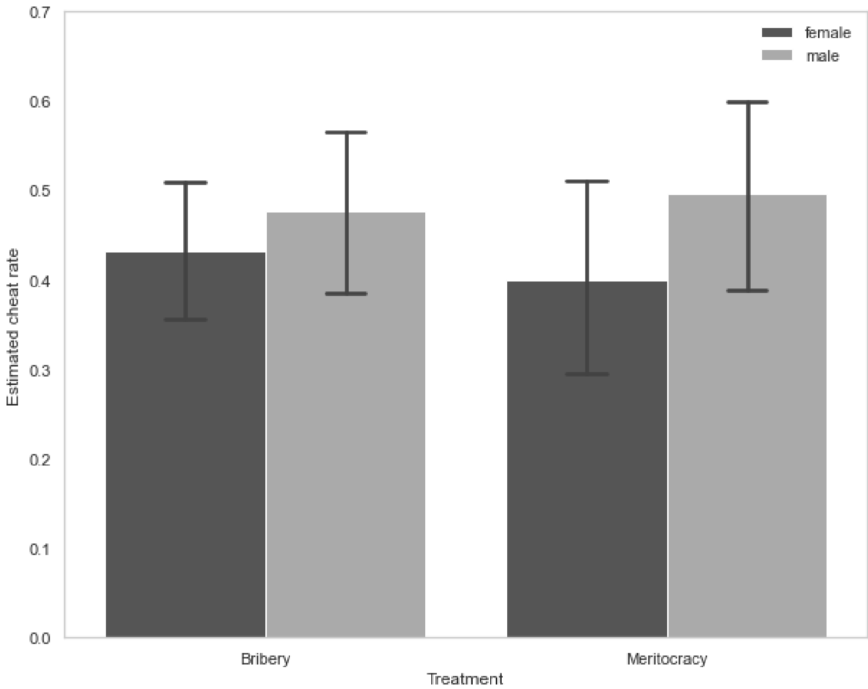


Table A.2.: Regressions on job selection and ability

	Public sector		
	(1)	(2)	(3)
Treatment	0.266	-0.042	-0.108
	(0.179)	(0.577)	(0.592)
Ability	-0.032	-0.050	-0.044
	(0.027)	(0.042)	(0.043)
Treatment*Ability		0.030	0.035
		(0.054)	(0.056)
Risk preferences			-0.065
			(0.046)
Prosocial preferences			0.044
			(0.180)
Male			-0.097
			(0.182)
Intercept	-0.053	0.122	0.303
	(0.300)	(0.434)	(0.465)
Observations	218	218	218
Pseudo R^2	0.011	0.012	0.022

Notes: This table shows Logistic regressions of the relationship between job selection and ability. The dependent variable is public sector which takes a value of 1 if a participant chooses Option 2 and 0 otherwise. Treatment is a binary variable which takes a value of 1 if this is the Bribery treatment and 0 otherwise. Standard errors are in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Table A.3.: Regressions on propensity for dishonesty and other attributes in the Meritocracy treatment

	Cheat rate					
	(1)	(2)	(3)	(4)	(5)	(6)
Ability	0.011					0.011
	(0.011)					(0.012)
Risk preferences		-0.017				-0.033
		(0.019)				(0.020)
Prosocial preferences			-0.227***			-0.231***
			(0.079)			(0.078)
Male				0.108		0.134*
				(0.077)		(0.078)
Age					0.014	0.012
					(0.011)	(0.010)
Intercept	0.338**	0.506***	0.521***	0.389***	0.114	0.161
	(0.110)	(0.078)	(0.050)	(0.057)	(0.255)	(0.260)
Observations	96	96	89	96	96	89
R^2	0.009	0.008	0.074	0.020	0.019	0.143

Notes: The table shows OLS estimates of the relationship between individuals' cheat rates and their characteristics in the Meritocracy treatment. Robust standard errors are in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Table A.4.: Regressions on propensity for dishonesty and other attributes in the Bribery treatment

	Cheat rate					
	(1)	(2)	(3)	(4)	(5)	(6)
Ability	0.012					0.004
	(0.009)					(0.009)
Risk preferences		-0.001				0.001
		(0.015)				(0.016)
Prosocial preferences			-0.263***			-0.258*
			(0.058)			(0.058)
Male				0.050		0.051
				(0.061)		(0.066)
Age					0.012	0.010
					(0.010)	(0.010)
Intercept	0.323***	0.451***	0.565***	0.426***	0.160	0.252
	(0.094)	(0.057)	(0.040)	(0.039)	(0.239)	(0.231)
Observations	153	153	143	153	153	143
R^2	0.010	0.001	0.121	0.005	0.011	0.133

Notes: The table shows OLS estimates of the relationship between individuals' cheat rates and their characteristics in the Bribery treatment. Robust standard errors are in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Table A.5.: Regressions on job selection and other attributes with pooled data

	Public sector				
	(1)	(2)	(3)	(4)	(5)
Ability	-0.028				-0.020
	(0.027)				(0.027)
Risk preferences		-0.078*			-0.064
		(0.044)			(0.046)
Prosocial preferences			0.061		0.074
			(0.177)		(0.180)
Male				-0.205	-0.110
				(0.172)	(0.182)
Age					0.016
					(0.026)
Intercept	0.075	0.033	-0.245**	-0.122	-0.164
	(0.286)	(0.165)	(0.109)	(0.118)	(0.668)
Observations	218	218	216	218	213
Pseudo R^2	0.004	0.001	0.003	0.005	0.015

Notes: The table shows Logistic estimates of the relationship between individuals' selection into the public sector and their characteristics. Standard errors are in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Table A.6.: Regressions on job selection and other attributes in the Meritocracy treatment

	Public sector				
	(1)	(2)	(3)	(4)	(5)
Ability	-0.050				-0.043
	(0.042)				(0.045)
Risk preferences		-0.047			-0.003
		(0.072)			(0.077)
Prosocial preferences			0.213		0.238
			(0.300)		(0.311)
Male				-0.424	-0.364
				(0.287)	(0.302)
Age					0.032
					(0.037)
Intercept	0.123	-0.227	-0.448**	-0.161	-0.576
	(0.434)	(0.270)	(0.175)	(0.202)	(0.989)
Observations	82	82	82	82	82
Pseudo R^2	0.013	0.004	0.005	0.021	0.040

Notes: The table shows Logistic estimates of the relationship between individuals' selection into the public sector and their characteristics in the Meritocracy treatment. Standard errors are in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Table A.7.: Regressions on job selection and other attributes in the Bribery treatment

	Public sector				
	(1)	(2)	(3)	(4)	(5)
Ability	-0.019				-0.011
	(0.035)				(0.036)
Risk preferences		-0.099*			-0.098*
		(0.055)			(0.059)
Prosocial preferences			-0.048		-0.029
			(0.221)		(0.225)
Male				-0.061	-0.072
				(0.317)	(0.217)
Age					0.012
					(0.039)
Intercept	0.080	0.191	-0.111	-0.101	-0.014
	(0.379)	(0.209)	(0.141)	(0.146)	(0.942)
Observations	136	136	134	136	134
Pseudo R^2	0.002	0.017	0.001	0.001	0.017

Notes: The table shows Logistic estimates of the relationship between individuals' selection into the public sector and their characteristics in the Bribery treatment. Standard errors are in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Table A.8.: Regressions on bribe demand and individuals' characteristics

	Bribe demand			
	Meritocracy	Meritocracy	Bribery	Bribery
	(1)	(2)	(3)	(4)
Cheat rate	23.577**	25.824**	16.995**	11.278**
	(11.153)	(21.656)	(13.046)	(13.049)
Risk preferences		-0.958		5.031*
		(4.557)		(2.561)
Prosocial preferences		7.281		-15.530
		(14.707)		(9.970)
Male		-4.129		5.161
		(14.471)		(9.200)
Intercept	62.485***	64.202***	77.327***	69.648***
	(8.732)	(21.512)	(7.658)	(12.756)
Observations	20	20	46	46
R^2	0.092	0.114	0.032	0.150

Notes: The table shows OLS estimates of the relationship between bribe demand and individuals' characteristics. Model 1-2 use data from the Meritocracy treatment, whereas model 3-4 employ data from the Bribery treatment. Robust standard errors are in parentheses. *p<0.10, **p<0.05, ***p<0.01.

A.2. Robustness check

In further regression analyses, we employ the number of correct guesses in *the-guess-game* as an alternative measure of dishonesty. Note that there are some individuals who do not complete 30 rounds, thus, in this section we only consider individuals who complete all guesses.[17] The results of regressions with this measure are consistent with the findings in the regressions with cheat rates, illustrated in Tables A.9, A.10, and A.11. Our findings are also robust against changes in regression models such as OLS or Logistic models. To be specific, we find that there is a positive relationship between the number of correct guesses and the selection into the private sector. Additionally,

[17] 17 participants in the Bribery treatment and 1 participant in the Meritocracy treatment do not complete all 30 rounds, thus they are excluded in the robustness check.

the number of correct guesses is negatively correlated with pro-social preferences which indicates that pro-social individuals are more honest than individualistic ones. We do not find any significant effects of ability, risk preferences and gender on the number of correct guesses. Finally, bribe demands in both treatments are positively correlated with the number of correct guesses, which indicates that individuals who have a higher propensity for dishonesty are more likely to demand higher bribes.

Table A.9.: Regressions on job selection and the number of correct guesses

	Logistic		OLS	
	Public sector			
	Meritocracy	Bribery	Meritocracy	Bribery
	(1)	(2)	(3)	(4)
Number of correct guesses	-0.058**	-0.032*	-0.012**	-0.008*
	(0.028)	(0.019)	(0.005)	(0.004)
Intercept	0.251	0.261	0.543***	0.563***
	(0.459)	(0.323)	(0.105)	(0.079)
Observations	81	136	81	136
Pseudo R^2	0.050	0.015		
R^2			0.062	0.080

Notes: Model 1-2 display Logistic estimates and model 3-4 employ OLS estimates of the relationship between individuals' selection into the public sector and their number of correct guesses. Standard errors are in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Table A.10.: Regressions on the number of correct guesses and other attributes

	Number of correct guesses			
	Meritocracy	Meritocracy	Bribery	Bribery
	(1)	(2)	(3)	(4)
Ability		0.284		0.102
		(0.325)		(0.232)
Risk preferences		-0.814		0.745
		(0.499)		(0.425)
Prosocial preferences	-5.625***	-5.811***	-5.248***	-5.198***
	(2.011)	(1.499)	(1.496)	(1.503)
Male		3.369*		0.745
		(1.960)		(1.724)
Age		0.308		0.089
		(0.261)		(0.260)
Intercept	18.032***	8.986	17.214***	13.849
	(1.260)	(6.499)	(1.040)	(6.001)
Observations	88	88	143	143
R^2	0.071	0.140	0.001	0.079

Notes: The table shows OLS estimates of the relationship between individuals' number of correct guesses and their characteristics. Model 1-2 use data from the Meritocracy treatment, whereas model 3-4 employ data from the Bribery treatment. Robust standard errors are in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Table A.11.: Regressions on bribe demand and individuals' characteristics

	Bribe demand			
	Meritocracy	Meritocracy	Bribery	Bribery
	(1)	(2)	(3)	(4)
Number of correct guesses	0.943**	1.033**	1.064**	0.811**
	(0.446)	(0.866)	(0.492)	(0.485)
Risk preferences		-0.958		4.463*
		(4.557)		(2.378)
Prosocial preferences		7.281		-14.158
		(14.707)		(9.977)
Male		-4.129		6.811
		(14.471)		(9.165)
Intercept	57.769***	59.037**	69.307***	63.266***
	(10.647)	(25.576)	(9.405)	(14.149)
Observations	20	20	46	46
R^2	0.092	0.114	0.080	0.181

Notes: The table shows OLS estimates of the relationship between bribe demand and individuals' characteristics. Model 1-2 use data from the Meritocracy treatment, whereas model 3-4 employ data from the Bribery treatment. Robust standard errors are in parentheses. *p<0.10, **p<0.05, ***p<0.01.

