Three Essays on Unethical Behaviour and Deterrence Mechanisms in Contests

By

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Declaration

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I acknowledge the support I have received for my research through the provision of an Australian Government Research Training Program Scholarship.

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Abstract

This thesis consists of three self-contained essays. We study undesirable behaviors such as cheating and self-sabotaging in contests in a laboratory environment.

The first paper proposes a new anti-doping policy. In a conditional superannuation scheme, athletes have to pay a certain fraction of their proceeds from sports into a fund from which they can draw only well after their careers and if they have never been caught doping. Theoretically, this fund has two important advantages over conventional anti-doping policies such as bans and fines. It does not lose its deterrence effect when athletes approach the end of their careers (unlike bans), and it can deal with the widespread problem that drug cheats are often only found out much later when the detection technology has caught up with doping practices. We build a model of a dynamic sporting contest, implement it in the laboratory and compare the performance of our policy to that of traditional policies. Our policy compares favorably with respect to doping prevention and the quality of resulting sporting contests.

In the second paper, we study a tournament that rewards not only winners but also losers with extremely bad performance, which creates an incentive for underdogs to under-perform deliberately. Such a contest scheme is often employed to improve the long term competitive balance. We design two treatments, with or without the leaderboard, to investigate whether social status can reduce this self-sabotaging behaviour. The leaderboard of all participants' ranked performance is used as a proxy of social status. Our results show that underdogs respond to the monetary self-sabotaging incentives in contests. In addition, individuals tend to self-sabotage just enough when the leaderboard is displayed to everybody. Without the leaderboard, players self-sabotage more excessively. We conjecture that by achieving exactly the level of performance that gives the consolation prize, tankers in the leaderboard treatment want to signal that they understand the game well and they tanked to receive the consolation prize.

The third paper addresses an agency problem in a contest between two contestants, each with a manager. Individuals that are engaged in contests have strong incentives to cheat. Sanctions are designed to deter potential cheaters. Often other agents in the contestant's team (e.g., a coach of an athlete) or company (a manager of an R&D engineer) have a benefit from cheating and can influence on the cheating decision. If only the contestant is punished for cheating, an agency problem arises. We show theoretically, that extending the liability from the contestant to the manager reduces cheating only if fines are sufficiently high. Otherwise over-all cheating rate increases. Experimental tests confirm that for high fines joint liability is effective in reducing cheating, while predicted detrimental effect of joint liability when fines are low does not materialise.

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Chapter 1

Introduction

In economics it is generally accepted that a contest is a good mechanism to increase motivation and to improve productivity. While individuals have incentives to put forth greater effort in contests, they also have greater incentives to cheat if that is possible (Faravelli et al., 2015). Dishonesty in contests can take various forms. Almost all kinds of cheating in contests fall into one of two broad categories: “cheating to win” and “cheating to lose” (Preston and Szymanski, 2003). “Cheating to win” refers to contestants attempting to increase their relative performance artificially to get ahead. This could be athletes abusing drugs to improve athletic performance in professional sports or employees sabotaging co-workers when competing for promotion within a corporation.

Counter-intuitively as it is, “cheating to lose” means contestants under-performing deliberately in order to lose. This incentive problem is often created as a by-product of the need to maintain long term competitive balance. In major sports leagues, the draft order is determined by the inverse order of previous season’s standings, with the worst performing team receiving the first pick (or the largest probability to get the first pick if a draft lottery is used). This design gives teams that are not good enough to have a shot at the championship an incentive to “race to the bottom” by losing deliberately with the aim of improving their position in the draft. While perverse draft incentives are specific to professional sports, there are other domains where very bad performance is more beneficial than just bad performance. In the context of industrial policy, where governments intervene to support domestic industries, government handouts might increase with worse performance. In this case a deliberately bad firm performance might pay once the resulting subsidies are accounted for.

In reality, contests often suffer from agency problems that exacerbate the cheating incentives. A contestant is often paired up with an agent who assists the contestant in the contest. Think of an athlete and her coach in sports or a subordinate and her senior manager during a promotion period. In what follows we refer to this additional agent (i.e., coach, senior manager) as a manager. In a contestant-manager relationship, the contestant's cheating decision can be influenced by the manager. For example, a coach may ask an athlete to take illicit substances to boost performance, or a team doctor might inject an athlete with banned substances without her knowledge. A senior manager may suggest an investment banker to recommend inferior financial products for a higher commission in order to get promoted. Agency problems arise when the manager has some control over the cheating decision and manager's incentives differ from that of the contestant. Misaligned incentive often exists because the manager's remuneration package is usually positively related to the contestant's performance, while punishment for detected cheating only affects the contestant. Think of an athlete who are banned for using drugs, with no direct consequence to her coach. Think of a investment banker who is fired for breaking the rules, with no direct consequence to her senior manager. Such agency problems imply that the standard deterrence of punishing a cheating contestant solely may be ineffective.

In his seminal work on crime and punishment, Becker (1968) shows that deterrence regimes generally have two distinct features, the magnitude of the punishment and the probability of being caught. The relative efficiency of sanctions is typically studied through comparing the relative impact of detection probabilities and fine levels by varying them while keeping the expected punishment constant. The discussion of specific forms of sanctions in the literature is relatively limited. Therefore, this thesis which consists of three self-contained essays, investigates different forms of dishonest behaviors and appropriate deterrence mechanisms that curb specific cheating behavior in contests-like situations. Since cheating is usually conducted secretly in real life, reliable data from the field is not available. In addition, given a specific contest, the manipulation of deterrence mechanisms for the purpose of field experiments is practically impossible. Consequently, we use laboratory experiments for our empirical tests.

In Chapter 2, we study doping behavior in sports contests among three heterogeneous players and examine whether an innovative anti-doping scheme of "conditional superannuation", is more effective at reducing doping than two traditional anti-doping instruments: fines and bans. In reality, dopers who are tested positive for performance-enhancing drugs (PEDs) could face fines and/or bans. However, testing technologies, despite of their continuous improvement, cannot keep abreast of new developments in PEDs. When there are no tests to detect more sophisticated PEDs or doping methods, the practices are risk free at the time of engaging in misconducts. To overcome the problem of delayed detection, we propose a conditional superannuation system, under which athletes are required to put a part of their winnings and sponsorship money into a superannuation account. After retirement, they are allowed to access the money paid into this account only if they have never been found guilty of doping.

To investigate the likely impact of such a policy, we first build a model of a three-player dynamic contest game. Three players are heterogeneous in the sense that they have different time-varing abilities assigned to them. Each player has to make a doping decision first and then an effort decision. A player's performance is determined based on the ability, the effort and the doping decisions. We then introduce three different anti-doping schemes to the contest. Due to the complexity of the game, solving for the subgame-perfect Nash equilibrium is impractical. It is possible to make some predictions on cheating and effort though. We can establish that cheating is reduced at the expense of competitiveness (i.e., lower effort exertion).

We set out to test empirically which anti-doping measure is the most efficient in reducing cheating but not effort. For this we take our model to the lab and use a real effort task in which experimental subjects have to perform in four different treatments: (i) a benchmark treatment where no penalty is applied, (ii) a fine treatment, (iii) a ban treatment and (iv) a conditional superannuation treatment. In each treatment, individuals have to conduct four sets of real-effort tasks under two payment schemes. After measuring subjects ability in the real effort task under the piece rate scheme, they compete three times against the other two subjects in a contest. The three anti-doping policy treatments are made comparable by choosing the treatment specific parameters such that the expected loss from detected cheating across treatments are the same.

While the theory suggests the same deterrence effect, using a pooled logistic regression model, we observe that the conditional superannuation scheme yields a lower amount of cheating than both the fine and the ban schemes. We run a pooled OLS model on effort exertion and find that none of the anti-doping policies reduces the competitiveness of the game significantly. This contradicts the theoretical model predictions. Moreover, the effort level is slightly higher in the conditional superannuation treatment than the fine treatment. Together with its important advantage of being effective with delayed detection, we conclude that the conditional superannuation scheme is more efficient than traditional schemes.

In Chapter 3, we examine self-sabotaging behavior in contests between two players of different ability - a favorite and an underdog. This captures situations where underdogs have an incentive to lose deliberately instead of trying to win. The incentive to self-sabotage exists in contests where not only the winner but also losers that perform particularly badly are rewarded. Typical examples of such contests are match-fixing and major sports leagues that award priority draft picks to the worst performing teams. Since there is no clear line between losing deliberately or losing genuinely, it is difficult, if not impossible, to clearly identify self-sabotaging in practice. As a result, no direct deterrence mechanism is ever used to target this undesirable behavior. In standard economic models where money is the only concern, underdogs should always self-sabotage for financial gains in a penalty-free environment. This is clearly not always happening in reality. We hypothesize that due to image concerns, underdogs are willing to engage in a costly status seeking activity by sacrificing the monetary gain for a higher rank in contests.

In order to test whether and how people respond to the self-sabotaging incentive, we implement a real-effort task under two payment schemes in the baseline treatment where deliberate under-performance is allowed. In the first part of this treatment, subjects have to attempt eight addition questions under a piece rate scheme. Subjects can choose between submitting an answer or skipping the question. For each and every question, subjects are notified if their first submission is incorrect and asked if they would like to attempt the question again. This enables a subject to proceed without changing an obviously wrong answer. Once all eight questions are completed, subjects are ranked and paired up according to their performance such that each contest contains one favourite and one underdog. The paired subjects compete with each other in solving a new set of eight addition questions over three periods. A subject gains one point for solving the question, loses one point for making an incorrect submission and gains nothing for missing the question. At the end, the winner receives 15 AUDs and the loser receives nothing. However, we compensate those particularly bad performing losers (i.e., those who have a final score of one or less) with 5 AUDs as a consolation prize. This creates the monetary incentive for underdogs to achieve a lower score than they should be (i.e, to lose with a score of one or less). The design allows us to study and derive clean measures of two forms of self-sabotaging behavior in a controlled manner, "active self-sabotaging" and "lack of trying". The former refers to when underdogs make obvious wrong entries and the later refers to when they skip the question without trying.

Our treatment variation, is the introduction of a leaderboard in the contests. This enables us to test if subjects engage in costly status seeking activities. At the end of each contest in one treatment, a leaderboard that displays rankings, scores and profile pictures of all subjects in a session is shown to the public. If the preference for a higher rank exists, underdogs are expected to self-sabotage less frequently in this treatment.

Our results provide evidence that underdogs self-sabotage for monetary gain. We identify both types of self-sabotaging to have taken place in our experiment. Our model suggests that it is optimal for an underdog to start off trying for higher scores, and only active self-sabotaging if and only if the winning probability becomes sufficiently low. However, we find that the majority of underdogs do not play according to the theoretical optimum. Instead, our data shows that those worst performing losers skip the questions right from the beginning. Namely, underdogs are more likely to exhibit "lack of trying" behavior, rather than "active self-sabotaging". For the variation of the availability of the leaderboard, the amount of self-sabotaging decisions is insensitive to the leaderboard. However, the degree of self-sabotaging is significantly less severe in the leaderboard treatment where underdogs tend to self-sabotage just enough for the monetary gain. That is, the propensity to stick to the maximum score that still yields the consolation prize (i.e., finishing with a final score of exact one) is higher when the leaderboard is shown. We conjecture that by doing this, underdogs send a signal to the public that they understand the experiment well, rather than having weak basic math skill.

In Chapter 4, we investigate an under-researched agency problem in contests. In a contest between two contestants, each contestant works together with a manager as a team by simultaneously deciding on whether the contestant should cheat or not. Within each team, one of the two individual cheating decisions is randomly selected as the contestant's final decision. Knowing the cheating decisions of all players, contestants compete with each other by exerting costly effort to gain a share of a fixed monetary prize. Since the contestants are the ones who carry out unethical actions, by default they receive the whole punishment if caught cheating. Since there is no consequence for the manager to cheat, an agency problem arises due to the conflict of interest between the contestant and the manager. Because the later always has the incentive to cheat even if cheating harms the former. Extending punishment to the manager is the obvious candidate to solve the agency problem.

Our setting consists of two punishment schemes, an individual liability scheme where the fine is borne by the contestant alone and a joint liability scheme where the same fine is shared by both the contestant and the manager. We compare the two schemes in terms of the average cheating rate in equilibrium. Our theoretical analysis shows that the joint liability scheme does not guarantee a lower rate of cheating than the independent liability scheme. The equilibrium deterrence effect of the punishment schemes is dependent on the size of the fine (and the effectiveness of cheating). When the fine is high (or cheating is relatively ineffective), then joint liability results in an over-all reduction of cheating. When the fine is low, the joint liability scheme backfires in equilibrium with a higher rate of cheating than in the individual liability scheme. The intuition for the backfiring is as follows: the total (low) fine is sufficient to deter contestants from cheating. Now this low fine is spread across the contestant and the manager. Since manager's and contestant's incentives are not perfectly aligned, a shared small fine does not change the manager's cheating behaviour but increases the cheating incentive of the contestants.

Based on these theoretical predictions, we use a two-by-two treatment design to study cheating behavior with the presence of the agency problem in the laboratory. On one dimension, we vary the punishment schemes (individual vs. joint). On the other dimension, we vary the magnitude of the fine (low vs. high). We obtain four treatments: joint liability with high fine, joint liability with low fine, individual liability with high fine, and individual liability with low fine. The parameters are chosen such that joint liability theoretically should reduce cheating in the high-fine treatments but should backfire if the fine is low. The experimental data reveals that managers are less likely to cheat under the joint liability scheme than under the individual liability scheme, regardless of the size of the fine. However, contestants only react to joint liability by cheating more when the fine is low. Overall, we find that the joint liability high fine treatment outperforms the other three treatments. While the theory prediction shows that the deterrence effect of the joint liability low fine treatment should be lowest, we observe the same deterrence effects across the joint liability low fine treatment and the independent liability treatments (high fine and low fine). Overall, the empirical results suggest that joint liability performs at least as good as individual liability, which leads to the policy suggestion that backfiring of joint liability is less of a concern than predicted by the theory. Moreover, we also find no treatment effect on contestants' efforts. The major factor that affects the competitiveness is the implemented cheating decision of the team. Taking the opponent's cheating decision as given, over-exertion of effort is significantly higher if one's own implemented decision is to cheat. This suggests that contestants become over-competitive as they intend to make their cheating decision count.

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By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

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Chapter 2

An Experimental Comparison of Anti-Doping Measures in Sporting Contests

2.1 Introduction

The use of performance-enhancing drugs (PEDs) is rife in many competitive sports. Over the past years, cycling, weightlifting and boxing are the three Olympic sports in which PED-use by athletes is documented to be most extremely widespread. Especially in the cycling world, doping, which was allowed in the early years of the Tour de France, has become more frequent rather than less after its ban in the mid-1960s. After the revelations around the the drug use of the then legendary cyclist Lance Armstrong, public trust in conventional prevention measures has reached a low point. Currently, a drug cheat that is caught might lose a considerable amount of money (loss of sponsorship, prize money, etc.) and will typically be banned from competing for a certain period of time. The current anti-doping regime has two considerable weaknesses. Since doping practices are typically slightly ahead of the test technology, many cheats are only caught years after the actual doping happened. This severely reduces the deterrence effect of the loss of prize money and sponsorship contracts, as well as that of bans. Athletes can count on having finished their career by the time they are finally caught. Secondly, the current system of bans fails to provide strong anti-doping incentives to athletes that are close to the end of their careers. If I am planning to retire soon anyway, then a potential future ban does not feature much in my decision to dope or not.