A.3. Experimental instructions

Welcome

Welcome and thank you for participating! In this experiment you will perform several tasks during which you can earn "points". The points you earn will be converted to Euros at an exchange rate of **€0.03 per point** and be paid to you at the end of the experiment. Your point earnings will depend on your decisions, on other participants' decisions and on a bit of luck. How this all works and how much you can earn will be explained below - **thus, please follow the instructions carefully.**

The experiment will consist of two parts, and you will be paid based **EITHER** on how many points you earned in part 1 **OR** on how many points you earned in part 2. Which part will be used for your payment will be determined randomly at the end of the experiment. The chance that you will be paid for part 1 is 30% and the chance that you will be paid for part 2 is 70%.

Part 1 of the experiment consists of 4 different games or tasks. If you are paid for part 1, you will be paid based on your **total point earnings from all 4 tasks**.

Part 1: Individual characteristics

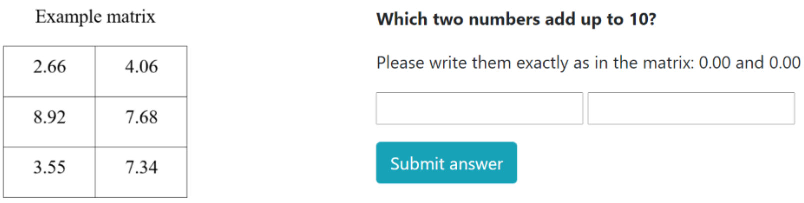
Instruction of Task 1

This game consists of 30 rounds. In each round you must guess the outcome of a digital die throw. Just like an ordinary die our digital die has 6 sides, and each possible outcome (1, 2, 3, 4, 5 or 6) is equally likely. You earn **9 points** for a correct guess and **3 points** for an incorrect guess. There is an **8-minute** time limit for the **30 rounds**, but you can directly proceed to the next task as soon as you have finished the 30 rounds. If you finish 20 rounds within the 8-minute time limit, you will receive a BONUS of **20 points**. If you finish all 30 rounds within the 8-minute time limit, you will receive another **10 points**. In the event that you do not finish the game before the timer expires, you will receive points only for the rounds that you have completed. This task requires you to make quick decisions. Don't overthink it!

Instruction of Task 2

In this game your task is to look at tables like the one shown below and to find two numbers that add up to 10.

Figure A.10.: Sample table screen



As soon as you have found two numbers that you think add up to 10, enter them in the boxes on the right hand side and then press the "Submit answer" button. The next screen will inform you how many tables you have correctly solved so far. You have **3 minutes** in total, and your task is to solve as many tables as you can during that time. You will earn **25 points** for every table you solve correctly.

Instructions of Task 3

In this task, you choose one of six options. Then, you will toss a digital coin. There is a 50-50 chance for either "Heads" or "Tails". Your payoff depends on the outcome of the coin flip and on which option you picked, as shown in the following table.

Table A.12.: Lottery payoff

	Heads	Tails
Option 1	42 points	42 points
Option 2	36 points	54 points
Option 3	30 points	66 points
Option 4	24 points	78 points
Option 5	18 points	90 points
Option 6	3 points	105 points

Instructions of Task 4

For this task the computer will randomly select **ONE** of the participants in today's experiment to play the role of "person X". This person X will then be randomly and anonymously paired with one of the other participants. If the computer selects **YOU** to be "person X", there is nothing for you to do in this task. However, you will still receive a payment. How much you will receive will be decided by the person you have been randomly paired with.

If you are **NOT** "person X", you will be asked to make 6 different decisions about allocating points between yourself and person X. The picture below shows an example.

Figure A.11.: Example of allocation decision

You receive	90	91	93	94	95	96	98	99	100
	○	○	○	○	○	○	○	○	○
Other receives	100	94	88	81	75	69	63	56	50

As you can see, there are nine options to choose from and your choice determines the point earnings for both you and person X.

When you make your decisions, you will not know whether it really is you or whether it is somebody else who has been randomly paired with person X. If it **IS** you, **ONE** of your 6 point-allocation choices will be implemented for real. To determine which one, your screen will display a 6-sided die as soon as you have submitted your 6 decisions. You roll the die by clicking on a button. The outcome of the die (each number is equally likely) determines which of your 6 decisions will be implemented.

We ask you to take each of your 6 decisions seriously. Make your decision under the assumption that it will count, because if it turns out that it does count, you will want to have picked your most preferred option, and if it turns out that it does not count, there is no harm in having picked your most preferred option.

Part 2: Recruitment process

Ability guess

Before we explain the details of part 2, here is a question for you: [the number of participants in the session] participated in Task 2 of part 1. You correctly solved [the number of tables]. How do you think you performed relative to the others? If your guess is correct, you will be paid 10 bonus points.

Please choose your answer:

- I was among the top 20% performers.
- Between 21% and 40% of people performed better than I did.
- Between 41% and 60% of people performed better than I did.

- Between 61% and 80% of people performed better than I did.
- I was among the bottom 20% performers.

You will now have to make a decision about how to proceed with the experiment. There are two options to choose from. What is common to both options is that you will play the find-the-numbers game from part 1 again. In other respects, the two options differ from each other. We will now describe each option in detail. Please read these descriptions carefully so that you can make an informed decision about which option to take.

Option 1

This option will consist of the following stages.

Stage 1A: Play the find-the-numbers game again

If you choose option 1, then the first thing that will happen is that you play the find-the-numbers game from part 1 again. Your score will be recorded.

Stage 1B: RED group or GREEN group

Next, the computer will rank your score against the scores of everyone else who has chosen option 1. If it turns out that you are among the **25% with the LOWEST score**, the computer will inform you that you are in the **RED group** and you will receive 200 points. There is nothing else for you to do at that point. Please wait for further instructions. If you are among the **75% with the HIGHEST score**, the computer will inform you that you are in the **GREEN group** and you will continue with stage 2.

Stage 2: A bonus round of play

Remember that you will only enter this stage if you are in the **GREEN group**. If you reach this stage, you will receive 550 points. On top of that, you will have the chance to obtain a bonus payment of 50 points. To get the bonus, you must play the find-the-numbers game for a third time. The score you achieve this time will be compared to the score achieved by "person X". This is the same "person X" as in the last task of part 1 of the experiment. If your score in this extra round is greater than that of person X, you will receive the 50-point bonus payment. If both of you have obtained the same score, the computer will decide randomly (with a 50-50 chance) whether or not you get the bonus payment. If person X's score is greater than yours, you will not get any bonus points.

If you are person X:

In case the computer has selected YOU for the role of person X, you will receive 200 points for participating in part 2 and you will now play the find-the-numbers game with the chance of obtaining 50 bonus points. However, you will not be asked to choose between Option 1 and Option 2, and you will also not participate in Stage 1A or Stage 1B.

*The computer will compare your score in this extra round of the find-the-numbers game with the score achieved by ONE of the **GREEN group** members (randomly selected). If your score is greater that his/hers, then you are paid the 50 extra points. If your score is lower, you do not get the extra points, and if there is a tie the computer decides this at random. Finally, in the event that nobody chooses Option 1, you will be paid the 50 extra points regardless of your performance in the find-the-numbers game.*

Stage 3: The bad luck draw

There is no task for you in this stage but irrespective of whether you are a member of the **GREEN group** or a member of the **RED group** the computer will now perform the "bad luck draw". With a 99% chance this does not change anything. But with a 1% chance the "bad outcome" occurs. If this happens, your Option 1 earnings (as described above) will be annulled and will be replaced by a lump sum payment of 150 points for choosing Option 1. If you have the role of "person X" the bad luck draw does not apply to you.

Stage 4: Extra points generated by Option 2 participants

In this final stage, there is again nothing to do for you, but irrespective of whether you are a member of the **GREEN group**, or a member of the **RED group**, or you are person X, you may receive some extra points now which are generated by participants who chose Option 2. How this works is explained below in the explanations for Option 2.

Option 2

[*Bribery Treatment:* Option 2 has the same stage 1A and stage 1B as Option 1, and in stage 1B your score will be compared to the scores achieved by the other people who chose Option 2. However, unlike in Option 1, there is a possibility that you might be **eligible for buying a free pass**. A free pass means that the computer will put you in the **GREEN group** even if you are not a top 75% performer. In this case you would simply replace an actual top 75% performer. However, this person would never be informed about this. The computer would merely tell him/her that he/she has ended up in the **RED group**.

Note that not everybody is eligible for a free pass. Who is and who is not eligible is determined by the computer after everybody has chosen between Option 1 and Option 2. The computer is programmed to make **half of the people in Option 2** eligible for a free pass. Thus, no matter how many people choose Option 2 there is a 50-50 chance that you are eligible.

For a chance to buy the free pass you must click the "Apply for free pass" button. If you do that and it turns out that you **ARE** eligible, the computer will give you the free pass and you are now guaranteed a place in the **GREEN group**. However, in this case the computer will also subtract the **free pass FEE of 50 points** from your balance!

If it turns out that you are NOT eligible, or if you do not apply for a free pass in the first place, there is no fee for you to pay.

So, the timing of Option 2 is as follows:

1. The computer checks how many people have chosen Option 2 and makes half of them eligible for a free pass.
2. Everybody in Option 2 individually decides whether or not to apply for a free pass.
3. Those who do apply for a free pass, will now (depending on their eligibility) either receive their free pass and pay the 50-point fee, or will proceed without a free pass and without having to pay the fee. Those who do not apply for a free pass proceed as normal (no fee).
4. **Stage 1A:** You play the find-the-numbers game. Of course, if you have the free pass, your performance will not matter. You will be in the **GREEN group** for sure.
5. **Stage 1B:** When calculating the ranking the computer will treat those with a free pass as if they had outperformed everyone else, regardless of their actual performance. All others will be ranked behind the free pass holders according to their actual scores. The top 75% performers in this modified ranking list will be put into the **GREEN group**. This includes all free pass holders and the best performers without a free pass. The remaining 25% with the lowest score will be

put into the **RED group**.]

[*Meritocracy Treatment:* Option 2 has the same stage 1A and stage 1B as Option 1, and in stage 1B your score will be compared to the scores achieved by the other people who chose Option 2.]

If you end up in the **RED group**, you will receive 200 points for participating in Option 2. There is nothing else for you to do right now. Please wait for further instructions. If you end up in the **GREEN group**, you will now continue with stage 2.

Stage 2: Authorizing a money transfer

Remember that you will enter this stage only if you are in the **GREEN group**. If you reach this stage, you will receive 500 points. Stage 2 of Option 2 is very different from Stage 2 of Option 1. It involves two players who assume different roles. **Your role will be that of Player A.**

The other role of **Player B** will be assumed by another participant in the experiment. This other participant has completed Part 1 of today's experiment but will not be asked to make a choice between Option 1 and Option 2, and will not participate in Stage 1. Who takes on the role of Player B is determined randomly by the computer. However, the computer will ensure that player B and person X from Option 1 are **NOT** the same person.

Player B is guaranteed a payoff of 200 points for part 2 of today's experiment. On top of that, he/she is eligible to receive an ADDITIONAL amount of 200 points. However, these additional points will be paid out to him/her **only if they are authorized by Player A** (your role).

To make the authorization decision the computer will ask Player A to enter a "demand" (any number between 0 and 200 points) as a compensation for giving the authorization. Let's call this number X. If Player A enters a demand of X=0 point, he/she authorizes the transfer unconditionally. If Player A enters a demand X>0, then the transfer will only be authorized if Player B accepts the demand and pays Player A the X points.

To determine Player B's decision the computer will ask Player B to indicate the **MAXIMUM** number of points he/she is willing to pay for the authorization even before Player B learns how much Player A actually demands. If Player B is willing to pay X points or more, then the transfer is authorized and Player A obtains the X additional points, while Player B receives 200-X points. If Player B's willingness to pay is lower than X points, then the transfer is **NOT** authorized. In this case both Player A and

Player B receive 0 points.

Stage 3: Generating points for everyone

In this stage, all participants who selected Option 2 (not including Player B) are invited to work on the find-the-numbers game again to generate additional points **for everyone**. This works as follows. As before, each person works for 3 minutes. When the 3 minutes are over, the computer will calculate the **average find-the-numbers score** achieved by the Option 2 participants. Then, it will do the following calculation.

Table A.13.: Generating points for everyone

	2 x Average score achieved
+	10
-	0.1 x Average demand ("X") made in Stage 2
=	**Extra points per person**

All participants in today's experiment (all Option 1 choosers, all Option 2 choosers, person X and Player B) will individually receive these extra points on top of any other earnings they have achieved in part 2.

Figure A.12.: Summary of Meritocracy Treatment

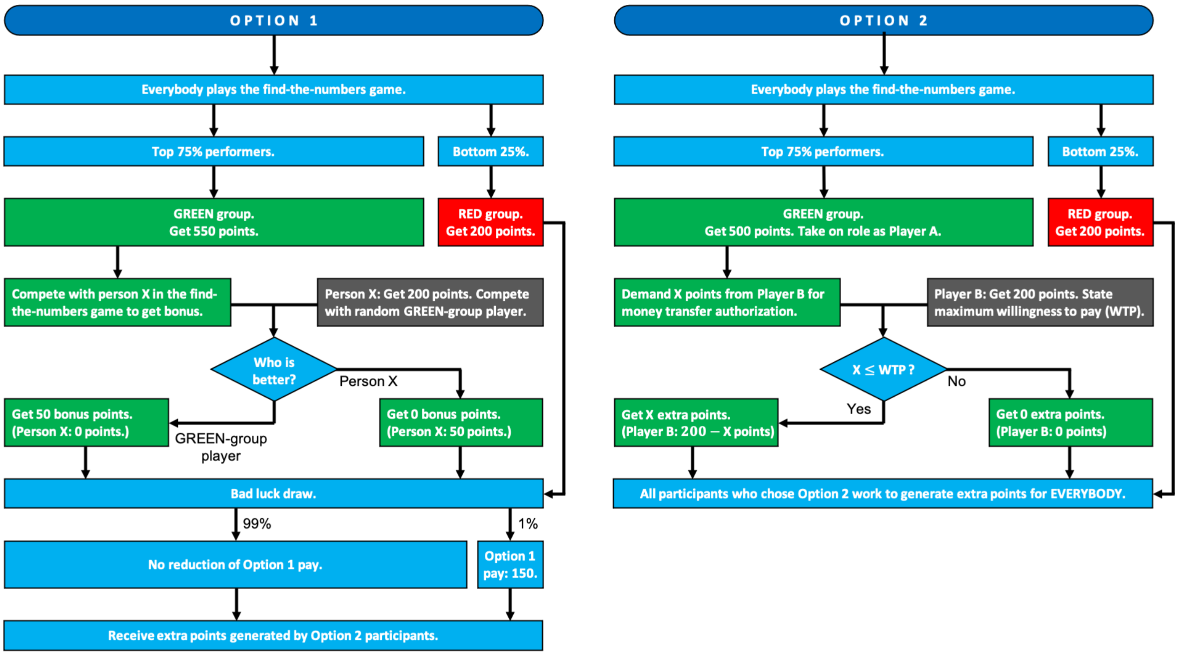
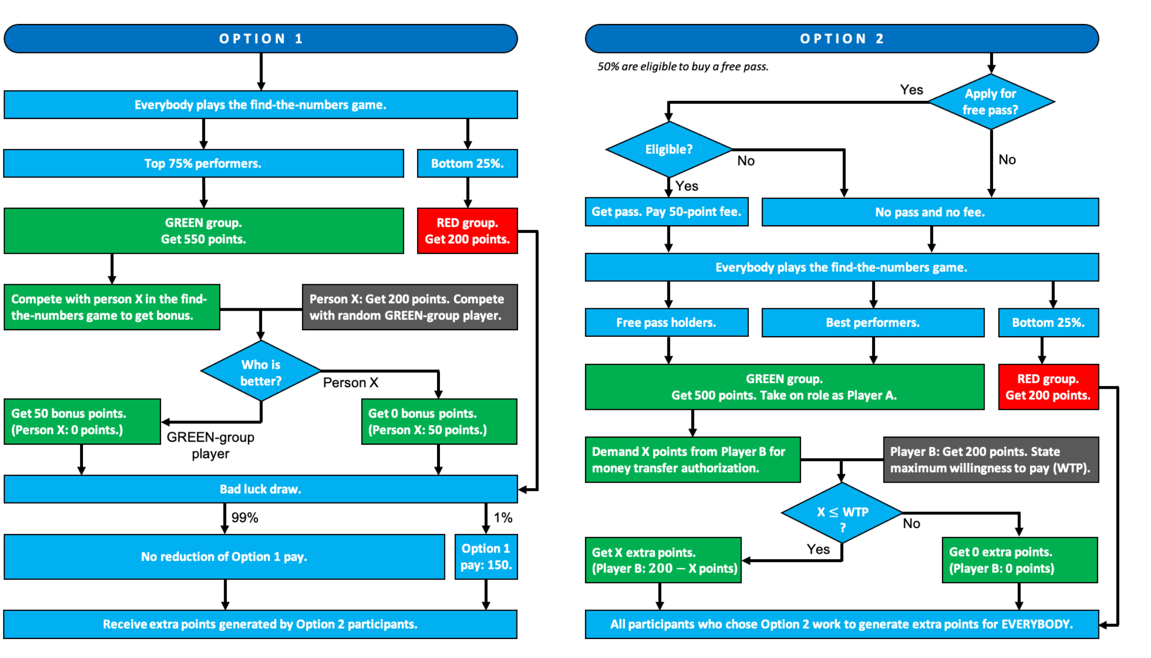


Figure A.13.: Summary of Bribery Treatment



B. Appendix to Chapter 2

B.1. Additional results

Table B.1.: Demographic attributes of participants by treatments

	Baseline	Verification	Reaction	Reporting
Male	65%	61%	64%	60%
Age				
18-30	28%	25%	19%	25%
31-59	67%	71%	78%	70%
60+	5%	4%	3%	5%
Education				
No or other academic title	12%	16%	14%	12%
Bachelor degrees	66%	57%	62%	62%
Post graduate degrees	22%	27%	24%	26%
Nationality				
US	98%	93%	92%	96%
Non-US	2%	7%	8%	4%
Observations	216	190	190	218

Table B.2.: Cheat rates and average reported dies by treatments in Round 2

	Baseline	Verification	Reaction	Reporting
Report die	4.22	3.77	3.91	4.17
	(1.72)	(1.87)	(1.78)	(1.90)
True die	3.74	3.20	3.36	3.61
	(1.72)	(1.78)	(1.79)	(1.87)
Share of cheating	16%	15%	18%	18%
Observations	108	95	95	114

Notes: Standard deviations are in parentheses.

Figure B.1.: Verification share based on reported states in Round 2 by treatments

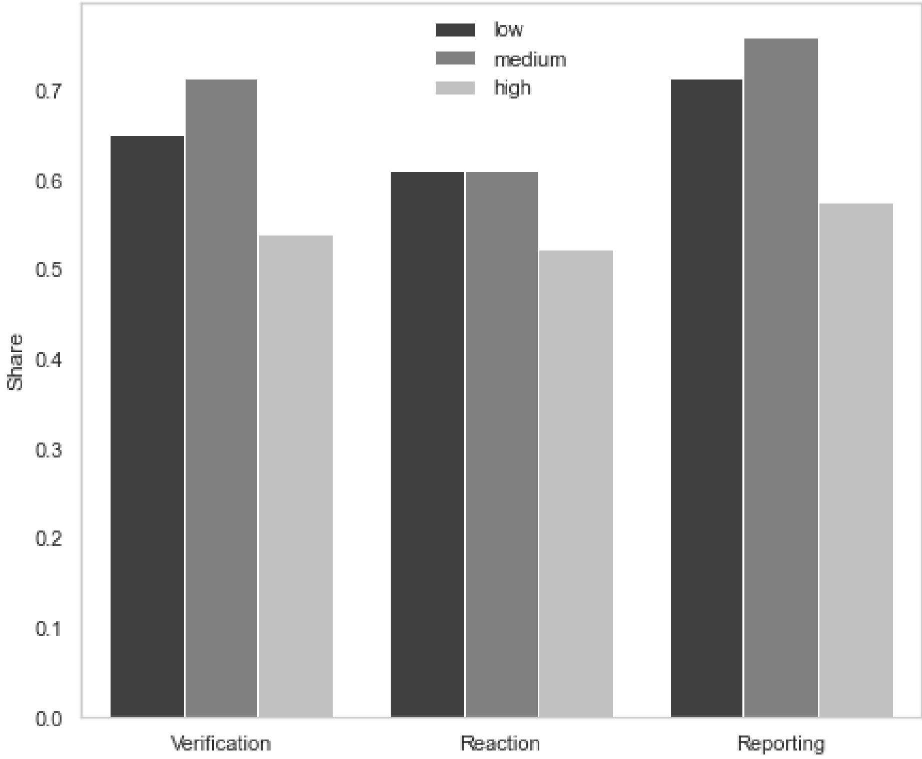
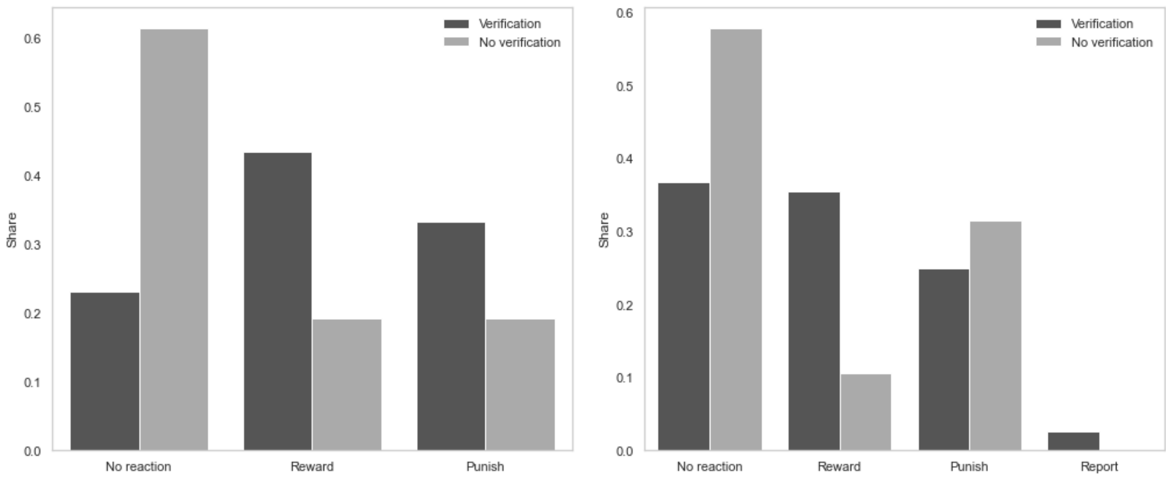