In the light of the disadvantages of the current system, we are proposing an alternative or supplementary measure: conditional superannuation. Athletes have to contribute part of their winnings and (ideally sponsorship money) into a pension fund and will only receive payments out of the fund at some elapsed time after their career if they have never been found guilty of doping. This measure has the potential to overcome these two disadvantages of the current system. The athlete's balance will increase during their career, which ensures that the loss from being found guilty increases over time. Hence, the deterrence effect is maximized at the end of the career, when bans lose their effectiveness. Moreover, it is possible to set the date when a decision on payouts is made such that enough time has elapsed and testing of old samples with modern techniques has made sure that no cheating that could not be detected previously has occurred.

While in theory, advantages of conditional superannuation appear to exist, it is unclear how athletes actually react to such a measure. It considerably changes doping incentives but also incentives to exert training effort over an athlete's career. The changing incentives, together with general-equilibrium effects stemming from athletes competing with others, makes it hard to evaluate the likely performance of a conditional superannuation system on the base of theory alone. For this reason, we implement different measures in a real-effort contest experiment with the salient characteristics of sports contests and compare their performance. Three experimental subjects compete in three consecutive contests for prize shares, where the share of a prize an athlete receives is determined by a linear contest-success function with performances being the input. Subjects' performances are determined by three components: (i) the training effort, which is measured as the real effort in an adding-up task; (ii) an endogenously given time-varying ability parameter and by (iii) the doping decision. We compare the behavior under three different anti-doping regimes: (i) a fine regime, where a doper pays a fine in the magnitude of her prize share for the period she was caught in; (ii) a ban regime, where a caught doper is excluded from the next contest and (iii) the conditional superannuation regime, where an athlete will be paid the withheld fraction of their prize money only if they were never caught doping. In order to make the three treatments comparable we calibrate the models by choosing enforcement parameters such that the expected loss from doping is equalized across treatments. As a benchmark, we add a control treatment without any anti-doping policy in place.

We find that our conditional superannuation policy does clearly better at deterring athletes from doping than bans. This is mainly due to the problem that bans lose their deterrence effect once an athlete has decided to retire. The superannuation policy is also slightly better at deterring doping than fines. While this difference is not large and only marginally significant, we consider conditional pension funds superior to fines. The reason is that our scheme in the experiments also delivers better competition through higher efforts than the fine regime. An additional advantage of the conditional superannuation scheme over fines, which we abstracted from in our simple experiments, is the important feature that it can make use of delayed detection.

2.2 Related literature

Tournaments are used as an incentive device to allocate resources efficiently. Ehrenberg and Bognanno (1990) show the incentive effect of tournaments by studying a set of golf tournament data. They find that by adjusting the reward structure and the prizes in tournaments, players' performance can be influenced directly. In tournaments, it is the participants' relative performance that determines their payoff. Compared to other common incentive schemes, such a noncompetitive piece rates, tournaments can often increase average effort levels, with a positive effect on output levels (Lazear and Rosen, 1981). However, unlike any noncompetitive payment scheme, competition discourages cooperation. Not only that, it can cause destructive activities such as sabotage (Lazear, 1989). By sabotaging, a player might damage other competitors' performance with the intent of increasing their own chance of winning. Lazear (1989) addresses the problem of sabotage in a theoretical framework and shows that the smaller the prize gap between winners and losers, the lower the incentive to sabotage. Sabotage is not the only drawback in tournaments. The problem of cheating (i.e. doping in sports) is another severe issue.

While there is not much empirical work that looks at doping prevention, the fight against doping has been looked at theoretically. The early literature on doping using game and decision theoretical methods is nicely summarised in Dilger et al. (2007). Typically, the doping decision generates a social dilemma situation: everybody staying clean is socially optimal, but individually athletes have an incentive to dope. Berentsen et al. (2008) introduce a whistle-blowing mechanism into a two-player game in which the loser can pay to report the winner for doping after the competition. Only the reported winner needs to take drug tests. The paper conducts a comparison of the whistle-blowing game with the normal inspection game where a third party has the final say on whether to test the winner or not. This whistle-blowing mechanism is more effective in lowering the probabilities of doping, and whistle blowing can induce a Pareto-optimal equilibrium. Furthermore, this mechanism is less costly as it requires fewer tests relative to the normal inspection game. Gilpatric (2011) models doping as a continuous (instead of a dichotomous) variable.[1] He studies two aspects of enforcement and finds that, firstly, correlated audits are more effective in reducing doping compared to independent audits. Secondly, an anti-doping policy that gives losers the prize money by default if winners get caught can reduce doping incentives. The latter result is in line with what Curry and Mongrain (2009) found in their paper,

[1] Kräkel (2007) arrived at similar results in a less general environment.

which focuses on the deterrence problem. In one of the most recent papers that specifically explores doping behavior, Ryvkin (2013) models a symmetric winner-take-all tournament game with an uncertain number of participants. In addition to the the general results that are along the lines of previous findings, his result of a non-monotonic penalty-testing frontier is of special interest. In a nutshell, the non-monotonic penalty-testing frontier describes the relation of the socially optimal equilibrium in which doping does not exist and the number of participants determined endogenously in the game. The minimal size of the penalty to stop doping is a non-monotonic function of the number of contestants. An individual's likelihood of winning the prize declines sharply with the number of potential contestants if there are already many competitors. Therefore, doping is less attractive to players in a massively big competition and doping-deterring fines decline. However, if the number of participants is moderate, then the marginal benefit of doping outweighs the cost of sharing the prize money with additional players. Hence, the incentive of doping grows with the number of contestants and fines have to increase. Similarly, the probability of getting caught that ensures a clean game in equilibrium as a function of the number of participants is also non-monotonic.

We are not the first to propose alternative ways of tackling the doping problem. First of all, there is always the option to reduce the doping incentives by modifying elements of the contest such as flattening the price schedule (Eber and Thépot, 1999) or making the sanctions for detected cheating rank-dependent (Berentsen, 2002). A range of similar proposals aim at establishing a social norm of non-doping in a sport, which then becomes self-enforcing due to social preferences (Breivik, 1992). Concrete proposals involve scrapping the list of banned substances with athletes keeping drug diaries (Bird and Wagner, 1997; Andreff, 2016).

Most of the existing empirical literature tests theoretical contest models with cheating in a controlled laboratory environment (Cason et al., 2010; Curry and Mongrain, 2009; Faravelli et al., 2015). This stems from the fact that doping is forbidden in real-word competitions, and therefore, field data on doping suffers from a severe observability problem. Abstract laboratory contests can either be conducted with real-effort tasks. More often then not, however, studies do not require any real effort by the participants. Instead, they simply have to choose numbers that represent effort levels with induced costs. Nonetheless, in real life "work involves effort, fatigue, boredom, excitement and other affectations not present in the abstract experiments" (Van Dijk et al., 2001).

As a consequence real-effort tasks have become more prevalent in experiments. Two of the most often used real-effort tasks are the Slider Task where subjects need to move slider bars on their screen to a predetermined position (Gill and Prowse, 2012) and the Matrix Task in which subjects have to collect numbers from given matrices to obtain a sum of 10 (Mazar et al., 2008). Both tasks require subjects to concentrate and repeat the same task, just like in a training process. However, neither of them capture the fact that as the training program continues, it progressively becomes more difficult to increase the performance as a consequence of increased training. To capture this feature we employ a task (summing up strings of one-digit numbers), which become increasingly difficult, as the number digits that have to be summed increases over time. One problem of real-effort tasks in experiments is often that the intended effort cost stemming from the task are not salient. Rather, subjects enjoy the tasks and also do not have any opportunity cost of time for working on the task, which leads to efforts becoming non-responsive to economic stimuli. For this reason, we induce effort cost by paying a wage for the time subjects do not use in the effort task (See Gächter et al., 2016, for a different clever way of inducing effort cost). Under this setup subjects lose money with every second they work on the effort task.

The remainder of the paper is structured as follows. Section 2.3 describes the theoretical framework of a heterogeneous N-player game under four types of punishment mechanisms. Section 2.4 illustrates the design of the experiment, which is based on our theoretical model. Section 2.5 reports the results from the analysis of the data. The paper concludes in Section 2.6.

2.3 The Underlying Model

Our model investigates four different enforcement regimes: (i) a penalty-free system; (ii) a fine system; (iii) a ban system; and (iv) a superannuation-fund system. In this section, we first discuss the penalty-free model in detail and then describe the three anti-doping regimes. In general it will not be possible to solve out for Subgame-Perfect Nash Equilibria. Heterogeneity in ability (in the subjects adding-up ability), together with complex enforcement regimes that have dynamic incentive effects make it impractical to solve for equilibrium. Hence, we derive a variety of predictions that can be derived without explicitly solving for equilibrium. We start with the penalty-free environment.

2.3.1 Heterogeneous N-Player Dynamic Competition without Enforcement

In the baseline model without penalties, n risk-neutral players participate over T consecutive seasons, which consist of one sports contest each. All players are indexed by i where $i \in I = \{1, 2, 3, \cdots, n\}$. It is assumed that athletes maximize their career expected payoffs. We assume that an athlete's performance q_i in a season depends on on her training effort e_i, natural ability r_i, and doping decision d_i. Unlike some of the aforementioned literature, effort and performance are two different concepts in our paper. Intuitively, a higher training effort level or ability implies a better performance. In addition, performance can be enhanced by using performance-enhancing drugs (PEDs) regardless of the potential health damages caused by such behavior in the long run. We assume these three factors to be complements, which implies that an increase of any of these factors increases the marginal impact of any of the other factors. The performance is simply assumed to be the product of the factors:

$$q_i = e_i r_i \delta(d_i) \tag{2.1}$$

$$\delta(d_i) = \begin{cases} 1 & d_i = 0 \\ \\ \delta & d_i = 1 \end{cases}$$

The ability level lies within an interval, $r_i \in [\underline{r}, \bar{r}]$ where $\underline{r}$ is the lowest ability level and $\bar{r}$ is the highest ability level among all players. A player who does not dope will have a doping multiplier of unity, while a doper receives a multiplicative performance boost of $\delta > 1$.

It is important to note that the doping decision, d_i, is a dichotomous choice variable with values of 0 for non-dopers and 1 for dopers. In what follows, we refer to the two possible actions as "C" for clean and "D" for doping. Note that effort and doping (e_i and d_i) are the only two choice variables in this model.

In each season subjects compete in a share-prize contest. In many sports individual contests use winner-take-all-like compensation schemes (e.g., virtually all elite tennis tournaments). However, instead of modeling a specific sports contest, we are interested in a certain period of the athlete's career or a whole season they played, which contains many competitions. We are also not only interested in the prize money athletes can earn but also in other kinds of performance-based income during that period, such as annual salary from clubs and sponsorship and advertising income. A share-contest setting was chosen, since there the payoff in a season depends on the relative performance of an athlete, which is very realistic. For simplicity, we just call this season payoff, despite its broader meaning, *prize money*. Once all individual performances are measured, an athlete's relative performances can be observed. We use the following simple linear contest function:

$$w_i = \beta(\triangle q_i) + \frac{1}{n} \tag{2.2}$$

where $w_i \in [0, 1]$ is the prize share received by i. The difference between player i's performance, q_i, and the average performance of all other $n-1$ athletes, $\bar{q}_{-i}$, is represented by $\triangle q_i$, where $\bar{q}_{-i} = \sum q_{-i}/(n-1)$. The parameter β denotes the reactivity to performance differences, and the last constant term, $1/n$ ensures that every player receives the same share if $\triangle q_i = 0 \forall i$.[2] The price shares of all competitors sum to one. Note that the contest-success function falls into the class of functions where success depends on the difference of efforts, which are less often used than effort-ratio based functions such as the very popular Tullock contest-success function. While effort-difference based contest-success functions are used less frequently than others, they still play an important role in the literature (see e.g. Baik, 1998; Che and Gale, 2000; Skaperdas and Vaidya, 2012). The purpose of using a linear effort-difference contest-success function is simplicity. On the other hand, our model has a limitation of losing some key features in the environment where doping is an issue. For example, one's choice of doping in contests normally depends on other competitors' decisions to using doping, whereas our model yields a result that athlete's cheating decision is independent of other athletes. However, other components of our environment are already reasonably complex. Hence, we chose a simple contest function with potential confusion of participants in mind.

To derive the expected payoff $E(\pi_i)$ for player i, we have to specify the effort cost of training and total prize money. We assume that the effort cost $C(e_i)$ satisfies $C^{'}(e_i) > 0$ and $C(0) = 0$. The total prize money is denoted by V. The expected payoff in a season, as a result, is given by

$$E(\pi_i) = w_i V - C(e_i). \tag{2.3}$$

Substituting the prize share function 2.2 into the payoff function 2.3, the expected payoff for player i can be written as

$$E(\pi_i) = \left[\beta\left(e_i r_i \delta(d_i) - \frac{\sum e_{-i} r_{-i} \delta(d_{-i})}{n-1}\right) + \frac{1}{n}\right] V - C(e_i)$$

[2]Note that keeping shares between 0 and 1 requires a restriction on β.

Given the payoff functions, player i is assumed to maximize her payoff by choosing a training level e_i and by making a doping decision, d_i. The first-order condition for the optimal training level requires

$$C^{'}\left(e_i^*(d_i)\right) = \beta V r_i \delta(d_i). \tag{2.4}$$

Hence, in our simple linear setting, player i's effort decision does not depend on what other players are doing. Also, the larger the prize, V, the more effort an athlete puts into training. Additionally, the optimal effort level is higher for dopers than non-dopers, as doping increases the marginal return to effort.[3]

Now, suppose that these contests are repeated multiple times and that the only parameter that varies is the athlete's ability level, r_{it}. Player i at any time t_0 maximizes his or her payoff from the future periods by choosing the optimal effort level as well as the best doping decision. From period t_0 to the final period, T, player i's total payoff to be maximized is

$$\sum_{t=t_0}^{T} E(\pi_{it}) = \sum_{t=t_0}^{T} \left[\beta\left(e_{it}r_{it}\delta(d_{it}) - \frac{\sum e_{-it}r_{-it}\delta(d_{-it})}{n-1}\right) + \frac{1}{n}\right] V - C(e_{it}). \tag{2.5}$$

Observe that in the case without enforcement, decisions are period-wise independent. Since there is no enforcement and *ceteris paribus* $w_{it}(d=1) > w_{it}(d=0)$, the optimal choice is to dope in all periods and to choose the effort according to Equation 2.4.

Remark 2.1. In equilibrium, subjects always dope in the penalty-free treatment.