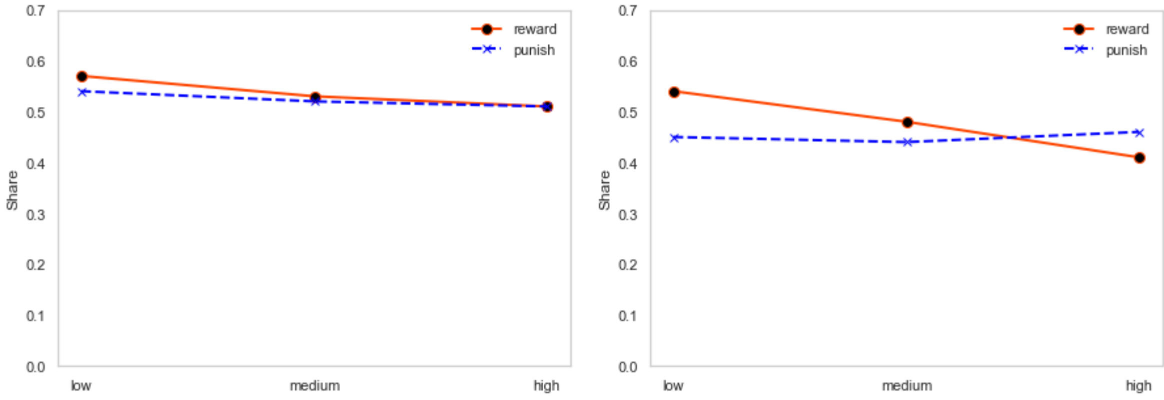
Figure B.2.: Reaction shares by verification decisions



(a) Reaction treatment

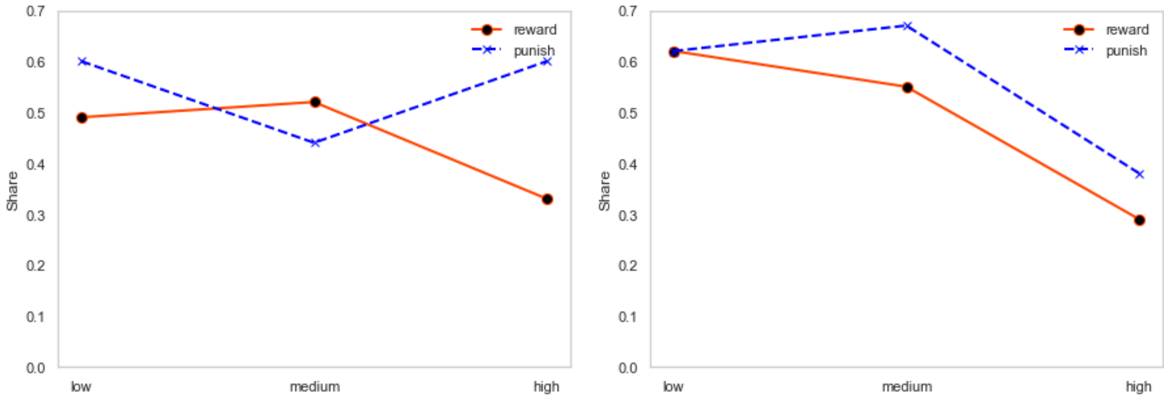
(b) Reporting treatment

Figure B.3.: Ratio of points to payoff in Round 1



(a) Reaction treatment (b) Reporting treatment

Figure B.4.: Ratio of points to payoff in Round 2



(a) Reaction treatment (b) Reporting treatment

Table B.3.: Mean points of reward and punishment in Round 2

	Reaction			Reporting			
	No reaction	Reward	Punishment	No reaction	Reward	Punishment	Report
Share	44%	27%	29%	45%	25%	25%	5%
Mean	–	4.54	5.37	–	4.53	5.89	–
		(3.92)	(5.08)		(4.16)	(4.41)	

Notes: Standard deviations are in parentheses.

Table B.4.: Effects of individual characteristics on honesty in Round 1

	Honesty			
	Baseline	Verification	Reaction	Reporting
Male	-0.416	-0.733	-0.397	-0.251
	(0.655)	(0.720)	(0.930)	(0.549)
Age	0.011	0.010	0.021	0.042
	(0.031)	(0.031)	(0.045)	(0.032)
Education	-0.135	1.064*	0.531	1.139**
	(0.419)	(0.549)	(0.667)	(0.519)
Risk preferences	0.214*	0.011	0.200	-0.239**
	(0.118)	(0.129)	(0.156)	(0.121)
Intercept	0.559	0.922	0.066	0.658
	(1.498)	(1.697)	(2.232)	(1.364)
Observations	108	95	95	114
Pseudo R^2	0.048	0.092	0.071	0.092

Notes: This table displays the Logistic estimates of the relationships between honesty and individual characteristics. The dependent variable is *honesty* which takes a value of 1 if an actor reports the true state of the die roll in round 1 and 0 otherwise. Standard errors are in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Table B.5.: Emotions of actors by treatments

	Baseline	Verification	Reaction	Reporting
Accomplished	4.72	5.00	4.29	4.37
	(1.76)	(1.51)	(1.69)	(1.84)
Self-worthy	4.77	4.73	4.45	4.32
	(1.70)	(1.67)	(1.77)	(1.87)
Guilty	3.00	3.29	2.91	2.89
	(1.93)	(2.09)	(1.93)	(2.09)
Blame-worthy	3.19	3.41	3.32	2.86
	(2.09)	(2.04)	(2.03)	(2.08)
Bad	2.83	3.04	3.00	2.66
	(1.89)	(2.01)	(2.07)	(2.02)
Humiliated	3.19	3.43	3.55	2.89
	(2.03)	(2.05)	(2.12)	(2.12)
Observations	108	95	95	114

Notes: Standard deviations are in parentheses.

Table B.6.: Pairwise correlations between actors' indicators of emotions

	Accomplished	Self-worthy	Guilty	Blame-worthy	Bad	Humiliated
Accomplished	1	.	.	.	.	.
Self-worthy	0.512	1	.	.	.	.
Guilty	0.305	0.281	1	.	.	.
Blame-worthy	0.289	0.272	0.845	1	.	.
Bad	0.297	0.266	0.816	0.830	1	.
Humiliated	0.318	0.275	0.715	0.772	0.762	1

Table B.7.: Emotions of beneficiaries by treatments

	Baseline	Verification	Reaction	Reporting
Admiring	4.13	4.49	4.42	4.18
	(2.00)	(2.01)	(1.93)	(1.89)
Grateful	4.32	4.86	4.64	4.29
	(1.85)	(1.94)	(1.88)	(1.93)
Disgusted	2.75	3.00	3.11	2.79
	(2.00)	(2.22)	(2.17)	(1.99)
Disappointed	3.07	3.05	2.79	3.01
	(2.02)	(2.04)	(1.83)	(2.08)
Observations	108	95	95	114

Notes: Standard deviations are in parentheses.

Table B.8.: Pairwise correlations between beneficiaries' indicators of emotions

	Admiring	Grateful	Disgusted	Disappointed
Admiring	1	.	.	.
Grateful	0.704	1	.	.
Disgusted	0.365	0.297	1	.
Disappointed	0.023	-0.043	0.628	1

Figure B.5.: Reaction in case of no verification in the Reaction treatment

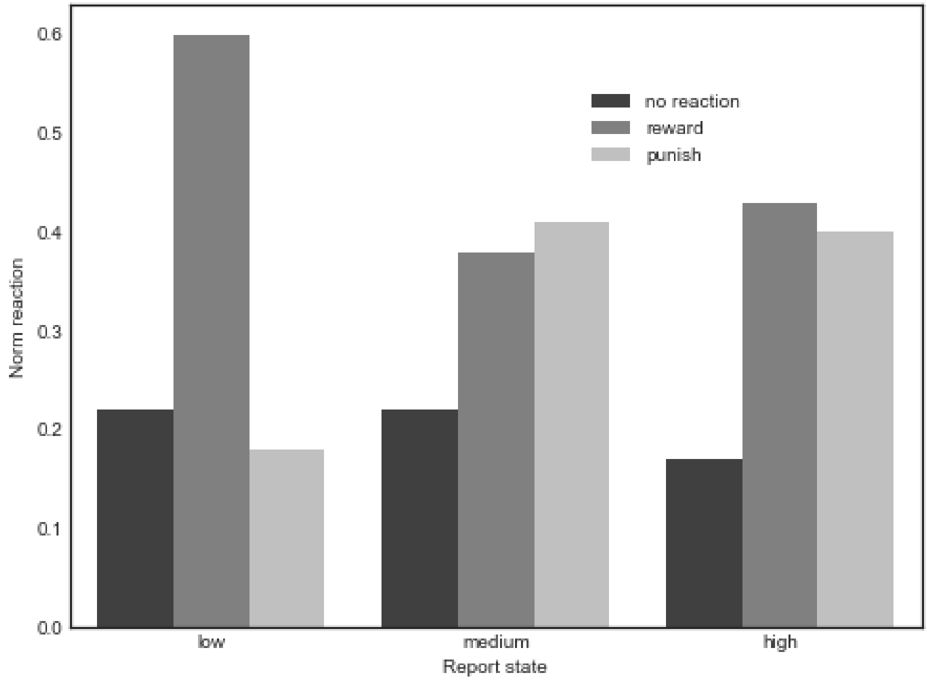
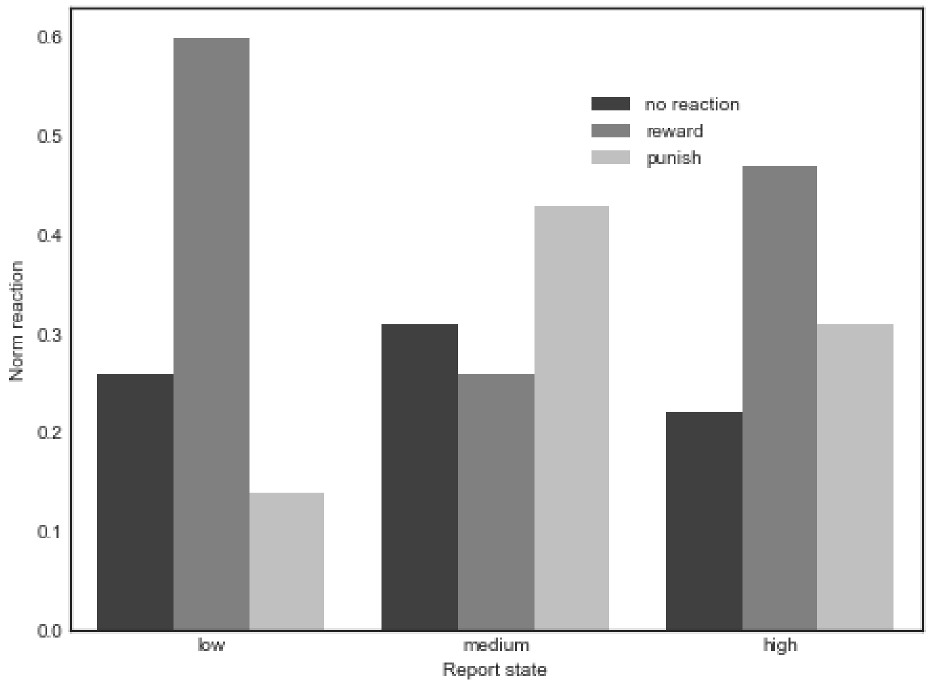


Figure B.6.: Reaction in case of no verification in the Reporting treatment



B.2. Instructions of the main experiment

Welcome

Welcome and thank you for participating! In this HIT you will perform a task during which you can earn “points”. The points you earn will be converted to $ at an exchange rate of **$0.03** per point and be paid to you at the end of the study. Your point earnings will depend on your decisions, on other participants’ decisions and on a bit of luck. How this all works and how much you can earn will be explained in the following—thus, **please follow the instructions carefully**.

In addition to the points you earn, you will receive **$0.80** for completing the HIT.

Charity

After this survey, we will make a donation to UNICEF. How much will be donated will depend on how you and others decide in the following tasks. In this HIT you will be matched with one other participant. At the end of the HIT 1/3 of all groups will be selected randomly and the charity will receive the sum of donations that was generated by these selected groups.

UNICEF supports programs through fundraising, advocacy and education that provide lifesaving medicines, better nutrition, clean water, quality basic education and emergency relief to children, women and communities in over 190 countries and territories. The charity partners with voluntary agencies engage in child relief to create a better world for children.

Instructions of Round 1

In this HIT you will be matched with another participant. One of you will be **Person A** and the other one will be **Person B**. You will interact with each other in **two rounds** in which you can earn points. At the end of the study, the sum of your points in both rounds will be converted to $ and paid out. If the sum of the two rounds is negative, you will just receive the $0.80 for completing the HIT.

In Round 1, Person A will roll a digital die and report the outcome of the die roll. This generates payoff for Person A, Person B and UNICEF. How much payoff is generated depends on the outcome of the die and the report of Person A.

The die is a digital six-sided die, on which each number has the same chance to be rolled. We define three states based on the outcome of the die:

- Rolling a 1, 2 or 3 is a **low state**

- Rolling a 4 or 5 is a **medium state**
- Rolling a 6 is a **high state**

The number of points for Person A and B are lowest if a low state is reported and highest if a high state is reported. The number of points for UNICEF depends on the true outcome of the die roll. If the reported state is higher than the true state, UNICEF receives fewer points than if the true state is reported. Please see below the full payoff table.

Table B.9.: Payoff allocation

True state	Report state	Payoff to Person A	Payoff to Person B	UNICEF
Low	Low	10 points	5 points	50 points
	Medium	20 points	10 points	35 points
	High	40 points	20 points	5 points
Medium	Low	10 points	5 points	50 points
	Medium	20 points	10 points	50 points
	High	40 points	20 points	20 points
High	Low	10 points	5 points	50 points
	Medium	20 points	10 points	50 points
	High	40 points	20 points	50 points

If Person A does **not** report the **true** state, a lottery will be played at the end of the round.

- With a 10% chance the **charity outcome** occurs and Person A's points for this round will be reduced by 40% and the points taken from Person A will be given to UNICEF. In addition, all points to Person A and B in the payoff table of Round 2 will be reduced by 20%.
- With a 90% chance the charity outcome **does not** occur. The points of Round 1 remain unchanged, and the payoff table of Round 2 will be the same as in Round 1.

[*Verification treatment:* Before the lottery is played out, Person B has to decide whether to learn the true state of the die or not. If Person B decides to learn the true state, it will be shown to Person B on the next screen.]

[*Reaction treatment:* Before the lottery is played out, Person B will observe the reported state and has to make two decisions.

First, Person B has to decide whether to **learn the true state or not**. If Person B decides to learn the true state, it will be shown to Person B on the next screen.

Second, Person B decides whether to **react to the choice of Person A**. Person B has the following options:

- No reaction: If Person B decides not to react, the round proceeds with the lottery as described above.
- Give points: To do so, Person B gives up his/her own points to increase the points of Person A. Giving up 1 point of the own payoff increases Person A's payoff by 2 points.
- Take points: To do so, Person B gives up his/her own points to decrease the points of Person A. Giving up 1 point of the own payoff decreases Person A's payoff by 2 points.]

[*Reporting treatment:* Before the lottery is played out, Person B will observe the reported state and has to make two decisions.

First, Person B has to decide whether to **learn the true state or not**. If Person B decides to learn the true state, it will be shown to Person B on the next screen.

Second, Person B decides whether to **react to the choice of Person A**. Person B has the following options:

- No reaction: If Person B decides not to react, the round proceeds with the lottery as described above.
- Give points: To do so, Person B gives up his/her own points to increase the points of Person A. Giving up 1 point of the own payoff increases Person A's payoff by 2 points.
- Take points: To do so, Person B gives up his/her own points to decrease the points of Person A. Giving up 1 point of the own payoff decreases Person A's payoff by 2 points.
- Change lottery: This option is only available if Person B decided to learn the true state before and if Person A did not report the true state. If Person B changes the lottery, the chance of the charity outcome in the lottery is increased to 40%.]

Instructions of Round 2

Round 2 proceeds the same way as Round 1. The only difference is that if the charity outcome occurred in the lottery at the end of Round 1, the payoffs for the die roll will be different. The number of points for Person A and B are still lowest if a low state is reported and highest if a high state is reported. The number of points for UNICEF still depends on the true outcome of the die roll. If the reported state is higher than the true state, UNICEF receives fewer points than if the true state is reported. However, the absolute number of points is different. The following table shows payoffs if the charity outcome occurred in Round 1.

Table B.10.: Payoff table if the charity outcome occurred in Round 1

True state	Report state	Payoff to Person A	Payoff to Person B	UNICEF
Low	Low	8 points	4 points	50 points
	Medium	16 points	8 points	38 points
	High	32 points	16 points	14 points
Medium	Low	8 points	4 points	50 points
	Medium	16 points	8 points	50 points
	High	32 points	16 points	26 points
High	Low	8 points	4 points	50 points
	Medium	16 points	8 points	50 points
	High	32 points	16 points	50 points

As in Round 1, if Person A does not report the true state, a lottery will be played at the end of the round. With a 10% chance the **charity outcome** occurs and Person A's points for Round 2 will be reduced by 40% and the points taken from Person A will be given to UNICEF. With a 90% chance the charity outcome **does not** occur, and nothing happens.

[*Verification treatment (or Reaction treatment or Reporting Treatment):* Before the lottery is played out, Person B has the same reaction options as in Round 1.]

Questionnaires

Please answer a few more questions. This will only take a moment and you'll receive your survey code right after these last questions.

If someone gives you a chance to choose between the following two options, which one will you choose?

- Option A: I will give you €10 if a fair coin lands head, and €2 otherwise.
- Option B: I will give you €5.
- These two options are really indifferent to me.

If participants choose Option A, they will be asked the following question. If someone gives you a chance to choose between the following two options, which one will you choose?

- Option A: I will give you €10 if a fair coin lands head, and €2 otherwise.
- Option B: I will give you €6.
- These two options are really indifferent to me.

If participants choose Option B, they will be asked the following question. If someone gives you a chance to choose between the following two options, which one will you choose?

- Option A: I will give you €10 if a fair coin lands head, and €2 otherwise.
- Option B: I will give you €4.
- These two options are really indifferent to me.

Imagine the following situation: you won €1000 in a lottery. Considering your current situation, how much would you give to others (for example: family, friends, charity, etc.)?

We are now asking you for your willingness to behave a certain way. Please state your evaluation on a scale from 0 to 10. 0 means "completely unwilling to do so" and 10 means "very willing to do so".

Please indicate, in general, how willing or unwilling you are to take risks?

0 1 2 3 4 5 6 7 8 9 10

How willing are you to return a favor that someone has done for you?

0 1 2 3 4 5 6 7 8 9 10

How willing are you to punish someone who treats **you** unfairly, even if there may be costs for you?

0 1 2 3 4 5 6 7 8 9 10

How willing are you to punish someone who treats **others** unfairly, even if there may be costs for you?

0 1 2 3 4 5 6 7 8 9 10

B.3. Instructions of norm elicitation

In the following we will show you the instructions of a survey that we call ORIGINAL survey and that was conducted on MTurk in February 2022. You will NOT participate in the ORIGINAL survey. Instead, we will ask you questions about the ORIGINAL survey. After you finish the HIT, one of the questions we ask you will be randomly selected. Your answer to the selected question will determine whether you receive the bonus of $1.20. We will explain the conditions of earning the bonus at the beginning of each question.

[Instructions of the original survey]

Descriptive norm

In the following you are asked to give a percentage prediction. For each question, you need to predict two different numbers (the third one will be filled in automatically to add up to 100). If one of these questions is selected for the bonus payment, the computer will in addition select one of the lines of the question. If your prediction in this line is within +/- 10% of the true percentage, you will receive the bonus.

Question 11: In your opinion, if the true state is low, what percentage of participants (on a scale from 0 to 100) will report a low state?

Question 12: In your opinion, if the true state is low, what percentage of participants (on a scale from 0 to 100) will report a medium state?

Question 13: In your opinion, if the true state is low, what percentage of participants (on a scale from 0 to 100) will report a high state?

Injunctive norm (part 1)

In the following, we will ask you **how appropriate** certain decisions are (i.e., consistent with moral or proper social behavior). If one of these questions is selected for the bonus payment, you will receive the bonus if your answer is also the **most common answer** of all participants today. Thus, your goal is to give the answer that the **majority of other participants** will choose.

Please state your evaluation on a scale from 1 to 4. 1 means “very inappropriate” and 4 means “very appropriate”.

Question 21: Suppose Person A observes a low state, how appropriate is it to report a low state?

Question 22: Suppose Person A observes a low state, how appropriate is it to report a medium state?

Question 23: Suppose Person A observes a low state, how appropriate is it to report a high state?

Injunctive norm (part 2)

In the following, we will ask you for the **most appropriate decision** in different situations (i.e., consistent with moral or proper social behavior). If one of these questions is selected for the bonus payment, you will receive the bonus if your answer is also the **most common answer** of all participants today. Thus, your goal is to give the answer that the **majority of other participants** will choose.

Please answer the following questions.

Question 31: Suppose Person A reports a low state and Person B does not verify. What is the most appropriate reaction? (no reaction, give points, take points)

Question 32: Suppose Person A reports a medium state and Person B does not verify. What is the most appropriate reaction? (no reaction, give points, take points)

Question 33: Suppose Person A reports a high state and Person B does not verify. What is the most appropriate reaction? (no reaction, give points, take points)

Question 41: Suppose Person A reports a low state and Person B verifies and finds out that the true state is low. What is the most appropriate reaction? (no reaction, give points, take points, change lottery)

Question 42: Suppose Person A reports a medium state and Person B verifies and finds out that the true state is low. What is the most appropriate reaction? (no reaction, give points, take points, change lottery)

Question 43: Suppose Person A reports a high state and Person B verifies and finds out that the true state is low. What is the most appropriate reaction? (no reaction, give points, take points, change lottery)

C. Appendix to Chapter 3

C.1. Proof of lemmas

Proof of Lemma 1:

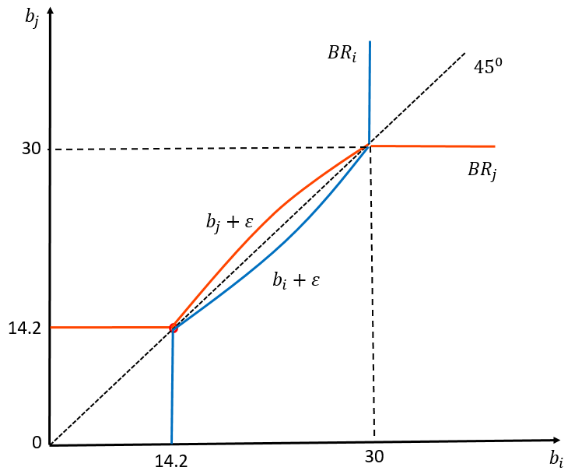
For simplicity, denote $c_j = 1$ and $c_i = c$. Thus, c represents the asymmetry in ability of players. Given that $e_1^* = \frac{Vc}{(c+1)^2}, e_2^* = \frac{V}{(c+1)^2}$, total effort can be written as $e = e_1^* + e_2^* = \frac{V}{c+1}$. Taking the first order condition of e with respect to c yields $-\frac{V}{(c+1)^2}$ which is smaller than zero. This indicates that efforts decrease in the asymmetry in ability of players.