2.3.2 Heterogenous N-Player Dynamic Competition with Fines

Now suppose a fine system is introduced to prevent athletes from doping. In this dynamic game, dopers have a positive probability (p) of being caught. The fine for being caught is

[3] To see this, note that $\beta V r_i \delta > \beta V r_i \Rightarrow C^{'}\left(e_i^*(d_i=1)\right) > C^{'}\left(e_i^*(d_i=0)\right) \Rightarrow e(d_i=1)^* > e(d_i=0)^*$.

the loss of the total prize share. The chance of being falsely convicted for doping is zero by assumption.

The payoff function for player i in any period, t, is given by the equation

$$E\left(\pi_{it}^{f}\right) = \{[1 - p(d_{it})]w_{it}V\} - C(e_{it}) \tag{2.6}$$

$$p(d_{it}) = \begin{cases} p & d_{it} = 1 \\ 0 & d_{it} = 0 \end{cases}$$

where e_{it}, r_{it}, w_{it} and $p(d_{it})$ represent player i's effort level, ability level, prize share and probability of getting caught. The variable $p(d_{it})$ is a function of d_{it}, representing a positive probability of being caught doping, p, for PED-using athletes and 0 for all clean players.

As a result, player i's future payoff starting from period t_0 to period T can be written as

$$E\left(\Pi_{t_0}^{f}\right) = \sum_{t=t_0}^{T} (1 - p(d_{it})) \left\{\beta \left(e_{it}r_{it}\delta(d_{it}) - \frac{\sum e_{-it}r_{-it}\delta(d_{-it})}{n-1}\right) + \frac{1}{n}\right\} V - C\left(e_{it}\right).$$

Player i chooses the optimal training level in every period starting from the current period with the aim of maximizing the future payoff under the fine system. Observe that – as in the no-penalty regime – the choices only impact payoffs in the current period. Hence optimal efforts are given by similar first-order conditions.

We have the following findings on efforts in the fine system:

1. If player i does not dope, then the first-order condition is identical to Equation (2.4)

$$C'\left(e_{it}^{f*}(C)\right) = \beta V r_{it}. \tag{2.7}$$

2. If player i is a PED user, then the first-order condition is

$$C^{'}\left(e_{it}^{f*}(D)\right) = (1-p)\beta V r_{it}\delta. \tag{2.8}$$

The relationship between $C'\left(e_{it}^{f*}(C)\right)$ and $C^{'}\left(e_{it}^{f*}(D)\right)$ is ambiguous. If $(1-p)\delta > 1$, player i's optimal effort is higher under the doping case (i.e.,$C'\left(e_{it}^{f*}(D)\right) > C'\left(e_{it}^{f*}(C)\right)$), and vice versa. In our experiment, the probability of getting caught (p) and the doping efficiency (δ) are set to 30% and 1.2, respectively, which implies that equilibrium efforts are higher without doping (as $(1-p)\delta = 0.7 \times 1.2 = 0.84 < 1$). Similarly, we can compare the efforts of dopers and non-dopers in the penalty-free and fine treatments.

Remark 2.2. For the same ability r_i a doper will exert higher effort in the penalty-free treatment than in the fine treatments, while non-dopers will exert the same effort.

We now turn to the doping decision:

1. The expected payoff in any period t, given player i plays C and exerts the optimal effort $e_{it}^{f*}(C)$, can be written as

$$E(\pi_{it}^{f}|C) = \left\{\beta\left(e_{it}^{f*}(C)r_{it} - \frac{\sum e_{-it}r_{-it}\delta(d_{-it})}{n-1}\right) + \frac{1}{n}\right\}V - C\left(e_{it}^{f*}(C)\right).$$

2. Likewise, the expected payoff, given player i plays D is

$$E(\pi_{it}^{f}|D) = (1-p)\left\{\beta\left(e_{it}^{f*}(D)r_{it}\delta - \frac{\sum e_{-it}r_{-it}\delta(d_{-it})}{n-1}\right) + \frac{1}{n}\right\}V - C\left(e_{it}^{f*}(D)\right).$$

Doping is optimal, whenever

$$E(\pi_{it}^{f}|C) < E(\pi_{it}^{f}|D).$$

With the anti-doping fine, the difference between a doper's payoff and a non-doper's payoff depends not only on their respective performances, but also on the other competitors' average performance, which in itself depends on the competitors abilities, efforts and doping decisions. Since the effort-cost functions are unknown and might differ across athletes, we cannot fully characterize the equilibrium. We can derive the following prediction though.

Remark 2.3. *Ceteris paribus, in the fine treatment the incentive to dope increases with the expected average performance of the competitors.*

This is the case, since the difference between the doping and non-doping payoff increases in the average performance of the others. The intuition behind this is that there is less to lose from being caught doping if the competitors perform well and leave little of the share to the athlete. To summarize, the fine regime reduces both the incentives to dope and dopers' incentives to exert effort. It is also worth noting that for time-invariant values of the probability of getting caught doping (p) and the doping efficiency (δ), doping decisions across different periods are independent in the fine regime. This implies that whatever happened in previous seasons should have no impact on current behaviour.

2.3.3 Heterogenous N-Player Dynamic Competition with Bans

In the ban treatment, an athlete who is caught doping will not be allowed to compete in the next season. The detection probability p remains the same as in the fine treatment.[4]

Player i's payoff function $E\left(\pi^b_{i,t}\right)$ in the current period *(t_0)* is identical to that in the penalty-free case because the consequences of being caught only materialize in the following period. Hence,

$$E\left(\pi^b_{i,t}\right) = w_{i,t}V - C(e_{i,t}).$$

[4] In reality, some bans extend to multiple seasons. In our model, however, the basic case with a one-season ban is studied.

While dopers can keep their prize money in the current period, they will be banned from next season's competitions and will receive a payoff of zero:

$$E(\pi^b_{i,t+1}) = [1 - p(d_{i,t})]\{w_{i,t+1}V - C(e_{i,t+1})\}.$$

We focus first on efforts. In the current period (t), player i maximizes the payoff by choosing the optimal effort, $e^{b*}_{i,t}$.

1. Given player i plays C in the current period, t, under the ban system, the first-order condition is
$$C'\left(e^{b*}_{it_0}(C)\right) = \beta V r_{it}. \tag{2.9}$$

2. Given player i plays D in the current period, t_0, under the ban regime, the first-order condition is
$$C'\left(e^{b*}_{it}(D)\right) = \beta V r_{it}\delta. \tag{2.10}$$

Remark 2.4. Efforts conditional on the doping decision in the ban regime are identical to those in the penalty-free regime.

While the optimal efforts are independent of anticipated behavior in future decisions, doping decisions depend on planned own and expected behavior of others in the future. Obviously, in the final season of an athlete, future bans have no deterrence effect.

Remark 2.5. In the final period all players dope in the ban treatment.

In the penultimate period, a player will foresee that if not caught she will dope in the final period and therefore will compare the contemporaneous gain from doping and the expected loss from next period. So, doping is profitable if

$$E(\pi_{it}|D) - E(\pi_{it}|C) - pE(\pi_{i,t+1}|D) > 0.$$

In an earlier period, the condition for doping also depends on the planned doping decision in the following period. In general, we can say that the doping incentive increases with the ability in the current period and decreases with the ability in the following period. This is indeed the case, as the contemporaneous gain from doping, $E(\pi_{it}|D) - E(\pi_{it}|C)$, increases with the ability, while the expected loss, $pE(\pi_{i,t+1}|D) > 0$, increases with ability in the following season.

Remark 2.6. *Ceteribus paribus*, we expect more doping in period $t < T$ the higher r_{it} and the lower $r_{i,t+1}$.

2.3.4 Heterogenous N-Player Dynamic Competition with Conditional Superannuation

The conditional superannuation fund policy refers to an arrangement whereby athletes have to make a compulsory contribution (to their super fund in each season). The contribution is a fixed proportion λ of their season's prize money. Early access to the accrued benefits is prohibited under this mechanism. Athletes can make withdrawals from their super account post-retirement if and only if they are not caught violating anti-doping policy in any period. In other words, if a doper is caught once during their career, they lose their entire fund balance. Moreover, the contribution is compulsory and needs to be made continuously until the end of their sports career. Again, dopers face the same probability of getting caught doping (p) as in the other regimes.

Under this regime, a player who is caught doping in a certain period leads to the loss of past and expected future superannuation payments. This makes the decision for an athlete very complex. However, if an athlete had been caught at any stage in the career, then the future optimal behavior is straight forward. Recall that then further doping no longer has additional cost and regardless of the doping behaviour any future price money will be taxed at tax rate λ. Consequently, all caught dopers will dope in the future and the optimal effort is determined by $C'\left(e_{it}^{s*}(D)\right) = (1-\lambda)\beta V r_{it}\delta$.

On the other hand, if player i has never been caught previously and is coming up to decide in period t_0 the the relevant future payoff is

$$E\left(\Pi_i^s\right) = \sum_{t=t_0}^{T} \left(1-\lambda\right) w_{it} V - C(e_{it}) + \left(\prod_{t=t_0}^{T} \left(1-p(d_{it})\right)\right) \left(\sum_{t=1}^{T} \lambda w_{it} V\right)$$

.

If a player is planing not to dope in the future, then the optimal effort in all future periods is equal to the non-doping efforts in the other environments.

Remark 2.7. An athlete under the CSF scheme, who has not yet been caught and plans never to dope in the future, will choose the same effort as all non-dopers in the fine and ban treatments.

More generally, the first-order condition for the effort of an athlete in period t_0, with a plan for future doping decisions under the CSF regime becomes

$$C^{'}\left(e_{i,t_0}^{s*}(d_{i,t_0})\right) = \left[(1-\lambda) + \left(\prod_{t=t_0}^{T} \left(1-p(d_{it})\right)\right)\lambda\right] \beta V r_{i,t_0} \delta(d_{i,t_o}). \tag{2.11}$$

Remark 2.8. In the superannuation treatment, for a given doping decision in the current period the current effort declines with the number of planned future doping seasons.

The intuition behind this is simple. The more often future doping is planned, the higher the probability of being caught at least once and – therefore – the lower the expected superannuation return from this period's prize money. Whether a doper optimally exerts more effort than a non-doper is ambiguous (similarly to what is found under a fine system). In our experiment, with $p = 0.3$, $\delta = 1.2$ and $\lambda = 0.35$, it turns out that a once-off doper optimally exerts more, while repeat dopers optimally exert less effort than a player who plans always to stay clean.

The doping decision in the CSF treatment is extremely complex, as the expected loss from doping in a certain period depends on the future plans of doping and on efforts for all possible contingencies but also on the superannuation already accrued. Since the contemporaneous gain from doping increases with own ability, we can at least make the following remark.

Remark 2.9. In the CSF treatment, *ceteribus paribus*, the likelihood of doping increases with ability.

2.4 Experimental Design

Based on the model, our experiment includes four treatments, namely (i) *a punishment-free* treatment, (ii) a *fine* treatment, (iii) a *ban* treatment and (iv) a *conditional superannuation fund (CSF)* treatment. To complement the theoretical analysis of the different anti-doping regimes above, we study and compare their effectiveness in the laboratory. All subjects started with a non-competitive real-effort task which was paid via a piece-rate. This is the same real-effort task that was used in the subsequent three-period contest with a doping option. The purpose of the piece-rate task before the actual contest is to allow the participants to familiarize themselves with the task. Additionally, the piece-rate performance can be used as a productivity measure that is not influenced by competition. In the real-effort task, subjects had to add strings of single-digit numbers. This task differs from most existing mental arithmetic tasks used in previous research, as in our task items become increasingly difficult. The first question involves adding two randomly generated single-digit numbers. After the participant solves this question correctly, the subject moves on to the next item, which requires the addition of three single-digits, then four, five and so on. We use this arithmetic task for two reasons. Firstly, it is easy to understand and requires no prior knowledge. Secondly, it allows us to generate increasing marginal costs of working on the tasks. For this we allowed participants to decide when they wanted to stop working on the task and paid them one Experimental Currency Unit (ECU) per second not used out of the maximum of 240 seconds. As the time requirement to solve another task increases with the tasks solved to far, the opportunity cost of solving an additional sum also increases.

Participants should optimally stop when the benefit of solving an additional sum (piece rate or higher share of prize money) is exceeded by the opportunity cost.

In the initial fixed-rate effort task, subjects were paid 15 ECUs for every sum solved in addition to the one ECU per second left after they quit adding numbers. So, participants should optimally stop exerting effort, whenever they realize that solving the next sum requires more than 15 seconds. In the three-period contest game with doping, participants are divided into groups of three, where each period they (after deciding on doping) compete for a share of a prize of 600 ECUs. The share is determined according to the contest-success function detailed above. Note that effort in our experiment is determined by the total number of solved additions. For example, if a subject solves five tasks, the effort level is then five. Here, a participant should optimally stop exerting effort once the additional share of the prize gained for another unit of efforts falls short of the opportunity cost (which is equal to the number of seconds required to form the next sum).

2.4.1 Parameters for Determining Performance

The relevant variables to calculate participants' share of a prize in a particular contest round are the performances q_{it}. As in the theoretical model, the performance score q_{it} for participant i in period t was determined by multiplying three factors: the time-varying ability level (r_{it}), the doping bonus ($\delta(d_{it})$) and the effort (e_{it}), which was equal to the number of solved sums:

$$q_{it} = r_{it}\delta(d_{it})e_{it}.$$

To differentiate players within a group, in each period we assign three different ability levels to the group members: low ($r_{it}^L = 2$), medium ($r_{it}^M = 3$) and high ($r_{it}^H = 4$). Every subject has different ability levels in their three periods, and no two group members have the same ability level in the same period. Hence, the average ability was identical in each period and all subjects had each of the ability levels exactly once. Subjects knew the ability levels of all three group members for all three periods in advance.

In all treatments and periods, players were asked if they want to cheat or not (to improve their scores in that round). Subjects were aware of the treatment-specific consequences of detected cheating. The cheaters received a cheating bonus of 20% on their performance (i.e., $\delta(d_i) = 1$ if $d_i = 0$ and $\delta(d_i) = 1.2$ if $d_i = 1$). Next, subjects were asked to calculate sums in order to establish their effort level. They could decide when to stop solving sums. Once the performances were determined, the shares of the prize were determined. The reactivity to the performance difference, β, from Equation (2.2) was set to a value of $1/100$. This implies that the price money for contestant i in period t becomes

$$w_{it}V = 200 + 6 \times \left(q_{it} - \overline{q}_{-it}\right),$$

where $q_{it} - \overline{q}_{-it}$ is the different between $i's$ performance and the average of the other two group members' performance. In addition to the share of the prize money, players were also paid 1 ECU per second not used for calculating sums from the effort stage. The same process was repeated in the next two periods. The difference across periods were the altered ability parameters.

In order to make the three different anti-doping enforcement schemes comparable, it was necessary to choose the parameters such that the expected losses from detected doping were equalized. In the *fine*, *ban* and *CSF* treatments, the probability of detection was set to 0.30. Recall that any subject's gain in the *share-prize competition* consists of two parts: the prize share and the saved time, or:

$$Payoff = Prize\ Share + Time\ Saved.$$

In the *fine* treatment, if one gets caught, he or she loses all the prize money in that round, but could still keep the money from saving their time at the rate of 1 ECU per second. The expected loss for dopers in any period is

$$E(Loss_{fine}) = p \times Prize\ Share = 0.3 \times Prize\ Share. \tag{2.12}$$

Making the Ban and Fine Treatments Comparable

In the second treatment, the captured doper is banned from the following period and is paid merely a fixed base salary, S, during the period of suspension. Given that dopers who are found guilty of using PEDs are not allowed to participate, their share of the prize is automatically lost and therefore, the expected loss for first-time dopers in this case is

$$\begin{aligned} E(Loss) &= p \times (Prize\ Share + Time\ Saved) - pS \\ &= 0.3 \times (Prize\ Share + Time\ Saved) - 0.3S. \end{aligned}$$

Under the assumption of identical doping behavior and effort exertion in the *fine* and *ban* treatments, setting expected losses under both schemes equal allows us to determine a residual payment for a banned subject. It turns out that using the behavior of subjects in the *fine* treatment as the common behavior, a residual payment of $S = 110$ ECU equalizes expected losses. Note that these expected losses are only accruing in the first two periods, since a ban has no deterrence effect in the last period.[5]

Making the CSF and Fine Treatments Comparable

In the *CSF* treatment, the compulsory contribution, λ, needs to be determined. Assuming that θ is the probability that an individual dopes in any period the total expected loss under

[5] The problem of a missing competitor in a group due to a ban was solved by substituting the performance of another player in the session into the share-price calculation.

the *CSF* system can then be expressed as the probability of getting caught at least once multiplied by the total contribution over the three periods:

$$
\begin{aligned}
E(Total\ Loss_{super}) &= (1-(1-p\theta)^T)(T\lambda Prize\ Share) \\
&= (1-(1-0.3\theta)^3)(3\lambda Prize\ Share).
\end{aligned}
$$

In order to solve for the equalizing contribution rate, this expected loss is equalized with the expected loss in the fine treatment from (2.12). Simplifying and assuming identical behaviour yields

$$(1-(1-0.3\theta)^3)\lambda = 0.3\theta.$$

Invoking again the same-behaviour assumption, the probability that a player dopes in any period θ is taken directly from the *fine* treatment data. There are 11 dopers out of 63 participants in every period under the *fine* system, producing a probability of 11/63 if a random player and period is picked. Solving out, the equalising *CSF* contribution rate becomes 35% of the prize money.

2.4.2 Laboratory Implementation

The experiment used subjects drawn from the population of the University of Adelaide Experimental Lab (AdLab) Database. Sessions for this experiment were conducted at the computer laboratory of the University of Adelaide. There was a total of 270 participants in twelve sessions for four treatments, which were recruited using Ben Greiner's ORSEE (Greiner, 2015). Each of them were allowed to register for one session only. Before the experiment started, subjects were randomly assigned to a computer in the lab. Communication was forbidden once the subjects entered the lab. The experimental treatments were programmed in Urs Fischbacher's *Z-tree* (Fischbacher, 2007). The instructions were provided at the beginning of each part and were read aloud by the experimenter. Before the competition part of the actual experiments began, subjects had to answer a set of control question regarding the contest success function. Subjects were paid at the end of the experiment at the exchange rate of one AUD for 70 ECU. Participants earned about 17 AUD on average for one hour of their work.

2.5 Results

This section presents our results. Our aim is to identify which anti-doping regime does best in preventing doping but without overly reducing efforts. First, we report results that provide an overview over aggregate differences across treatments. We conduct regression analysis on the level of an independent observation. A deeper analysis of doping behavior follows, where we exploit the panel structure by estimating random-effect panels. Finally, we compare effort levels in the four treatments using individual-level observations and panel data analysis.

2.5.1 Aggregate Results

In our experiment, group members remain fixed for all three periods, which means that every group forms an independent observation. As a result, group average values are used in the non-parametric two-sample Wilcoxon rank-sum tests used to investigate treatment differences. Table 2.1 shows the group doping fraction, group average effort level and group average payoffs in our four treatments: (i) *No punishment* system; (ii) *Fine* system; (iii) *Ban* system; and (iv) *Conditional Superannuation Fund* treatment, under both piece rate and share-prize contest payment schemes. The fraction of doping is calculated as the total number of doping actions experimental subjects took divided by the total number of doping decisions within a group over the three periods. In treatments (i), (ii) and (iv), the total number of doping decisions made is nine. In the *Ban* treatment, the number of doping decisions in a group can be smaller as suspended players did not have a choice.

Table 2.1: Fraction of Doping, Average Effort and Average Payoffs in the Four Treatments

Types of Punishments	N Participants	Probability of Doping	Average Effort	Average Payoffs
Piece Rate				
No punishment	78		9.385	250.859
Fine	63		9.206	240.349
Ban	60		10.117	237.433
CSF	69		10.101	218.420
Share-prize Contest				
No punishment	78	0.872	9.350	974.518
Fine	63	0.175	8.899	936.518
Ban	60	0.306	9.852	953.453
CSF	69	0.106	9.725	900.920

According to Table 2.1, the fraction of dopers in the three treatments with enforcement is significantly lower compared to that in the *No-punishment* treatment ($p < 0.0001$ for all pairwise comparisons).[6] In terms of the doping fraction in the three treatments with punishments, the *Fine* and *CSF* treatments have a significantly lower probability of doping than the *Ban* treatment, with $p = 0.0104$ and $p = 0.0002$, respectively. The lowest probability of doping is observed in the *CSF* treatment. However, it is not significantly different from that in the *Fine* treatment ($p = 0.1649$). On aggregate, our anti-doping policies discourage subjects' doping effectively compared to the *No-punishment* treatment. Furthermore, the *CSF* and *Fine* systems are more effective than *Bans*.

The average effort level is higher in the *piece rate* setting than in the *contest* for all treatments. This effort difference between the two incentive schemes is, however, not significant. The p-values of a Wilcoxon singed-rank test for matched group averages are 0.8588

[6] All tests on doping use two-sided Mann-Whitney U-tests, with the fraction of doping decisions in a group over the three rounds as an independent observation.

for the *No-punishment*, 0.6513 for the *Fine*, 0.9702 for the *Ban*, and 0.4653 for the *CSF* treatments. In the *piece-rate* game, all subjects were provided with identical instructions regardless of which treatment they participated in, and therefore, no treatment effects should be observed. If there are any, they are credited to natural individual differences. In our case, treatments have no significant impact on average effort under the *piece rate* scheme (p-values of 0.6215 for *No-punishment* versus *Fine,* 0.4038 for *No-punishment* versus *Ban,* 0.2639 for *No-punishment* versus *CSF,* 0.1826 for *Fine* versus *Ban* and 0.8401 for *CSF* versus *Ban,* respectively). However, there is a weakly significant effect comparing the *CSF* to the *ban* treatment ($p = 0.0974$). In the *share-prize contest,* in which treatment differences are to be expected, surprisingly, only one treatment difference is significant. In the *CSF* treatment, we observe a weakly significant positive effect on effort level compared to the *Fine* system ($p = 0.0602$). Similarly, there are no big differences in payoffs in the share contests. Aside from the *Bans* compared to *Fines* ($p = 0.0602$), payoff differences in the *share-prize contests* across treatments are not significant and remarkably small.

Figure 2.1 shows the evolution of the proportion of dopers over the three periods in all four treatments. Unsurprisingly, the *No-punishment* treatment has the highest proportion of dopers with values above 80% for all three periods. Based on our model, all players should dope under this system because there are no consequences of doping. The reason behind the existence of some non-dopers is likely be the existence of some moral cost. On the other hand, the probability of doping within the *CSF* treatment is always lowest among all punishments in each period and lies in the range between 10% and 17%. The proportion of dopers under the *Fine* system is slightly larger than that under the *CSF.* As for the *Ban* treatment, doping fractions in the first two periods are similar to those observed in the *Fine* and *CSF* treatments, while this proportion soars to a much higher level (60%) in the last period. This is as predicted by the theory. With respect to doping prevention, fines and conditional superannuation are preferable to bans, since they do not suffer from the lack of deterrence in the last season of a competitor.

Figure 2.1: Probability of Doping Over Time

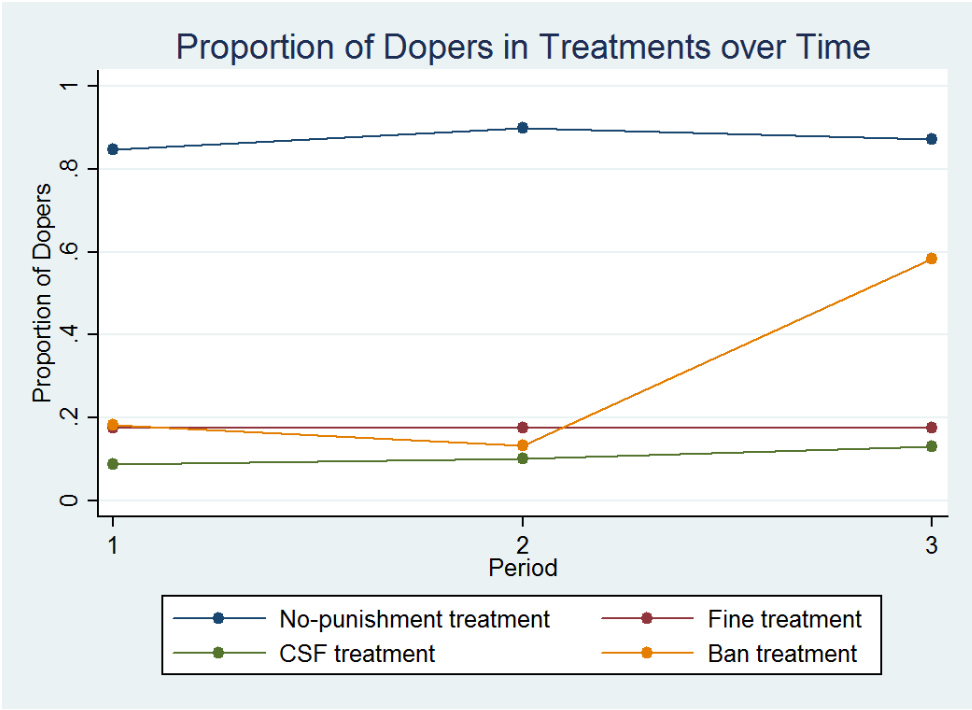
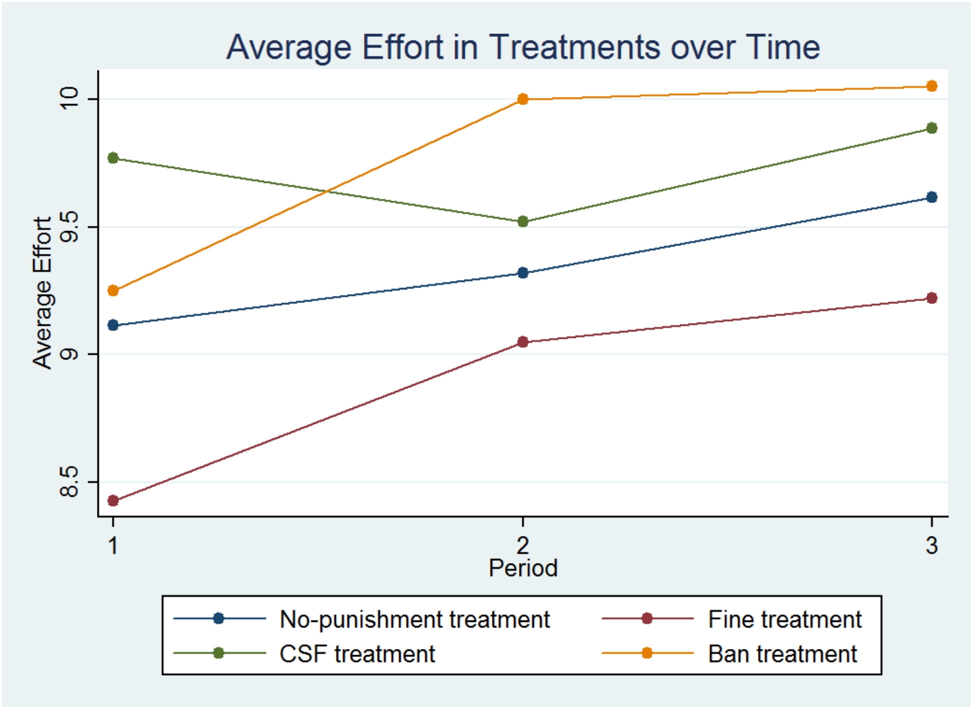


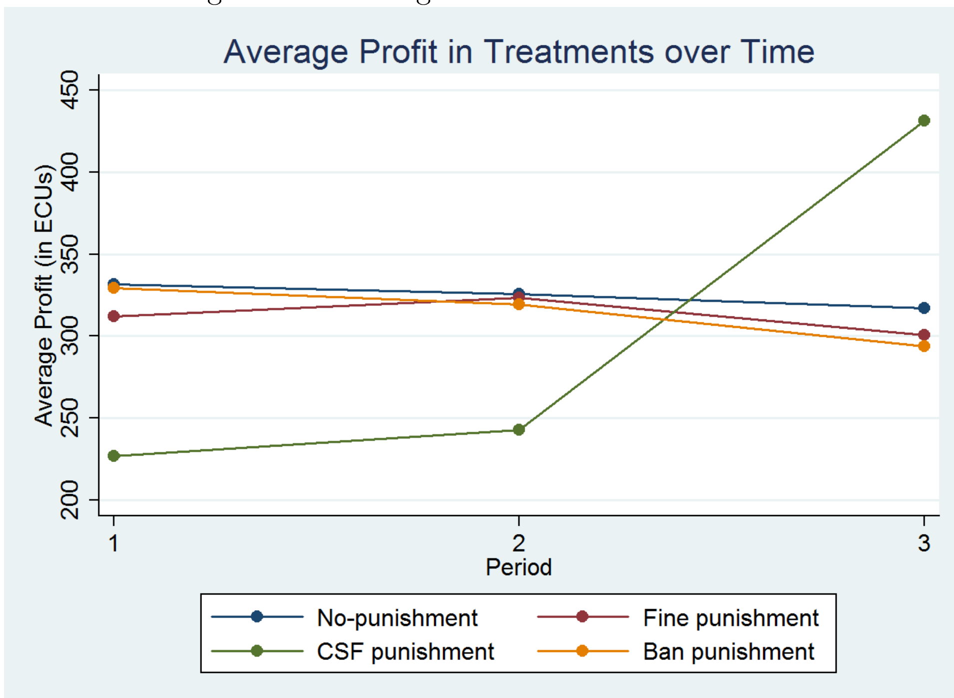
Figure 2.2 illustrates an overview of the effort level in the four treatments. Subjects' average effort levels typically lie within the interval $[8.5, 10]$. A monotonically-increasing effort level over the three periods is found under the *No-punishment, Fine* and *Ban* treatments, indicating that subjects from these three treatments became more and more competitive in the *contest*. Moreover, subjects in the *Ban* treatment exerted the highest effort level in all the periods compared to those who were in the *No-punishment* treatment. Participants under the *Fine* system had the lowest effort level in all periods. As far as the *CSF* treatment goes, the average effort level decreases from period 1 to period 2, but then climbs to a new higher level in period 3.