Proof of Lemma 2:

Given the expected payoff functions in section 3.3.2, I derive the best response functions in the symmetric contest for each player.

$$b_i = \begin{cases} 14.2 & \text{if } b_j < 14.2 \\ b_j + \varepsilon & \text{if } 14.2 \leq b_j < 30 \\ 30 & \text{if } b_j \geq 30 \end{cases} \text{ and } b_j = \begin{cases} 14.2 & \text{if } b_i < 14.2 \\ b_i + \varepsilon & \text{if } 14.2 \leq b_i < 30 \\ 30 & \text{if } b_i \geq 30 \end{cases}$$

Figure C.1.: Best response functions in the symmetric contest



In the following, I denote a superscript n as non-briber and b as briber. First, consider $\max\{b_i, b_j\} < 14.2$. Without loss of generality, assume that the offer of player i is accepted. The expected payoff of each player can be written as

$$\pi_i^b = 100 - b_i + 0.8 \cdot 100 \cdot \frac{(1+\frac{1}{9}b_i)^2}{(1+\frac{1}{9}b_i+1)^2}$$
$$\pi_j^n = 100 + 0.2 \cdot 100 + 0.8 \cdot 100 \cdot \frac{1}{(1+\frac{1}{9}b_i+1)^2}$$

Note that the briber gets a maximum payoff at $b = 14.2$, thus, he/she has an incentive to deviate upward. Thus, $\max\{b_i, b_j\} < 14.2$ is not an equilibrium.

Second, consider $14.2 \leq \max\{b_i, b_j\} < 30$. Without loss of generality, assume that the offer of player i is accepted. The expected payoff of each player can be written as

$$\pi_i^b = 100 - b_i + 0.8 \cdot 100 \cdot \frac{(1+\frac{1}{9}b_i)^2}{(1+\frac{1}{9}b_i+1)^2}$$
$$\pi_j^n = 100 + 0.2 \cdot 100 + 0.8 \cdot 100 \cdot \frac{1}{(1+\frac{1}{9}b_i+1)^2}$$

Note that $\pi^b > \pi^n$ for $b < 30$, thus, the non-briber has an incentive to deviate upward. Hence, $14.2 \leq \max\{b_i, b_j\} < 30$ is not an equilibrium.

Next, consider $\min\{b_i, b_j\} > 30$. At a bribe level $b > 30$, e.g. $b = 31$, the briber obtains a payoff of 122.3 which is smaller than a payoff of 122.81 at a bribe $b = 30$. Therefore, the briber has an incentive to deviate downward. This shows that $\min\{b_i, b_j\} > 30$ is not an equilibrium.

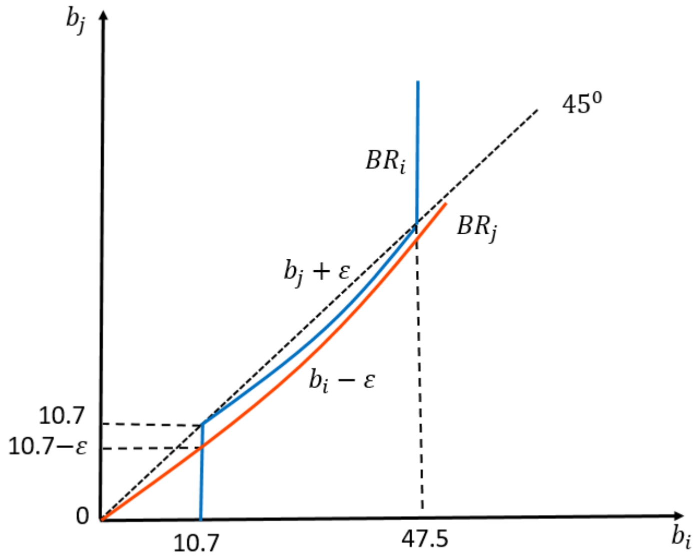
Finally, I prove that $b_i = b_j = 30$ is an equilibrium. This bribe level is obtained where both players are indifferent between bribing and not bribing. This yields a payoff of $\pi_i = \pi_j = 122.81$. On the one hand, given $b_i = 30$, if player j deviates to $b_j = 30 + \varepsilon$, ($\varepsilon > 0$, small enough), he/she obtains a payoff smaller than 122.81. Therefore, player j has no incentive to deviate upward. On the other hand, given $b_i = 30$, player j is indifferent between offering $b_j = 30$ and offering $b_j = 30 - \varepsilon$ ($\varepsilon > 0$) because he/she obtains the same payoff of 122.81. Therefore, player j has no incentive to deviate downward. A similar argument can be applied to player i. This indicates that $b_i = b_j = 30$ is the equilibrium bribe in the symmetric contest.

Proof of Lemma 3:

Given the expected payoff functions, I derive the best response functions in the asymmetric contest for each player.

$$b_i = \begin{cases} 0 & \text{if } b_j = 0 \\ 10.7 & \text{if } b_j < 10.7 \\ b_j + \varepsilon & \text{if } 10.7 \leq b_j < 47.5 \\ 47.5 & \text{if } b_j \geq 47.5 \end{cases} \quad \text{and } b_j = \begin{cases} 12.7 & \text{if } b_i = 0 \\ b_i - \varepsilon & \text{if } b_i > 0 \end{cases}$$

Figure C.2.: Best response functions in the asymmetric contest



Recall that player i is referred to the strong player and player j is referred to the weak player. First, consider $b_i = b_j = 0$. If no player offers any bribe, they get a payoff of $\pi_i = 144.44, \pi_j = 111.11$, respectively. Given that $b_i = 0$, player j can get a maximum payoff of 111.2 at a bribe $b_j = 12.7$. Therefore, player j has an incentive to deviate upward. Hence, $b_i = b_j = 0$ is not an equilibrium.

Second, consider $b_j \geq b_i > 0$. The expected payoff of player j when his/her bribe is accepted can be written as

$$\pi_j^b = 100 - b_j + 0.8 \cdot 100 \cdot \frac{(1 + \frac{1}{9}b_j)^2}{(1 + \frac{1}{9}b_j + 2)^2}$$

Note that player j can get a payoff of at most 111.2 which is smaller than when player j offers a lower bribe than player i. Therefore, player j has an incentive to deviate downward which proves that $b_j \geq b_i > 0$ is not an equilibrium.

Next, consider $0 \leq b_j < b_i < 10.7$. The expected payoff of player i can be written as

$$\pi_i^b = 100 - b_i + 0.8 \cdot 100 \cdot \frac{2^2(1 + \frac{1}{9}b_i)^2}{(2(1 + \frac{1}{9}b_i) + 1)^2}$$

Player i maximizes his/her expected payoff at the bribe of $b_i = 10.7$. Thus, he/she has an incentive to deviate upward which indicates that $0 \leq b_j < b_i < 10.7$ is not an equilibrium.

Then consider any $b_i > 10.7$. From above argument, the best response of player j is $b_j = 0$ when $b_i > 0$. The expected payoff of player i when his/her bribe is accepted can be written as

$$\pi_i^b = 100 - b_i + 0.8 \cdot 100 \cdot \frac{2^2(1 + \frac{1}{9}b_i)^2}{(2(1 + \frac{1}{9}b_i) + 1)^2}$$

Player i can get a maximum payoff of 142.31 at a bribe $b_i = 10.7$. Therefore, player i has an incentive to deviate downward which indicates that $b_i > 10.7$ is not an equilibrium.

Finally, I prove that $b_i = 10.7, b_j = 10.7 - \varepsilon$ for $\varepsilon \in (0, 10.7)$ is an equilibrium. The expected payoff of player i can be written as

$$\pi_i^b = 100 - b_i + 0.8 \cdot 100 \cdot \frac{2^2(1 + \frac{1}{9}b_i)^2}{(2(1 + \frac{1}{9}b_i) + 1)^2}$$

Solving the maximization problem yields a bribe level of $b_i = 10.7$ which gives player i a maximum payoff of 142.31 and player j a payoff of 122.74. Given $b_i = 10.7$, if player j offers $b_j \geq 10.7$, he/she gets a lower payoff than 122.74. Therefore, player j has no incentive to deviate upward. Given $b_i = 10.7$, player j is indifferent between offering $b_j = 10.7 - \varepsilon$ or offering $b_j = 10.7 - \varepsilon - \delta, \delta > 0$. Therefore, player j has no incentive to deviate downward. Given $b_j = 10.7 - \varepsilon > 0$, if player i offers $b_i < b_j$, he/she gets a payoff of at most 128.96. Therefore, player i has no incentive to deviate downward. Finally, given $b_j = 10.7 - \varepsilon > 0$, if player i offers $b_i > 10.7$, he/she gets a lower payoff than 142.31. Therefore, player i has no incentive to deviate upward. This completes the proof that $b_i = 10.7$ and $b_j = 10.7 - \varepsilon$ is the equilibrium bribe in the asymmetric contest.

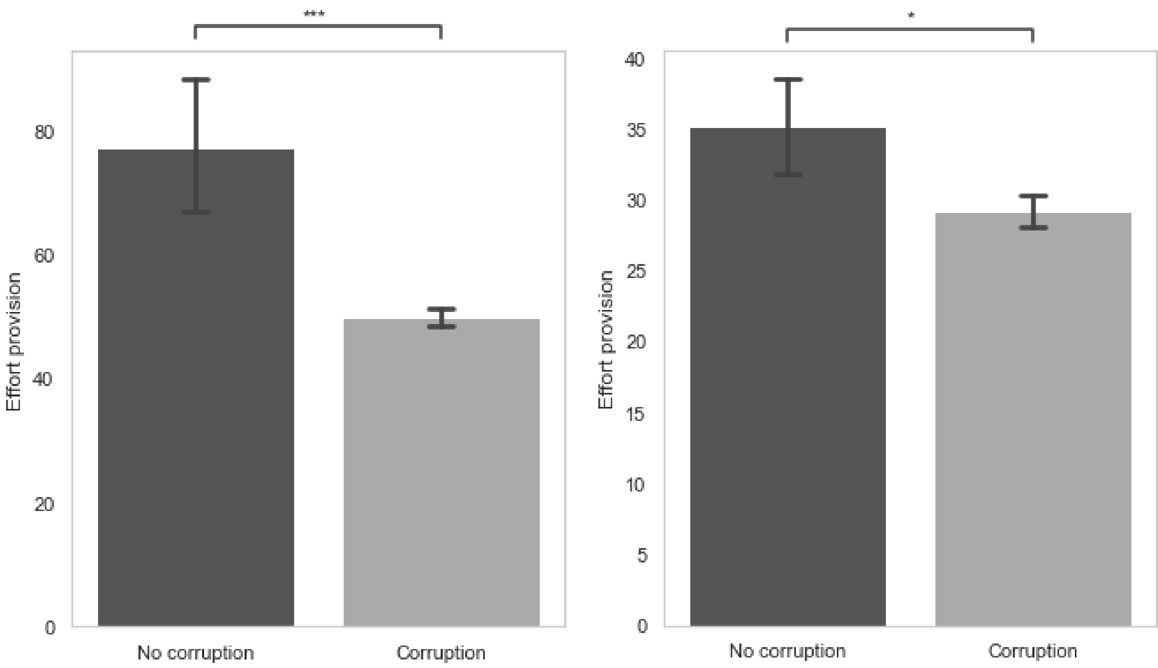
C.2. Additional results

Table C.1.: Balance of covariates

	Treatment			Symmetry vs Asymmetry
	Symmetry	Asymmetry	Pooled	P-value
Bribe level	22.277	10.812	16.545	0.000
	(3.620)	(3.636)	(1.638)	
Effort	63.167	38.774	50.971	0.000
	(2.935)	(2.845)	(2.275)	
Risk preferences	5.11	4.953	5.034	0.578
	(1.942)	(1.820)	(1.879)	
Prosocial preferences	28.802	17.837	23.319	0.000
	(22.954)	(19.739)	(22.041)	
Male	0.465	0.500	0.482	0.649
	(0.501)	(0.502)	(0.501)	
Age	23.651	24.00	23.825	0.105
	(7.528)	(4.799)	(6.297)	
Observations	86	86	172	–