Figure 2.2: Average Effort Levels Over Time



In Figure 2.3, the trends of average period profit in the *contest* for the four treatments are presented. Firstly, the *No-punishment,* the *Fine* and the *Ban* system have very similar average profits and all of them experience a moderate decrease in profits over the three periods. This profit decline is consistent with the increasing competitiveness in the *contest,* as displayed in Figure 2.2. Recall that subjects in the *CSF* treatment were required to make a contribution out of their prize money into their super account and the account balance will be returned to them as a lump sum in period 3 if they were not caught cheating in any period. Due to this property, profits are much lower in the first two periods of the *CSF* treatment but much higher in the final period, compared to the other three treatments. As is the intention of a superannuation scheme, a part of the income is delayed.

Figure 2.3: Average Period Profit Over Time



Fact 2.1. *The aggregate results provide some support for our conditional superannuation scheme. It delivers lower doping frequencies than bans, without the effort damaging effect of fines.*

In what follows, we will have a deeper look and will investigate if the results persist, when we analyze individual behaviour. We start by checking if individuals's effort choices are roughly rational.

2.5.2 Efforts, Optimality and Profits

In what follows we dig deeper into individual differences in effort exertion behaviour and the impact of treatments. We are interested to understand how the different treatments impacted effort levels once we control for the innate mental calculation ability of subjects. We have seen above that on aggregate, the *CSF* treatment yielded higher efforts than the *fine* treatment, while dominating the *ban* treatment on the doping-prevention front. Now, we want to investigate if this observation still holds if we look at the individual level and control for subject characteristics that, if unevenly distributed across treatments, could be responsible for the results. First, we want to check if effort provision (i.e. the number of sums subjects chose to solve) in the baseline task with a piece rate payment is roughly rational and if there are differences in rationality across treatments. Recall that up until the piece rate task the treatments are identical, which means that if we observe significant differences in the level of rationality across treatments, which persist once we control for characteristics, then there would be doubt that the observed treatment differences in the competition rounds are causal.

To check this, we generate a variable capturing how close a subject came to optimality when deciding when to stop exerting effort. The variable captures the net marginal benefit of the last-solved sum. A subject maximises her payoff if the net marginal benefit of the last-solved sum is positive, while the net marginal benefit of the next sum would be negative. The gross marginal benefit is fixed at 15 ECUs (i.e. the piece rate), while the marginal cost varies depending on the time an individual spends on the real-effort task. Recall that for every second used for solving the task questions, 1 ECU is deducted. Thus, marginal cost is equivalent to the seconds spent on an additional question. As a consequence, a negative value for the optimality variable (i.e. the net marginal benefit for the last-solved sum) suggests over-exertion of effort. Conversely, a large positive net benefit indicates, that it is likely that further effort would have been optimal. Figure 2.4 shows the distributions of the net marginal benefit of the last-solved sums across treatments. The distributions are very similar. The median subject (line within the boxes) in all treatments shows slight over-exertion of efforts. Mann-Whitney U-tests reveal that the location of the distributions are not significantly different. This implies that the degree of rationality in choosing when to stop forming sums does not significantly differ across subjects in different treatments.

Figure 2.4: Box Plot of the Net Marginal Benefit of Effort in the Piece Rate Task

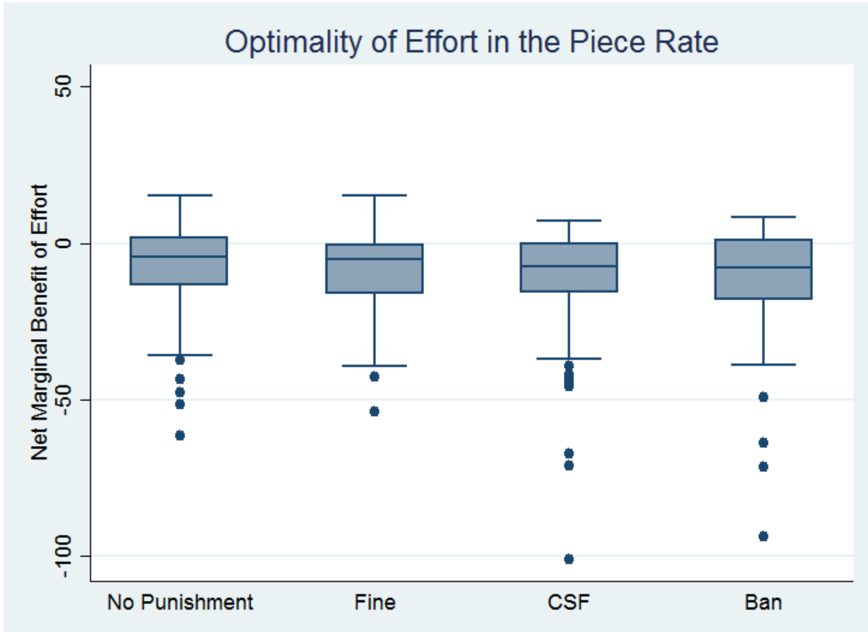


Table 2.2 reports a linear regression that confirms this finding. Here, we regress the optimality variable on individual characteristics (gender, age, degree, high-school math courses taken and arithmetic ability) of participants and on treatment dummies. The regression confirms our observation, as no significant differences across the treatments are found. Interestingly, none of the individual characteristics, except the arithmetic ability of subjects, had an influence on how well the subjects chose when to stop adding up numbers. Our variable capturing the calculation ability measures the calculation speed of a person relative to the speed of the fastest person in our sample. Suppose a person solved x sums. Then, her innate calculation ability was measured as the time it took the fastest person to solve x sums, divided by the time it took her. Hence, our measure takes a value of one for the fastest person and, for example, assigns a value of 0.5 to a person who took twice as much time calculating than the fastest person. We find that the innate calculation ability has a strongly significant positive impact on the net marginal benefit of the last sum solved. This effect is driven by participants with low calculation ability over-exerting effort. We conclude that for our analysis of individual treatment-specific doping and effort decision it is

necessary to control for innate calculation ability in order to exclude the possibility that our results are driven purely by random differences in calculation ability across subjects assigned to different treatments.

Table 2.2: OLS Estimation of Optimality in the Piece-Rate Task

Model	OLS
Dependent	Optimality
Innate Calculation Ability	37.8998***
	(7.5680)
Treatment (base=no enforcement)	
Fine	0.3057
	(2.7740)
Ban	-4.3296
	(2.7832)
CSF	-3.8490
	(2.7228)
Controls	yes
Intercept	-21.9866***
	(4.0534)
N	270

*** Sig. at the 1 % level, **Sig. at the 5 % level, *Sig. at the 10 % level

2.5.3 Individual Doping Behaviour

In this section, we check if our aggregate results on doping behaviour are robust in the sense that they survive an in-depth analysis, whereby we control for individual characteristics. We conduct random-effect regressions on the binary variable, *dope*, which captures if a subject doped. Recall that we have three subjects each competing three times with one another. Therefore, we have to take into account the correlation within a subject's behaviour across time and across subjects and time. There are different strategies to deal with this – explicit modeling of the dependencies or allowing for clustering by adjusting standard errors.

We report the results for both, clustered standard errors at group level, and random-effect models.[7]

Table 2.3 presents four specifications. Specifications 1a and 1b estimate average treatment effects on the likelihood of a subject doping, while specifications 2a and 2b further investigate where the treatment effects come from. We control for innate calculation ability, assigned ability and subject characteristics. Specifications 1a and 1b yield large and significant negative average marginal effects for all three treatments with enforcement.

Fact 2.2. *Doping occurs significantly more often without enforcement than under any of the three deterrence regimes.*

In both the random-effect model and in the model with clustered standard errors, doping prevention with *Bans* is significantly less effective than with *Fines* or a *CSF* ($p \in [0.001, 0.021]$ for the two pairwise comparisons in the the two specifications). The *CSF* further tends to lower the doping frequency when compared to the *Fine* treatment. However, this difference is only weakly significant ($p = 0.0658$ in 1a and $p = 0.0827$ in 1b). One possible explanation for the better performance of the *CSF* regime is loss aversion. Although 35% of athlete's winning prize is allocated to the superannuation fund every round, this fund is still a part of her total wealth accumulated. Therefore, subjects with loss-averse preferences are less prone to dope to avoid losing this part of wealth acquired in the previous periods. However, the possible impact of loss aversion on cheating is not the same in the *Fine* and the *Ban* treatments since those who are caught cheating are never endowed with the monetary payoff lost at the first place. Therefore, although the expected loss is made the same across three treatments, loss aversion could play a role on deterring cheating in the *CSF* treatment but not in the *Fan* and the *Ban* treatments.

[7] We also estimated a multi-level effect model that allowed for random-effects at both the group and subject level. The contribution of the random intercept at the group level to explaining the variance in doping was not significantly different from zero.

Fact 2.3. *The CSF system tends to be more effective in deterring doping compared to both the Fine system and the Ban system. The Ban system has the weakest deterrence effect among the deterrence systems.*

Surprisingly, both the *innate mental calculation ability* as well as the exogenously assigned ability level have no significant effect on the doping decision. This is surprising, since theory predicts that doping should be more profitable for higher-skilled athletes. In specifications 2a and 2b, we add period dummies and a final-period-ban treatment interaction. Recall that a *Ban* should not have any deterrence effect on doping in the last season of an athlete's career. This is also the case in our experiment. By adding a dummy for the final period in the ban treatment, we can check if this is driving the results that the *Ban* treatment does less well in doping prevention than the others. This is exactly what we find. The coefficient is highly significant and large. Moreover, once we control for this end-game effect, the probability of doping in the *Ban* treatment is no longer significantly different to the other enforcement methods ($p > 0.8617$and $p > 0.8489$ versus *Fine*; $p > 0.1869$ and $p > 0.1542$ versus *CSF*). So, the poor performance of the *Ban* system is entirely driven by the lack of deterrence in the last period. The slight advantage of the *CSF* system over the *fine* is robust and persists in both extended specifications.

Fact 2.4. *The weaker performance of the ban system stems entirely from the lack of deterrence in the last season.*

Table 2.3: Estimated Marginal Effects on Doping Probabilities

Model	1a Panel Logit RE individual	1b Pooled Logit clustered group	2a Panel Logit RE individual	2b Pooled Logit clustered group
Calculation Ability	-0.1393	-0.1611	-0.1501	-0.1663
	(0.1184)	(0.1127)	(0.1179)	(0.1129)
Assigned Ability (base = Low)				
Medium	-0.0258	-0.0259	-0.0277	-0.0264
	(0.0274)	(0.0280)	(0.0260)	(0.0280)
High	0.0295	0.0296	0.0318	0.0294
	(0.0281)	(0.0302)	(0.0264)	(0.0302)
Period (base = Period 1)				
Period 2			0.0075	0.0085
			(0.0266)	(0.0246)
Period 3			0.0179	0.0175
			(0.0300)	(0.0301)
Treatment (base = No Enforcement)				
Fine	-0.7017***	-0.6992***	-0.6761***	-0.6761***
	(0.0425)	(0.0465)	(0.0445)	(0.0477)
Ban	-0.5676***	-0.5711***	-0.6850***	-0.6869***
	(0.0494)	(0.0452)	(0.0462)	(0.0499)
CSF	-0.7773***	-0.7739***	-0.7582***	-0.7571***
	(0.0351)	(0.0390)	(0.0376)	(0.0407)
Ban Last Period			0.3053***	0.3054***
			(0.0617)	(0.0761)
Demographic Controls	yes	yes	yes	yes
N	810	810	810	810

*** Sig. at the 1 percent level, **Sig. at the 5 percent level, *Sig. at the 10 percent level

2.5.4 Individual Efforts

While the primary objective of anti-doping policies is to provide sufficient disincentives to athletes using PEDs, they should also alter the incentives to exert effort. Among two anti-doping policies, which are equally effective in reducing the incidence of doping, the one that provides stronger incentives for effort exertion is usually preferred, as it provides a higher quality of contest with better performances. Due to the complex incentives under a conditional pension system, theory does not make a clear prediction how efforts should differ when compared to other systems. The only clear prediction is that subjects who never dope should exert the same efforts across all treatments. In what follows, we have estimated two models with effort being the dependent variable. In both models, we take a conservative approach and allow for clustering at the group level. Random-effects models yield equivalent results. In the first model (1) in Table 2.4, we are interested in the over all treatment effect. Controlling for some individual characteristics (such as calculation ability, assigned ability, gender, math background and degree of study) we identify the treatment effects through treatment dummies. We find that, on average, the *CSF* increases efforts by close to one question (about 10 percent) compared to a system without any anti-doping policy ($p < 0.075$). Neither the Fine nor the Ban environments induce this surprising effect. There, the efforts are not significantly higher than in an environment without enforcement. Moreover, the *CSF* system yields significantly higher efforts than the fine system. This effect is not only strongly statistically significant ($p < 0.032$) but also economically relevant, since the average difference is about 12 percent.

Table 2.4: Estimated Effects on Efforts

Model	1 Pooled OLS clustered on group	2 Pooled OLS clustered on group
Calculation Ability	-1.3829 (4.4935)	-1.2949 (3.6283)
Calculation Ability^2	12.7542*** (4.0446)	12.7420*** (3.8482)
Assigned Ability (base = Low)		
Medium	0.9852*** (0.2016)	0.9581*** (0.1952)
High	1.2926*** (0.2148)	1.2885** (0.2064)
Period (base = Period 1)		
Period 2		0.3377* (0.1818)
Period 3		0.5275*** (0.1876)
Treatment (base = No Enforcement)		
No Enforcement x Dope		-1.7061*** (0.6468)
Fine	-0.2308 (0.4144)	-1.4458** (0.6625)
Fine x Dope		0.2026 (1.0123)
Ban	0.5836 (0.4887)	-0.9984 (0.7077)
Ban x Dope		2.0094** (0.8643)
CSF	0.9032* (0.5113)	-0.5329 (0.7003)
CSF x Dope		1.2743 (0.9580)
Controls	yes	yes
Intercept	7.7177*** (0.9158)	8.9866*** (0.9755)
N	810	810

*** Sig. at the 1 percent level, **Sig. at the 5 percent level, *Sig. at the 10 percent level

Our second model (2) adds interactions between the treatment dummies and doping behaviour in an attempt to identify where the observed differences come from. The first interesting insight is a clear difference in behaviour depending on the existence of enforcement. Theoretically, doping and effort should be complements regardless of the presence of anti-doping rules. This is the case, since doping increases the marginal performance improvement from effort. However, increased effort for given doping is only observed in the treatments with enforcement. In the baseline treatment, subjects behave as if effort and doping were substitutes. Dopers in the baseline treatment reduce their efforts (as shown by the negative coefficient on the doping/no-enforcement interaction).

Moreover, model 2 allows us to tease out the driver of the higher efforts with a *CSF*. The higher effort in the *CSF* treatment compared to the treatment without enforcement is caused by the dopers. The dopers under a *CSF* solve on average three questions more (i.e. 30 percent) than dopers in the baseline (as shown by the difference between the doping-treatment interaction coefficients, which is significant at $p < 0.02$) . Given the high number of dopers in the baseline treatment this effect drives the main effect. The superior performance of the *CSF* scheme compared to enforcement with *fines* is mainly driven by the relatively low efforts non-dopers exert under the fine system (see the negative coefficient on the *fine* dummy). The difference in efforts of non-dopers between the *CSF* and the *fine* regime is significant ($p < 0.063$) and about the same size as the total effect from model 1.

2.6 Conclusion

Empirical evidence on doping behaviour is very rare, as reliable field data is unavailable. Doping behavior cannot be observed easily in real-world competitions, since it is always conducted in secret. Our solution to this observability problem is the use of laboratory experiments. This approach is clearly second-best, as the external validity depends on the artificial laboratory environment emulating the salient elements of the real world. In order to capture the most salient features of sporting contests with doping, we conducted multi-period real-effort contests with cheating. In three treatments, we pitted different anti-doping regimes against each other and compared the resulting behaviour. Our main aim was to see how an innovative conditional superannuation scheme would perform compared to traditional anti-doping measures, such as fines and bans. We find that a conditional superannuation system leads to less doping than bans and to better competition (through increased efforts) than a fine system. We believe that our results, together with the theoretical properties of conditional superannuation, make a good case for the introduction of such a system.

Chapter 3

Does Social Status Reduce Self-sabotaging Behaviour in Contests?

3.1 Introduction

In economics, the use of rank-order tournaments as efficient incentive devices for inducing effort has been extensively studied theoretically (Ehrenberg and Bognanno, 1990; Green and Stokey, 1983; Lazear and Rosen, 1981; O'Keeffe et al., 1984). In a standard tournament, the best performer receives the highest monetary prize, the second best performer receives the second highest prize and so on, which motivates players to exert their best effort. In practice, the use of tournament reward schemes is widespread. A typical example is a job promotion tournament where workers are motivated to work hard by the prospect of being promoted to a position with more prestige, influence and higher remuneration.

Tournament reward schemes are traditionally the major source of incentives to compete hard in professional sports. However, tournaments incentives have been shown to sometimes backfire and cause counterproductive behaviors such as cheating, sabotaging and self-sabotaging (Preston and Szymanski, 2003). When participants cheat or sabotage their competitors, they attempt to increase their chance to win illegitimately. Unlike in these cases, self-sabotage involves contestants deliberately under-performing in order to lose. While cheating and sabotaging can be the result of very strong incentives to win, self-sabotage is often the consequence of badly designed incentives. The major motivations behind self-sabotaging in competitive settings come from direct financial gain offered by a third party, such as in match-fixing or advantages like high draft picks that will pay off in the future. In an industry-policy context, local companies that are meeting global competitive challenges may have incentives to perform particularly poorly in order to receive handouts from the government. Some might argue that car manufacturing in Australia faced this perverse incentive in the decades before it ceased to exist.

Evidence of self-sabotage related to match fixing is rife in competitive sport including cricket, tennis, football, basketball. In 2000, the biggest cricket betting scandal was discovered. The former South African captain, Hansie Cronje, was charged with taking bribes from bookmakers and asking teammates to under-perform deliberately to manipulate the result of a match against India. Bag and Saha (2011) study incentives that are distorted by betting markets in a model where two bookmakers accept bets from two punters. In their model, one of the bettors is able to bribe a team for match-fixing. Their analysis shows that only the stronger team in the two-team contest will be bribed to self-sabotage. Saha (2015) extends this model to three teams and finds that the risk of self-sabotaging due to betting corruption is smaller in a three-team contest than in a two-team contest.

Besides self-sabotage driven by corruption in the betting market, tanking for the purpose of improving a team's draft position is often an issue. To enhance the long-term competitive balance, professional sports leagues like NBA, NFL and AFL employ different kinds of a reverse-order draft systems, which on average allocate more talented rookies to poorer performing teams. This creates an under-performance incentive for teams that find themselves in a position where winning a title becomes impossible. A large body of existing work using field data shows that contestants respond to this self-sabotage incentive (Balsdon et al., 2007; Duggan and Levitt, 2002; Taylor and Trogdon, 2002; Walters and Williams, 2012; Wolfers, 2006). Taylor and Trogdon (2002) examine three NBA seasons of games and provide strong empirical evidence that in the NBA teams that do not make the playoffs are more likely to lose when inverse-rank drafting or draft lotteries were employed[1]. When the incentive to lose was removed with an introduction lottery system that did not condition on actual performance, the likelihood of eliminated teams losing a game is not significantly higher than that of teams that are not eliminated anymore. Fornwagner (2018) analyses data from the NHL games and finds that teams react to dual incentives (i.e., the incentive for teams to win more games when there is still a chance to reach the playoffs and the incentive to lose more after being eliminated from playoff considerations). Moreover, by studying data on individual players level, she provides field evidence that better players played significantly less after the elimination of their team compared to before elimination. This means that poorer performance by eliminated teams can not be fully explained by lower motivation or disappointment. Instead, losing more is a strategic component for eliminated teams. As actual self-sabotage behavior is not readily identifiable in the field, we opt for the controlled environment of the laboratory. Hence, our paper uses experimental methods to study individual self-sabotaging behavior in a two-player contest where both the winner and the loser who performed particularly badly receive a monetary reward and consolation prize, respectively. This situation best captures the scenario where firms have an incentive to perform badly in order to receive government handouts or the practice of the AFL to award priority draft picks to teams who have particularly bad win-loss ratios[2].

While weaker teams may have an incentive to lose on purpose, there are many situations where they choose to forgo monetary gains or future advantages and instead give their best effort in tournaments. Potential explanations are a joy of winning for winning's sake, pride and the seeking of status. Status is typically defined as the ranking in a hierarchy that is publicly recognised. People's concern for status, which induces individuals to care about

[1] In draft lotteries the probability of receiving a better draft position increases with the overall league rank from the best to the worst.

[2] Up to 2012, there was an objective criterion for a priority pick. Since then the granting of priority draft picks has become discretionary in order to reduce tanking.

their position relative to other individuals in a reference group is well-documented (Brown et al., 2008; Clark et al., 2008; Clark et al., 2010; Luttmer, 2005). Agents have a hard-wired preference for higher ranks because a better relative standing typically brings external benefits such as greater access to resources (Ball et al., 2001) or peer recognition (Mas and Moretti, 2009). Rege (2008) implies that people care about status because it serves as a signal of non-observable ability. In addition to the tangible benefits associated with status,, the desire for a higher rank by itself is often sufficient to internally motivate individuals to exert more effort. Blanes i Vidal and Nossol (2011) employ a field experiment where they show that workers who are paid a flat rate become more productive merely because they are provided with feedback of their rank-order position with respect to productivity and pay. In a similar natural experiment, Tran and Zeckhauser (2012) examine the impact of ranking information on the performance of students. Students are randomly divided into three groups: an unranked control group, a group where students receive information about their rank only and a group where the ranking is made public. The data shows that the control group is outperformed by the two treatment groups, while the performances in the two treatment groups are not significantly different. These findings indicate that the performance incentives provided by rankings operate intrinsically rather than through reputation concerns. This intrinsic motivation does not require social recognition and can be explained by competitive preferences or a natural desire of dominance in competitions (Charness and Grosskopf, 2001; Rustichini, 2008).

Other studies, however, show that public recognition of high rankings feature in people's preferences. A large body of existing literature provides evidence for the presence of costly status seeking behavior (Friedman and Ostrov, 2008; Hopkins and Kornienko, 2004; Huberman et al., 2004). Costly status seeking subsumes behaviors where individuals have a willingness to pay for higher publicly observable status. Hopkins and Kornienko (2009) propose a model where consumers decide how to split income between consumption of a normal good and a status good. To strive for status, agents spend more on positional goods at the expense of the normal good when those who consume less of the positional good become richer. A few experimental studies demonstrate that people engage in costly status seeking activities even when status does not provide any monetary return. Rustichini and Vostroknutov (2008) develop two games, a game of skill and a game of luck, where the outcome of the former reveals the ability of the person whereas that of the latter is uninformative. At the end of each game, players have the choice to decrease another player's monetary payment and publicly observed performance by paying a cost. They show that people spend more of their income to reduce performance of others in the game of skill. Moreover, participants spend their money mainly on those just above them, which reveals the intention to rise in the rankings. The authors conjecture that the performance in the skill game is a proxy for status, for which participants have social preferences exhibiting envy. Charness et al. (2011) show that players exert higher effort in a real-effort task when the ranking of performance of group members is revealed publicly. They are willing to incur a cost to improve their ranking artificially by sabotaging other group member's performance or by purchasing "redemption points", which increase performance observed by others but does not provide any monetary returns.

Other studies investigate status seeking activities under a flat-rate payment scheme or a standard tournament pay scheme. Eriksson et al. (2009) find that in standard tournaments where the winner receives a fixed payment whereas the loser receives no prize, the favorites do not slack off, and underdogs do not give up, even when the likelihood of winning is very low. We study a tournament where winners and particularly bad performing losers both receive a prize, which creates an incentive for underdogs to lose heavily. Performance is measured by scores obtained through solving real effort tasks. A correctly solved sum increases performance while an incorrectly solved sum reduces performance. Our main design innovation is that we do not only allow for insufficient effort (i.e., not working on a sum) but also for active self-sabotage (i.e., deliberate wrong entries). In order to be able to separate between mistakes and self-sabotage, we warn subjects if their first submitted sum has been wrong and ask them if they want to proceed or if they want to recalculate. For a treatment variation, we manipulate the feedback by showing a leaderboard of all players' ranked performance to the treatment group but not to the control group. Status is proxied by the ranking positions on the leaderboard. When subjects who lag behind intend to improve their status, they face a monetary opportunity cost for not losing with extreme poor performances (i.e., consolation prize). We reinforce the concept of status by displaying players' profile pictures and ranking on the leaderboard.

The aim of this paper is three-fold. First, we investigate how individuals respond to self-sabotaging incentives in competitive settings. Second, we explore the performance impact of showing a leaderboard which contains the performance and the ranking of all players to the public. Last but not least, we analyze the influence of the leaderboard on self-sabotaging behavior. There is only a limited amount of literature on self-sabotaging behavior. One big reason for this is the lack of field data that identify and quantify individual self-sabotage. It is inherently difficult to separate factors such as lack of ability, luck of incentives that lead to poor performance from self-sabotage. The appropriate use of experimental methods in this paper enable us to directly identify and measure self-sabotaging at both the aggregate and individual levels. Our real effort task allows us to further distinguish between two types of self-sabotaging, known as "active self-sabotage" and "lack of trying". Finally, properly designed experiments allow us to identify how status concerns interact with tanking incentives, which is impossible in reality.

Our results show that humans respond to tanking incentives in tournaments and that they regularly self-sabotage in order to receive a consolation prize. Moreover, individuals tend to self-sabotage just enough when the leaderboard is displayed to everybody. We observe that losers from the leaderboard treatment tend to finish the task with exactly the best performance for which still a consolation prize is paid. We conjecture that by ending up on exactly the level of performance that yields the consolation prize, tankers in the leaderboard treatment want to signal that they are actually not so bad at arithmetic but that they tanked to receive the consolation prize. Without the leaderboard, players self-sabotage more excessively. This does not translate to an overall difference in average performance across treatments though, as we see slightly less losers falling to the level of performance that pays a consolation prize when they are exposed to the leaderboard. In real world, the leaderboard is already widely used in sports competitions to elicit the desire for athletes to compete. Our results suggest that the leaderboard could also alleviate the incentive to tank. Moreover, since the incentive to lose also exists among firms when they compete for government handouts, rather than the market share, the leaderboard of firms profitability could be employed in industries as well.

The remainder of the paper is organized as follows. In the next section we introduce a simple environment of a two-player contest that offers rewards for the winner and sufficiently badly performing loser. The experimental design is described in Section 3.3. In Section 3.4, we present our behavioral hypotheses. Section 3.5 reports our results and Section 3.6 concludes.

3.2 Theoretical Framework

This section briefly presents a theoretical model of a modified two-player winner-take-all competition and basic predictions on self-sabotaging behaviors. In the competition, the winner receives prize money whereas the loser with a sufficiently poor performance, i.e., scoring below a threshold, x, receives a consolation prize. This consolation prize could represent a priority draft pick in sports leagues or subsidies in an industry-policy context.

We first give a brief specification of the model and demonstrate the tanking incentive, without fully characterizing equilibrium. The reason is that the game is very complex and that the precise equilibrium characterization depends on the ability of our subjects, which we cannot observe. Our superficial analysis suffices to demonstrate the tanking incentives.

Consider two homogeneous contestants, player i and player j, in a competition that consists of multiple stages, n. It is assumed that players are rational profit maximisers who are driven by monetary incentives alone. At each stage of the game, each player has a chance to improve or to impair his or her score depending on the strategy applied. There are three strategies for every player to choose from in every stage: *Try* to gain one point, *Skip* the current stage without changing the point balance and *Lose* one point deliberately. For each player who chooses to *Try*, there is a positive probability $p > \frac{1}{2}$, that he or she can increase the point balance by one. On the other hand, there is a probability of $(1 - p)$ that he or she may fail and lose a point instead. Trying causes a small effort cost ϵ. If a player selects *Skip*, he or she moves on to the next stage with the point balance remaining the same. Lastly, if a player opts to *Lose*, one point is deducted from the point balance with certainty. *Lose* also causes a tiny effort cost. By allowing players to choose *Lose*, we make active self-sabotaging behavior detectable in our model. At the end of the competition, the player with the higher (lower) score value is regarded as the winner (loser). The winner receives prize money π whereas the loser is compensated with a significantly smaller amount of v if he or she has a final score less than or equal to x. Otherwise, the loser receives nothing.

Assume that we are at the beginning of the competition. Both players have a strong monetary incentive to start off by trying to gain points in the early stage of the game because the winning prize π is significantly higher than the consolation prize v. Therefore, at the start, *Lose* is not optimal for both players. Note that at the beginning of the game, there are enough rounds left to bring the score down to x by deliberately losing scores even after a successful try. At any stage t of the game where $t \in [1, 2, \ldots, n-1]$, player i's and player j's score balances are denoted with S_{it} and S_{jt}, respectively. Moreover, the probability that player i will win the game is defined as $prob(S_{in} > S_{jn})$ and likewise, that player j will win the game is $prob(S_{jn} > S_{in})$. The winning probability at each point in time depends on the current scores and both players' future strategies. The winning probability increases with one's own score and decreases with the opponent's score. Consequently, the front-runner should never play *Lose* as long as she is not so far in front that she cannot mathematically lose the contest anymore.

Given this game has n stages in total, the number of stages left before the end of the game is $n - t$. In each and every stage, a player's point balance can be increased by one, decreased by one or stay unchanged. Consequently, the maximum possible increase as the maximum possible decrease of a player's point balance is the number of remaining stages itself. For example, at stage t, player i's final score is known to be within the interval $[S_{it} - (n - t),\ S_{it} + (n - t)]$. Self-sabotaging behaviors are expected to arise in situations in which winning is no longer feasible. We consider a scenario where one player is the definite winner, whereas the other is the definite loser with some periods left. In this situation, the gap between two players' point balances is greater than the number of stages left (i.e., $S_{it} - S_{jt} > n - t$). The leader can guarantee a win by skipping. The definite loser should now make sure that he can secure the consolation prize. In case of a current score of above x, some self-sabotage (choosing *Lose*) is optimal. However, this is attainable if and only if the difference between one's current score and the threshold is equal to or less than the remaining stages (i.e., $S_{jt} - x \leqslant n - t$). If there are not sufficiently many rounds lefts to reach the threshold by tanking, there is no monetary incentive for the definite loser to play either *Try* or *Lose*. Thus, we expect the definite loser to exert minimum effort by playing *Skip* for the rest of the game.