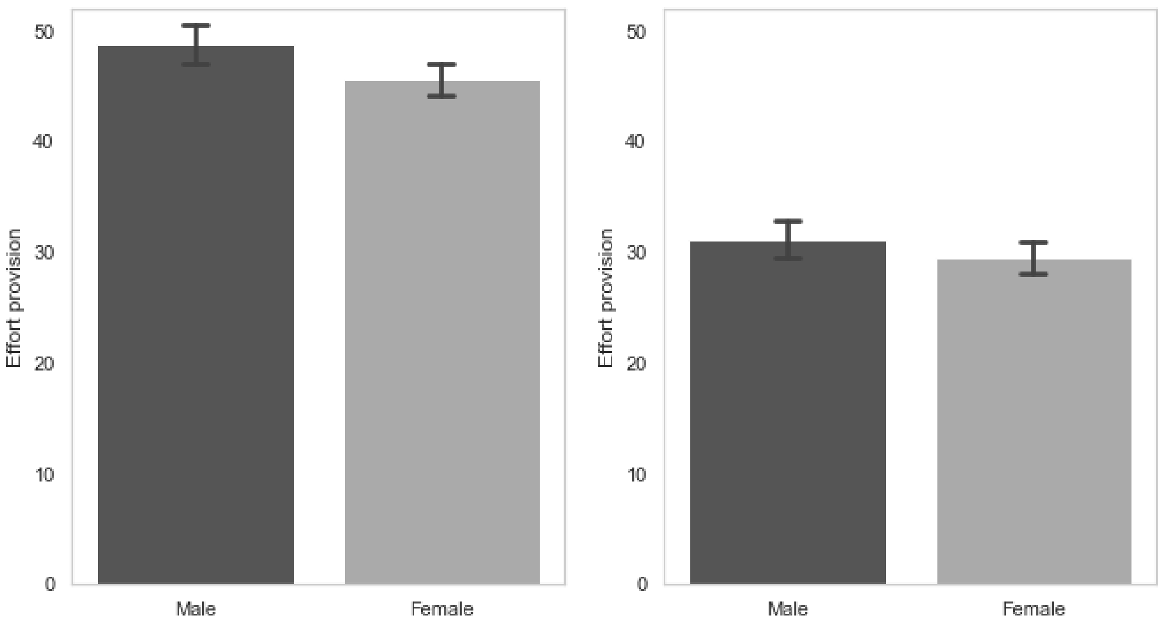
Notes: The table reports means and standard deviations of players' decisions and their characteristics as well as p-values for two-sided mean comparisons across treatments (Mann Whitney U test and proportion z-test).

Figure C.3.: Effort provision of groups with corruption and groups without corruption



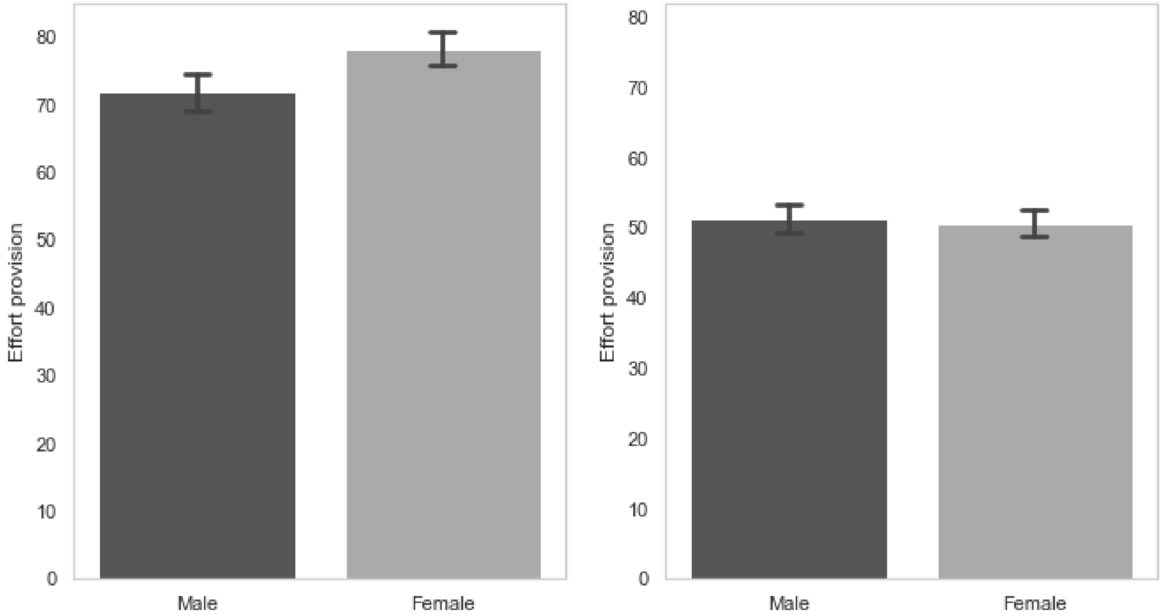
(a) SS-C treatment (b) AS-C treatment

Figure C.4.: Effort provision by gender in the asymmetric treatment



(a) AS-NC treatment (b) AS-C treatment

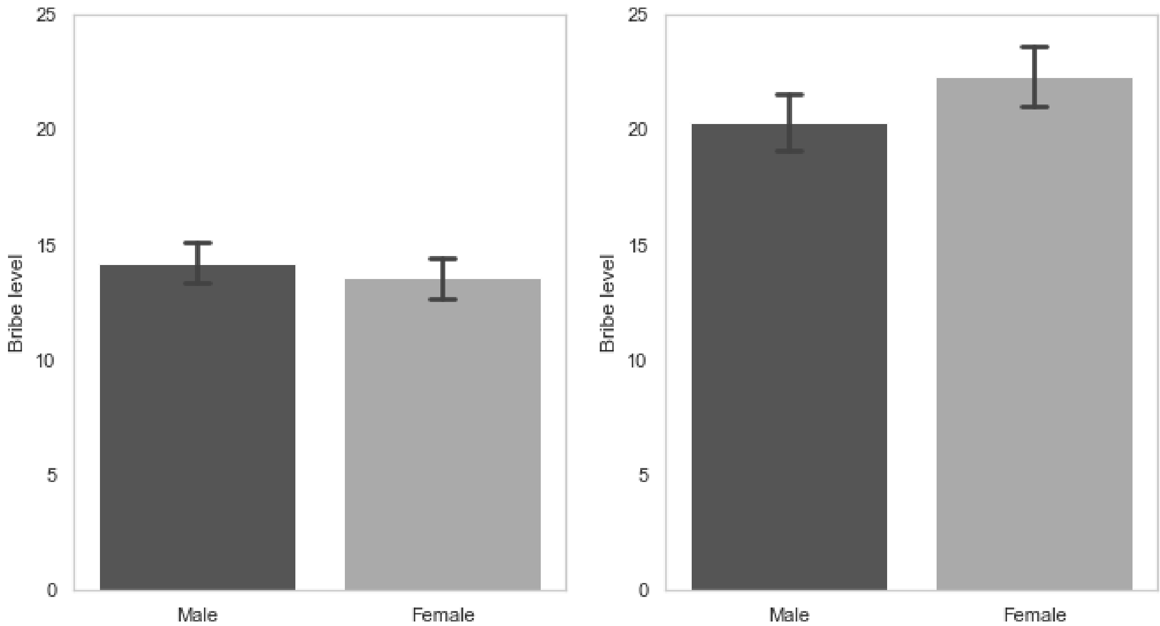
Figure C.5.: Effort provision by gender in the symmetric treatment



(a) SS-NC treatment

(b) SS-C treatment

Figure C.6.: Bribe levels by gender



(a) AS-C treatment

(b) SS-C treatment

Table C.2.: Regressions on determinants of effort provision in the contest with corruption

	Effort			
	SS-C	SS-C	AS-C	AS-C
	(1)	(2)	(3)	(4)
Bribe decision	-26.831***	-29.247***	-5.844***	-8.059***
	(5.337)	(5.489)	(1.742)	(1.907)
Bribe level		0.072*		0.105***
		(0.041)		(0.040)
Male	-3.349**	-3.354**	3.984***	3.391***
	(1.444)	(1.442)	(1.217)	(1.218)
Prosocial preferences	0.003	0.001	0.049*	0.051*
	(0.033)	(0.033)	(0.028)	(0.028)
Risk preferences	1.236***	1.157***	1.393***	1.396***
	(0.374)	(0.377)	(0.319)	(0.319)
Age	-0.084	-0.068	0.210	0.215**
	(0.095)	(0.095)	(0.106)	(0.105)
Intercept	73.985***	74.051***	20.232***	20.096***
	(5.967)	(5.964)	(3.904)	(3.894)
R^2	0.040	0.042	0.037	0.040
Observations	1720	1720	1720	1720

Notes: This table shows OLS regressions of determinants of effort provision in the contest with corruption (AS-C and SS-C treatment). The dependent variable is total effort in each group. The independent variables are bribe decision, bribe level and individuals' characteristics. Bribe decision is a binary variable which takes a value of 1 if at least one player offers a positive bribe and 0 otherwise. Bribe level is the accepted bribe offer. Robust standard errors are in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Table C.3.: Regressions on effort provision and individual characteristics in the contest with corruption

	Effort			
	AS-C			SS-C
	Aggregate	Strong player	Weak Player	Aggregate
	(1)	(2)	(3)	(4)
Male	4.133***	5.199***	0.273	-3.849***
	(1.231)	(1.375)	(0.723)	(1.474)
Prosocial preferences	0.061**	-0.054**	0.172***	0.023
	(0.028)	(0.026)	(0.025)	(0.033)
Risk preferences	1.348***	1.266***	1.011**	1.146***
	(0.318)	(0.316)	(0.203)	(0.378)
Age	0.215**	0.750***	-0.171***	-0.118
	(0.104)	(0.138)	(0.061)	(0.097)
Intercept	15.329***	-7.554**	7.310***	49.101***
	(3.431)	(3.756)	(2.146)	(3.037)
R^2	0.027	0.078	0.160	0.010
Observations	1720	860	860	1720

Notes: This table shows OLS regressions of relationships between individual characteristics and effort provision in the contest with corruption (AS-C and SS-C treatment). Model 1-3 employ data in the AS-C treatment, whereas model 4 analyses data in the SS-C treatment. In model 1 and model 4, the dependent variable is total effort in each group, whereas in model 2 and model 3 it is effort provided by a strong player and by a weak player, respectively. The independent variables are individuals' characteristics. Robust standard errors are in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Table C.4.: Regressions on effort provision and individual characteristics in the contest without corruption