Note that this does not mean that trying until the game is out of reach is part of all Subgame Perfect Nash Equilibria. It might be optimal for a player who has fallen behind to *Skip* or *Lose* before the game is out of reach. This is the case, whenever the winning probability conditionally on playing *Try* in the future becomes sufficiently small, such that it is better to make sure that the consolation prize remains reachable by skipping or self-sabotaging. If and when not trying becomes optimal depends on the parameters.

In what follows we describe the experimental setup, which is tailored to the study of the impact a leaderboard has on performance and self-sabotaging behavior in a competitive environment.

3.3 Experimental Design

Our experiments consist of two treatments. Within these treatments, pairs of subjects compete against each other in tournaments which are based on a real effort task. In what follows, we first explain the underlying real effort task. Next, we lay out how subjects are motivated and paid. Finally, the treatment variation is discussed.

3.3.1 The real effort task

In our experiment, we use a real effort task where subjects are incentivised to sum up streams of single-digit numbers in a given time. Each set of real effort tasks contains eight summation questions, which are identical for all the subjects in the same experimental session. There are five levels of difficulty for these summation questions. The difficulty of the tasks is varied by changing the number of digits that have to be added up. The simplest task requires adding seven digits, while sixteen digits have to be added in the most difficult task. Intermediate difficulties require the summation of nine, eleven and fourteen digits. Using different difficulty levels allows us to generate a spread in performance. Participants with better arithmetic skills will be able to solve the more difficult tasks. The difficulty levels are randomly chosen once for all treatments, such that we have the same sequence of tasks for both treatments. This excludes the risk that differences in behavior across treatments could be generated by variation of the drawn task difficulties.

Irrespective of the difficulty of a task, subjects have only 20 seconds to complete it. Whenever a new addition task starts, participants have a choice between two options: to attempt the questions by submitting an answer or to skip the questions by clicking the "LEAVE" bottom on the screen. If the question is solved, skipped intentionally or the time runs out, then the player moves on to the next question automatically. In the event that a participant submits a wrong answer, a dialog box informs the participant that the answer is incorrect. After seeing the message, participants are then required to make a choice between "GO BACK" or "CONTINUE". After clicking "GO BACK", the participant has another chance to solve the same question within the remaining time, or else to skip the question. "CONTINUE" submits the wrong answer. So a subject who presses "CONTINUE" is fully aware that the submitted answer will be wrong. For each task, the warning that an answer is wrong only appears once. The second wrong answer is registered without any chance of correction. This discourages trial-and-error behavior and makes tanking behaviour visible at the same time. The rules of how submission of answers occur are the same for all eight questions within a tournament. The rules are also commonly known and explicitly explained in the instructions.

3.3.2 Payment schemes

Each subject will participate in four rounds consisting of solving eight tasks. The first is a piece-rate round, followed by three competition rounds. In the piece rate round, participants are given eight real effort tasks to perform and they receive a fixed amount of $1 AUD for every correct answer they submit within the timeframe. When they submit a wrong answer or they do not submit an answer, their payment does not change. In other words, there is no penalty for wrong answers in the piece rate round. Consequently, individuals are incentivised to solve as many questions as they can. Hence, participant's performance in this round serves as a measurement of innate ability to perform the addition. After each task, subjects are informed if they solved it correctly. Additionally, the current payout is displayed.

The next three rounds are tournaments for which subjects are placed in groups of two. In each session, subjects are ranked according to their piece-rate performance and divided into the top and bottom half. Then the best subject from the top and bottom half are paired to form a group. The second-best of both pools form the next group and so on. This procedure ensures that there are ability differences within groups, that are similar across sessions. Thus, each group now has an underdog and a favorite. In order to obtain an adequate amount of self-sabotage behaviour exhibited by the underdog, we make each group an asymmetric contest. This is because in a symmetric contest, it is more likely that both competitors put forth as much effort as possible into winning the game without considering tanking as an option. At the beginning of the tournaments, subjects are reminded of their own and informed about their competitor's piece-rate performance. This helps subjects to form beliefs about the own and opponent's probability of solving a given task.

In the tournament subjects receive scores instead of a fixed piece rate. After a correct answer a point is added to the score, while a wrong answer leads to a deduction of one point. When a subject skipped the task or ran out of time the score remains unchanged. At the end of each eight-task tournament, the participant with the higher score in the group is declared the winner. The other subject is deemed to have lost the tournament. In case of ties, the winner is randomly determined by a coin toss. At the conclusion of the experiment, only one of the three contests is randomly selected for payment. The winner in this selected contest receives a prize of $15 AUD and the other subject receives either nothing or a consolation prize of $5 AUD if the final score was one point or lower. This compensation scheme gives runners-up a monetary incentive to self-sabotage, once they realize that their chance of winning the prize has become sufficiently low.

Throughout the contests, subjects are always informed about their updated own score as well as about the group member's score. If a player intends to deliberately lose the competition with a poor performance, he or she can choose to lose points by submitting the wrong answers or by simply not performing the task. We distinguish between these two types of self-sabotaging behaviors in our experiment. Firstly, with our answer checker design, subjects who click "CONTINUE" can be considered strictly self-sabotaging, as they deliberately lose a point. This kind of self-sabotaging is similar to scoring an own-goal in soccer or deliberately missing a ball in tennis. The other way of self-sabotaging is not trying, which is known as "lack of trying" self-sabotage. We can identify this behavior when underdogs skip the questions without prior submission, despite the fact that the first submission is checked by the computer before it has to be submitted. Notice that sometimes it might be optimal for favorites that are far in front to not to submit, since this guarantees a win with certainty. We are not counting these occurrence as self-sabotaging, as it is part of a winning strategy, just as not to attack can be optimal for a soccer team that is leading.

3.3.3 Treatments

At the beginning of the experiment a picture of each participant was taken. During the contests, in both treatments, a player's own profile picture is always displayed on the screen. In the LB treatment, after each eight-round contest, subjects see also a leaderboard which contains all subjects' profile pictures, scores and ranks within the session. We rank players in ascending order on the leaderboard. To reinforce the effect of the leaderboard, we ensure that subjects have sufficient time to read the information and recognize the people on it. Therefore, the leaderboard table is divided into multiple pages with each page showing eight players. Each page stays on the computer screen for 15 seconds without an option to skip. Where there were draws within a session, the ranking was determined randomly. The instructions clearly explained how the leaderboard would be displayed. Moreover, in contest rounds two and three subjects will have experience with the leaderboard procedure.

3.3.4 Procedure

The experiment was conducted at the University of Adelaide. All sessions were computerized and the software used was Z-tree (Fischbacher, 2007). In total, 138 individuals took part in our six sessions.[3] The first three sessions belonged to the NO LB treatment. A leaderboard is introduced to the last three sessions. Table 3.1 shows how sessions were related to treatments. All subjects were invited through the University of Adelaide Experimental Lab (AdeLab) online recruitment platform and each subject was allowed to join in one session only. Before the sessions started, subjects were randomly allocated to a seat in the lab and were informed that any type of communication between each other was not allowed during the whole experiment. Once participants were seated, we took profile pictures for all subjects and entered them in to the system. After that, the instructions were distributed and read out loud by the experimenter. Each session lasted approximately 60 minutes and the average profit earned was AUD 18.13, including a show-up fee of AUD 5.

Table 3.1: Information on the experimental sessions

Session number	Number of subjects	Number of groups	Treatment
1	26	13	*NO LB* treatment
2	26	13	*NO LB* treatment
3	22	11	*NO LB* treatment
4	22	11	*LB* treatment
5	22	11	*LB* treatment
6	20	10	*LB* treatment

[3] A coding error was made in the Z-tree program of the first two *LB* sessions and the first *NO LB* session. According to the instructions, a subject who loses the competition with a score less than or equal to one will receive the compensation. In the program, however, those who finish with a score value less than or equal to two rather than one are rewarded with the consolation prize. Seven subjects were affected by this error. In the main part of the paper we ignore this error and analyse the data as if no error was made, as the number of subjects affected was so low. In the Appendix, we conduct robustness checks on this assumption and report the results. Our analysis shows that the coding error does not change any findings.

3.4 Hypotheses

In this section, we present some hypotheses concerning the behaviors of the underdog and the favorite as we manipulate the visibility of the performance ranking. Our first prediction is about the impact of the tournament scheme on performance of favourites and underdogs, respectively. Standard tournament literature suggests that tournament incentives increase legal output (i.e., effort, performance) due to the competitive preferences (Sheremeta, 2018). Since our contest awards not only the winner but also the loser with extreme poor performance, we conjecture that, favorites tend to perform better than in the piece rate, while underdogs tend to perform worse in the contests. This is summarised in the first Conjecture.

Conjecture 3.1. *Compared to performance under a piece rate, the contest with consolation prize reduces the underdogs' performance but improves that of the favourites.*

Next consider self-sabotaging behaviour. Underdogs have a monetary incentive to perform worse than they would if they tried as hard as possible. In our experiment, a deliberate under-performance can be identified when underdogs use either the "LEAVE" button if they are already at or below the tanking threshold or the "CONTINUE" button if they are above the threshold. Consequently, we expect to observe these buttons being clicked more often by underdogs in the contests than in the piece-rate task. If this is true, then we have direct evidence of the presence of the self-sabotaging behavior. Moreover, favorites should never use the "CONTINUE" button during the contests. When the favourite clicks the "LEAVE" button, this is not regarded as self-sabotaging as it might be optimal if winning is the objective, as explained in the model section.

Conjecture 3.2. *Underdogs under-perform on purpose by clicking either the "LEAVE" button and/or the "CONTINUE" button. The number of clicks on these two buttons are significantly higher in the contests than in the piece rate, suggesting the presence of the self-sabotaging behaviour.*

The next Conjecture is with regard to the two different types of self-sabotaging. As shown in the theoretical framework, it is optimal for laggards to start off by performing the task to maximize the chance of winning and turn to self-sabotaging once they lag far behind and the chance of winning becomes too low. Since the threshold of poor performance is a final score of one, underdogs should not use "active self-sabotaging" by clicking the "CONTINUE" button in the first half of the task. This is because the maximum score one can achieve after the fourth question is four. Given there are four more questions left, individuals are able to get down to a score of one or less in the end. Given this constraint on optimal dynamics of effort over time, we expect rational laggards to exhibit "active self-sabotaging" more frequently than "lack of trying" self-sabotaging in our contests. However, many studies demonstrate that laggards are discouraged from expending effort due to disappointing outcomes in the past, which is known as the discouragement effect (Konrad, 2012). In the present application, those who lost in the previous competition may quit the contest in the early stage and lose the game deliberately due to "lack of trying" self-sabotaging behaviour. Overall, how underdogs self-sabotage and when do they start doing it remains an empirical question. This is stated in Conjecture 3.3.

Conjecture 3.3. *Rational underdogs should try for a higher score at the beginning of the contest and only start self-sabotaging actively by clicking the "CONTINUE" button after the first half of the competition. The discouragement effect might cause underdogs giving up earlier and conduct "lack-of-trying" self-sabotaging by clicking the "LEAVE" button early in the contest.*

Standard expected utility theory suggests that a rational individual aims to maximize his or her monetary payoff only. Provided that is the case, we should not observe any treatment effects since the monetary incentives are identical across the LB and NO LB treatments. In both treatments the winner receives AUD 15 whereas the loser with a poor performance receives a consolation prize of AUD 5. However, as shown in cited literature above, people are motivated not only by the prize money but also by non-monetary factors, such as their relative ranking in their reference group. Although the real effort task we employ in this experiment requires little background to understand, basic mathematics skills to attempt those summation questions are necessary. Therefore, the performance achieved in the experiment is a reflection of mathematics skills. According to Rustichini and Vostroknutov (2008), when the results of game reflects one's skill, players interpret the ranking of the results as a proxy for status. Consequently, our real effort task serves a purpose of motivating individuals to exert higher effort under the circumstances of showing performance and rankings to the public. In summary, the rationale behind higher effort exertion in the LB treatment is the preference for a higher rank. The ranking position on the leaderboard sends a signal about one's numeracy skill and demonstrates the person's positive traits like diligence and intelligence. We refer to this phenomenon as the leaderboard effect. Therefore, our fourth conjecture is as followed,

Conjecture 3.4. *The leaderboard has a positive impact on participants' performance and therefore, a higher average score is expected in the LB treatment than in the NO LB treatment.*

Based on previous conjectures, self-sabotaging incentives and the leaderboard effect are two countervailing effects on underdogs' performance. If the concerns for the visibility of outcomes outweigh the monetary compensation, the self-sabotaging behavior might not occur despite the financial incentives. In order to improve their scores that determine their ranking, which is available to everybody in a session, underdogs may engage in costly status seeking activities by forgoing the consolation prize. Across the two treatments, underdogs are expected to be more willing to sacrifice the consolation prize for a higher ranking on the leaderboard.

Conjecture 3.5. *Underdogs in the LB treatment are expected to self-sabotage less than those in the NO LB treatment.*

3.5 Experimental Results

The experimental results across the two treatments are summarized in this section. We report a series of findings that relate to the five Conjectures stated above. Firstly, we report some descriptive statistics on average performance and the proportion of losers with the consolation prize in each treatment. We then study the performance by different types of players (losers and winners) from which we derive the presence of the self-sabotaging behaviour. Next we investigating the impact of the leaderboard on the prevalence of self-sabotage. Lastly, we consider different types of self-sabotaging behaviours on the individual level.

3.5.1 Descriptive statistics

Table 3.2 lists the average performance under the two payment schemes. Consider the piece rate round first. The average performance under the piece rate is measured by the average number of questions solved. Two-sided Wilcoxon rank-sum tests are performed to test if there are any treatment effects on the average performance under the piece rate scheme. Subjects in the LB treatment, on average, solved 0.474 more question than those in the NO LB treatment. However, this difference is statistically insignificant with a $p-value$ of 0.1767

. Therefore, subjects' innate abilities to solve our real-effort summation tasks are believed to be the same across the subjects assigned to the two treatments.

Now consider the tournament rounds. Since all groups stay constant for three contests, each group constitutes one statistically independent observation. For a given treatment, the average group performance is slightly lower in most of the contests than in the piece rate, but the small difference is statistically insignificant. The only weakly significant increase of performance is found in the last contest in the NO LB treatment, as compared to the piece rate (sign-rank test; $p = 0.077$). This suggests that on aggregate, the contest does not increase performance.