	Effort			
	AS-NC			SS-NC
	Aggregate	Strong player	Weak Player	Aggregate
	(1)	(2)	(3)	(4)
Male	5.169***	8.680***	-2.097**	-7.662***
	(1.252)	(1.342)	(0.943)	(1.861)
Prosocial preferences	0.054*	-0.008	0.067**	0.051
	(0.033)	(0.032)	(0.028)	(0.046)
Risk preferences	0.352	-0.060	1.480***	4.140***
	(0.317)	(0.304)	(0.262)	(0.501)
Age	-0.499***	-0.683***	-0.326**	-0.418***
	(0.114)	(0.122)	(0.132)	(0.117)
Intercept	53.639***	43.196***	17.150***	66.439***
	(3.484)	(3.783)	(4.318)	(3.927)
R^2	0.023	0.065	0.076	0.057
Observations	1720	860	860	1720

Notes: This table shows OLS regressions of relationships between individual characteristics and effort provision in the contest without corruption (AS-NC and SS-NC treatment). Model 1-3 employ data in the AS-NC treatment, whereas model 4 analyses data in the SS-NC treatment. In model 1 and model 4, the dependent variable is total effort in each group, whereas in model 2 and model 3 it is effort provided by a strong player and by a weak player, respectively. The independent variables are individuals' characteristics. Robust standard errors are in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Table C.5.: Regressions on bribe decision and individual characteristics

	Bribe decision			
	AS-C			SS-C
	Aggregate	Strong player	Weak Player	Aggregate
	(1)	(2)	(3)	(4)
Male	-0.167	-0.006	-0.445***	0.330
	(0.132)	(0.153)	(0.162)	(0.267)
Prosocial preferences	-0.012***	-0.001	-0.018***	-0.017**
	(0.003)	(0.004)	(0.003)	(0.007)
Risk preferences	0.050	0.092**	0.154***	0.077
	(0.033)	(0.041)	(0.044)	(0.062)
Age	-0.005	0.030*	-0.030**	0.033
	(0.013)	(0.017)	(0.015)	(0.023)
Intercept	1.638***	-0.417	0.743	2.397***
	(0.382)	(0.457)	(0.464)	(0.662)
Pseudo R^2	0.011	0.007	0.042	0.025
Observations	1720	860	860	1720

Notes: This table shows Logistic regressions of relationships between individual characteristics and bribe decision in the contest with corruption (AS-C and SS-C treatment). Model 1-3 employ data in the AS-C treatment, whereas model 4 analyses data in the SS-C treatment. In model 1 and model 4, the dependent variable is bribe decision which takes a value of 1 if at least one player in a group offers a positive bribe and 0 otherwise, whereas in model 2 and model 3 it is a bribe decision of a strong player and of a weak player, respectively. The independent variables are individuals' characteristics. Standard errors are in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Table C.6.: Regressions on bribe level and individual characteristics

	Bribe level			
	AS-C			SS-C
	Aggregate	Strong player	Weak Player	Aggregate
	(1)	(2)	(3)	(4)
Male	-0.261	-1.194	-1.245	1.478*
	(1.018)	(0.918)	(1.074)	(1.409)
Prosocial preferences	-0.088***	-0.014	-0.080***	0.011
	(0.025)	(0.025)	(0.020)	(0.035)
Risk preferences	0.272	0.492**	0.680**	1.553***
	(0.257)	(0.116)	(0.271)	(0.374)
Age	-0.127	0.188	-0.030**	-0.255***
	(0.097)	(0.116)	(0.092)	(0.081)
Intercept	25.040***	4.757	10.516***	43.465***
	(2.970)	(3.088)	(2.992)	(2.877)
R^2	0.009	0.009	0.022	0.016
Observations	1720	860	860	1720

Notes: This table shows Logistic regressions of relationships between individual characteristics and bribe level in the contest with corruption (AS-C and SS-C treatment). Model 1-3 employ data in the AS-C treatment, whereas model 4 analyses data in the SS-C treatment. In model 1 and model 4, the dependent variable is a total bribe in each group, whereas in model 2 and model 3 it is a bribe level of a strong player and of a weak player, respectively. The independent variables are individuals' characteristics. Robust standard errors are in parentheses. *p<0.10, **p<0.05, ***p<0.01.

C.3. Experimental instructions

Welcome

Welcome and thank you for participating! In this experiment you will perform a task during which you can earn "points". The points you earn will be converted to Euros at an exchange rate of €0.06 per point and be paid to you at the end of the experiment. Your point earnings will depend on your decisions, on other players' decisions and on a bit of luck. How this all works and how much you can earn will be explained in the following—thus, **please follow the instructions carefully**.

The experiment will consist of two parts and each part will consist of 20 rounds. At the end of each part ONE round will be selected at random and you will be paid based on the total earning points in these two selected rounds. At the beginning of each round of each part you will be matched with one other player, randomly selected from participants in this experiment.

Part 1

Participants form groups of two in which one participant takes the role of **Player A** and the other participant takes the role of **Player B**. Your role will remain unchanged throughout the experiment. Part 1 will be repeated for 20 rounds and each round will proceed as follows. You and the player you are matched with will start each round with an account balance of **100 points** each and compete for a prize of **100 points**.

Decision task

[*Symmetric treatment:* Player A and Player B decide how many **contest tokens** to buy. **Each contest token costs Player A 1 point** and Player A can buy up to 100 contest tokens. **Each contest token costs Player B 1 point** and Player B can buy up to 100 contest tokens. Any points that have not been spent on the contest tokens will remain in your points balance.]

[*Asymmetric treatment:* Player A and Player B decide how many **contest tokens** to buy. **Each contest token costs Player A 1 point** and Player A can buy up to 100 contest tokens. **Each contest token costs Player B 2 points** and Player B can buy up to 50 contest tokens. Any points that have not been spent on the contest tokens will remain in your points balance.]

Determining the winner of the prize

After everyone has made the decision, the computer will calculate the total number of contest tokens bought by you and the other player and then **draw one contest token at random**. Each contest token has an equal chance of being selected. **The owner of the selected contest token will be the winner of the prize.**

If no one buys any contest tokens, no one will win the prize. Otherwise, your chance of winning the prize will be equal to your contest tokens divided by the total contest tokens bought by you and the other player.

$$\text{your chance of winning} = \frac{\text{your contest tokens}}{\text{your contest tokens} + \text{the other player's contest tokens}}$$

Thus, your chance of winning the prize increases in the number of contest tokens you buy and decreases in the number of contest tokens that the other player buys.

Example

1. If you buy 20 contest tokens and the other player buys 20 contest tokens, the total number of contest tokens is 40. Your chance of winning is $\frac{20}{20+20} = 50\%$ and the other player's chance of winning is $\frac{20}{20+20} = 50\%$.
2. If you buy 30 contest tokens and the other player buys 10 contest tokens, the total number of contest tokens is 40. Your chance of winning is $\frac{30}{30+10} = 75\%$ and the other player's chance of winning is $\frac{10}{10+30} = 25\%$.
3. If you buy 10 contest tokens and the other player buys 30 contest tokens, the total number of contest tokens is 40. Your chance of winning is $\frac{10}{10+30} = 25\%$ and the other player's chance of winning is $\frac{30}{30+10} = 75\%$.

Determining payoffs

If you **win** the prize, 100 points will be added to your points balance. Therefore, in this case:

$$\text{your points balance} = 100 \text{ - the number of points you spent on contest tokens} \\ + 100$$

If you **do not win** the prize, no points will be added to your points balance. Therefore, in this case:

$$\text{your points balance} = 100 \text{ - the number of points you spent on contest tokens}$$

Part 2

Participants form groups of two in which one participant takes the role of **Player A** and the other participant takes the role of **Player B**. Your role remains the same as in Part 1. Part 2 will be repeated for 20 rounds and each round will proceed as follows.

Part 2 will be very similar to Part 1. However, there will be one big difference: in each round of Part 2, participants are asked to make an additional decision (Decision 1) before moving to Decision 2 which is similar to Part 1. You and the player you are matched with will start each round with an account balance of **100 points** each and compete for a prize of **100 points**.

Decision 1

Player A and Player B decide whether they would like to buy **lottery tokens**. If a player would not like to buy, he/she will move to Decision 2. Otherwise, the player has to decide how many lottery tokens to buy. **Each lottery token costs each player 1 point**. In each round **only one player who would like to buy a higher number of lottery tokens is allowed to buy them**.

The player who is allowed to buy receives the lottery tokens and pays the cost. Any points that are not used to buy the lottery tokens are kept in the player's points balance. The player who is not allowed to buy receives no lottery tokens and does not have to pay. If two players would like to buy the same number of lottery tokens, the computer will randomly select the player to buy the lottery tokens. Lottery tokens bought in Decision 1 are used in Decision 2, as is explained below. At the end of Decision 1, the computer will show the number of lottery tokens, points balance that each player has. Then players will make Decision 2.

Decision 2

Decision 2 is similar to Part 1 of the experiment except the following differences. First, the endowment to buy contest tokens is the remaining points balance after Decision 1. Second, a player's total tokens are calculated as follows.

$$\text{your total tokens} = \left(1 + \frac{1}{9} \cdot \text{lottery tokens}\right) \cdot \text{contest tokens}$$

If a player has acquired lottery tokens in Decision 1, an additional lottery is played at the end of the contest. With a 20% chance the player who has lottery tokens loses the prize and the other player wins the prize. Otherwise, the contest winner is determined as in Part 1.

Example

1. If you have 6 lottery tokens in Decision 1 and you buy 10 contest tokens in Decision 2 and the other player has 0 lottery token in Decision 1 and buys 20 contest tokens in Decision 2, your total tokens are $6 \cdot 10 = 60$ and the other player's total tokens are 20. The total number of tokens is 80. An additional lottery will be played. With a 20% you will lose the prize and the other player will win it. Otherwise, your chance of winning is $\frac{60}{60+20} = 75\%$ and the other player's chance of winning is $\frac{20}{60+20} = 25\%$.
2. If you have 0 lottery token in Decision 1 and you buy 10 contest tokens in Decision 2 and the other player has 6 lottery tokens in Decision 1 and buys 20 contest tokens in Decision 2, your total tokens are 10 and the other player's total tokens are $6 \cdot 20 = 120$. The total number of tokens is 130. An additional lottery will be played. With a 20% chance you will win the prize and the other player will lose it. Otherwise, your chance of winning is $\frac{10}{10+120} = 7.7\%$ and the other player's chance of winning is $\frac{120}{10+120} = 92.3\%$.
3. If no one has any lottery tokens in Decision 1, then no additional lottery will be played. If you buy 20 contest tokens and the other player buys 10 contest tokens in Decision 2, the total tokens are 30. Your chance of winning is $\frac{20}{20+10} = 66.7\%$ and the other player's chance of winning is $\frac{10}{20+10} = 33.3\%$.

Determining payoffs

If you **win** the prize, 100 points will be added to your points balance. Therefore, in this case:

your points balance = 100 - the number of lottery tokens (if you have)
- the number of points you spent on contest tokens + 100

If you **do not win** the prize, no points will be added to your points balance. Therefore, in this case:

your points balance = 100 - the number of lottery tokens (if you have)
- the number of points you spent on contest tokens

Questionnaires

Please answer a few more questions. This will only take a moment and you'll receive your payment code right after these last questions.

Please state your evaluation on a scale from 0 to 10. 0 means "completely unwilling to do so" and 10 means "very willing to do so". Please indicate, in general, how willing or unwilling you are to take risks?

0 1 2 3 4 5 6 7 8 9 10

Imagine the following situation: you won €100 in a lottery. Considering your current situation, how much would you give to others (for example: family, friends, charity, etc.)?

What is your gender?

How old are you?

What is your field of study?

What is your nationality?

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Curriculum Vitae

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Eidesstattliche Erklarung

Hiermit erkläre ich, dass ich die vorliegende Dissertation selbstständig angefertigt und die benutzten Hilfsmittel vollständig und deutlich angegeben habe.

Mannheim, den 10 Juli 2023

Dam Thi Anh