We then perform two-sided Wilcoxon rank-sum tests on the group average score in each contest by treatments and find no evidence of the positive impact of the leaderboard on the aggregate performance ($p > 0.1$ for all pairs). Eriksson et al. (2009) obtained the similar result that the average performance of workers when paired with one of their peers is not improved by giving feedback on their relative performance. Although this result rejects Conjecture 3.4, we need to be careful with the interpretation of it. It does not mean that there is no leaderboard effect on the performance. The reasons are as follow. Firstly, our task consists of eight questions in total, which puts an upper limit on the performance that can be observed in our experiment. Compared to those who have already achieved the maximum score of eight in the NO LB treatment, subjects who would be willing to improve their performance due to the leaderboard effect are unable to do so. Secondly, one's performance is bounded by mathematical skills. Subjects may have already exerted the maximum level of effort under the NO LB treatment. By introducing the leaderboard, although there may be a preference for higher rankings, one cannot easily improve performance. Therefore, further regression analysis is needed to control for those restrictions.

Table 3.2 also reports the proportion of subjects who finished the task with a score of one or less in every round. In the contests, these subjects can be regarded as successful tankers as they received the consolation prize if that round was selected for payment. Note that this proportion is calculated as the number of subjects with a score of one or less divided by the total number of subjects in a given session. As already discussed, Conjecture 3.2 states that self-sabotaging should only exist among defeated players, meaning that this ratio is doubled if we only consider the defeated (e.g., total number of successful tankers divide by total number of losers). A significantly larger proportion of successful self-saboteurs is found in each and every contest round, compared to the piece rate round. This is statistically confirmed using McNemar's chi-square statistics ($p = 0.0164$ for the first contest versus the piece rate; $p = 0.0011$ for the second contest versus the piece rate and $p = 0.0105$ for third contest versus the piece rate).

Next we ask: does the leaderboard have a deterrence effect on self-sabotaging? Or in other words, is the proportion of successful self-saboteurs lower in the LB treatment than in the NO LB treatment? Surprisingly, Table 3.2 shows that the proportion is slightly larger in the LB treatment in contest 2 and contest 3. We then test the equality of the proportions across the two treatments round by round with the help of the two-sample proportions test. There is no significant difference ($p - values$ of 0.5679, 0.4947, 0.2310 and 0.3433 for the piece rate, contest 1, 2 and 3, respectively). This means that the leaderboard does not reduce the amount of successful tankers on an aggregate level as conjectured. As we will see later, the leaderboard still makes an unexpected difference.

Table 3.2: Average performance and proportion of successful tanking subjects

	N Participants	Average Performance	Proportion of Successful Tanking Subjects[4]
Piece Rate			
NO LB Treatment	74	4.689 (1.986)	5.405%
LB Treatment	64	5.125 (1.972)	7.813%
Contest 1			
NO LB Treatment	74	4.595 (2.669)	13.514%
LB Treatment	64	4.766 (2.524)	15.625%
Contest 2			
NO LB Treatment	74	4.459 (3.035)	20.270%
LB Treatment	64	4.641 (2.698)	15.625%
Contest 3			
NO LB Treatment	74	5.108 (2.551)	12.162%
LB Treatment	64	4.906 (2.480)	18.750%

3.5.2 Minimum score and within-pair performance gap by winners and losers

Figure 3.1 displays the range of variation of performances from the maximum to the minimum in the two treatments across the four rounds. As shown in every panel in the figure, two boxes (depicting the 25th to 75th percentile with the median represented as a line) are approximately balanced at the same level, indicating that evidently the central performance levels are similar in the treatments with and without the leaderboard. This again confirms that, contrary to Conjecture 3.4, the leaderboard does not have a positive impact on average performance. We observe that the maximum inside performance level (as evidenced by the adjacent value) stays at eight in both treatments in all four rounds. This maximum

[4]In the piece rate, this is the proportion of subjects with a score of one or less

performance requires subjects to solve all questions, which makes it impossible for those players to perform better in the LB treatment, even if they would like to put in more effort. On the other hand, the minimum inside effort level, which excludes outlier (i.e. the dots) is always lower in the contests of the NO LB treatment. More specifically, in the LB treatment, the minimum score sits at zero in three rounds of competitions while the minimum scores in the NO LB treatment range from -4 to -2. Without considering outliers in both cases. It is reasonable to assume that the minimum inside and the maximum scores solely determined by losers and winners, respectively. This suggests that the leaderboard may have an impact on the performance of losers only. Given that the threshold for the consolation prize is a score of one, there is neither a monetary nor a psychological incentives for underdogs to keep self-sabotaging after this threshold is reached. A much lower minimum score in the NO LB treatment is therefore an indication that the defeated players in the NO LB treatment exhibit unnecessary excessive self-sabotaging behaviour. Additionally, there is a visible larger variation of poor performance (i.e., performance that is below the medium) in the NO LB treatment as indicated by the wider lower interquartile ranges in contest 2 and contest 3, as compared to the LB treatment. This wider range means poor performance is more spread out over a larger range of values than good performance (i.e., performance above the medium). This visual finding points us to test statistically whether the leaderboard has an impact on how poorly losers perform.

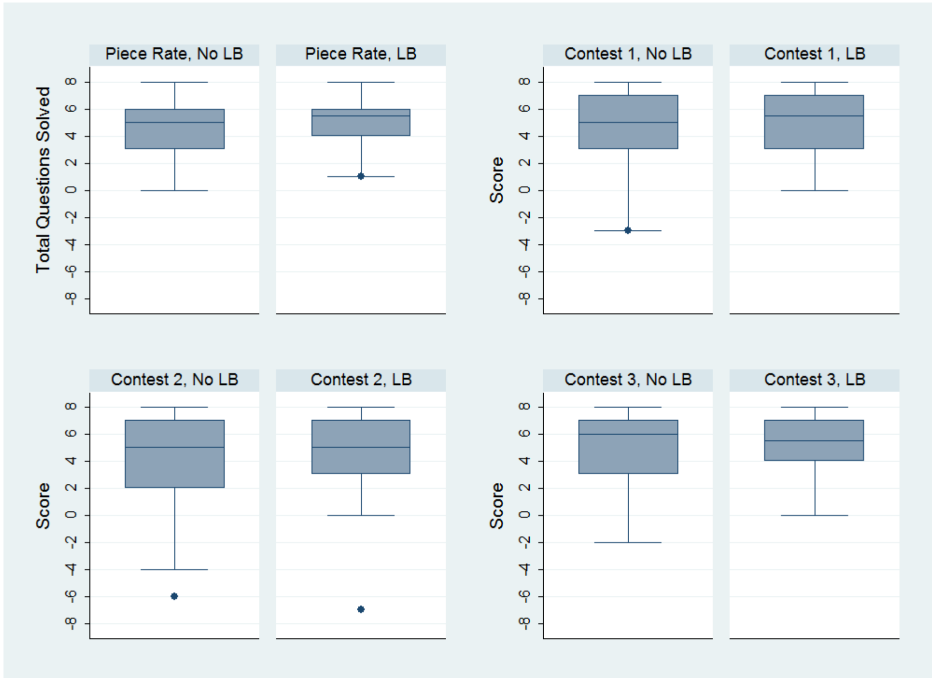


Figure 3.1: The distribution of the performance in two treatments over time

To test whether there is a treatment effect on the minimum performance exhibited by losers, we report non-parametric tests on the average performance and the performance gap of different types of players (i.e., winners or losers). As shown in Table 3.3, the average performance of winners is approximately double the size of that of the losers. For a given type of player, Mann-Whitney U tests fail to find significant differences between the distributions of average performance across two treatments ($p > 0.1$), which suggests that the leaderboard does not increase average performance of either type of players. However, winners' and losers' similar average performance across treatments might mask countervailing effects.

Regarding the performance gap, we define it as the difference between one's average score in contests and the points achieved in the piece rate. On average, winners obtained positive performance gaps of 0.5495 and 0.2292 in the NO LB and the LB treatments whereas losers in the NO LB and LB treatments have negative performance gaps of -0.4865 and -0.9375, respectively. We run Sign test of matched pairs and find that winners significantly improve their performance in contests than in piece rate ($p = 0.0002$; one-sided) whereas losers tend to have a significantly lower score in contests than in piece rate (p = 0.020; one-sided). That indicates that compared to the piece rate performance, winners tend to out-perform themselves while losers tend to under-perform, which confirms Conjecture 3.1.

Table 3.3: Summary statistics on average performance and performance gap by winners and losers

	Average Performance		Within Pair Performance Gap	
	Winners	Losers	Winners	Losers
NO LB Treatment	6.2973	3.1441	0.5495	-0.4865
	(1.4808)	(2.8472)	(1.5652)	(2.7695)
LB Treatment	6.2604	3.2813	0.2292	-0.9375
	(1.5844)	(2.4824)	(1.6637)	(2.4097)

3.5.3 Impact of the leaderboard on performance

Next, we run three OLS regressions to study individual's performance with robust standard errors clustered at the group level. We report the results of three OLS regressions in Table 3.4. In model (1), the dependent variable is individual's performance. The independent variables include the performance in the piece rate, the treatment dummy, time dummies and demographic variables. We find that subjects who perform better under a piece rate continue to perform significantly better in the contests.

In the second model, the dependent variable is the performance gap. Recall that the performance gap is defined as one's average performance in contests minus the piece-rate performance. The explanatory variables are the treatment dummy, time dummies and the player type dummy which equals 1 if the participant lost the contest and 0 otherwise. Further, we include an interaction variable between the treatment dummy and the player type dummy. Model (2) shows that losers tend to have a significantly lower performance gap than winners at the 1% level in both treatments. Given the opposite signs of the performance gap by winners and losers, this finding means that a loser (winner) performs significantly worse (better) in contests than in the piece rate. Hence, our subjects react to this special tournament design correctly. This is consistent with Conjecture 3.1. Note that in model (2), the significant difference in the performance gap of losers and that of winners is completely expected. Winners (losers) from the piece rate round are more likely to have higher (lower) effort and larger positive (smaller) performance gap in the contests. What we found interesting is the sign of the performance gaps of losers and that of winners. The significant negative (positive) performance gap of losers (winners) suggests a worse (better) performance in contests than in the piece rate. This agains shows that our subjects respond to dual incentives in contests correctly.

In the third model, we investigate the factors that impact the magnitude of the individual's performance gap. It shows that the magnitude of losers' under-performance is significantly larger than that of the winners' over-performance. This further confirms that losers and winners have different incentives to exert effort. Furthermore, in all three models, the insignificant coefficients on the treatment dummy confirm that the leaderboard does not have a positive impact on the average performance.

Table 3.4: Pooled OLS on performance and performance gap

Models	OLS	OLS	OLS
Dependent variable	performance	performance gap	absolute value of performance gap
	(1)	(2)	(3)
Piece rate point	0.7582***		
	(0.0796)		
Player type			
Loser		-1.2285***	0.9844***
		(0.4511)	(0.2917)
Treatment			
LB treatment	0.0966	0.0503	0.0381
	(0.3577)	(0.3851)	(0.2780)
Type#Treatment			
Loser#LB treatment		0.0238	-0.2506
		(0.5969)	(0.3984)
Time trend			
Contest 2	-0.0521	-0.0521	0.1354
	(0.2375)	(0.2379)	(0.2213)
Contest 3	0.4167	0.4167	0.0000
	(2.886)	(0.2886)	(0.2026)
Demographics	yes	yes	yes

*** Sig. at the 1 percent level, **Sig. at the 5 percent level, *Sig. at the 10 percent level

3.5.4 Impact of the leaderboard on self-sabotaging behavior

Our previous findings point us to investigate whether there is an impact of the leaderboard on the degree of self-sabotaging (i.e., extend of poor performance of losers). First, we classify all groups into three categories, which are denoted as Clean (no self-sabotage), At-One (self-sabotage ending up at a score of exactly one) and Below-One groups (where the self-saboteur ends up with scores below one). For any group, the winner is always considered not self-sabotaging. Hence, the group types are determined by what the losers do. If the loser from the group obtains a score higher than the tanking threshold, then the group is considered a Clean group. If the loser finishes the game with a score of one, the group is labeled as an At-One group. If the loser obtains a score lower than one, the group is known as a Below-One group. According to our data, there is no winner who finishes the task with a final score equal to or less than one. Thus, all groups should fit into these three categories.

The fractions of the three types of groups across the treatments are depicted in Figure 3.2. Since laggards in both At-One groups and Below-One groups receive the same consolation prize of AUD 5, there is no incentive for them to aim for a lower score. One would expect very few Below-One groups. We observe that in the LB treatment, there is a larger fraction of At-One groups compared to the negligible amount of Below-One groups. However, the NO LB treatment does not show the same pattern. In other words, when the leaderboard is displayed, more underdogs who opt for the consolation prize tend to try to deliberately with a score of one which is the exact tanking threshold.

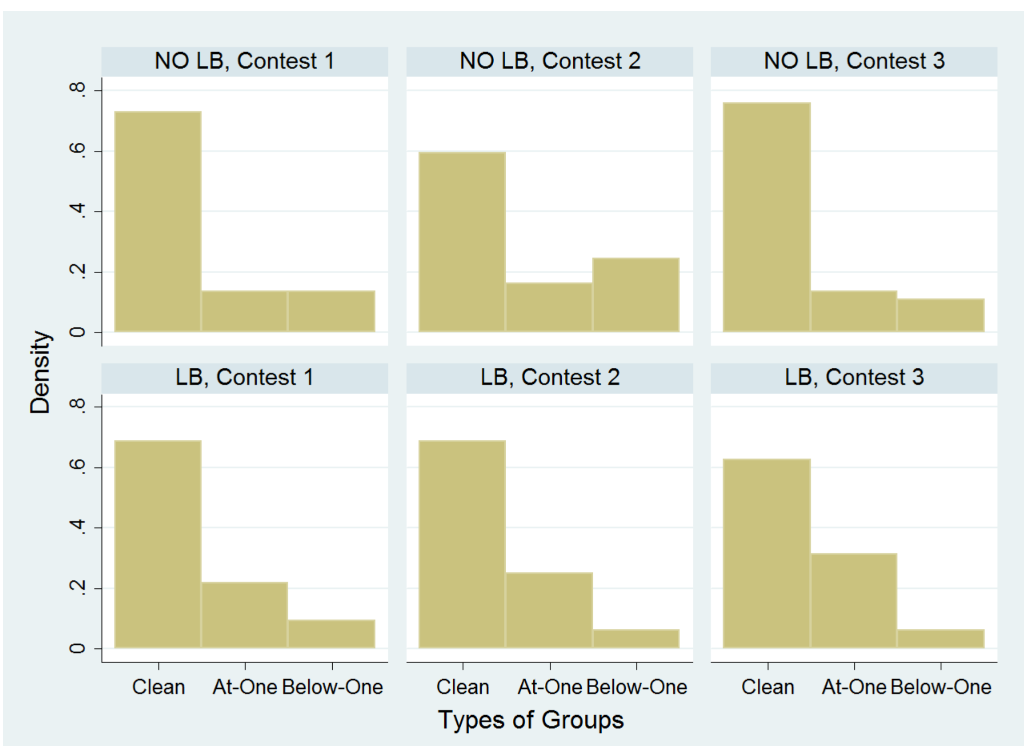


Figure 3.2: Fractions Of Three Different Types Of Groups In Two Treatments

To test this visual observation statistically, we run a Multinomial Logistic Regression of this three-level categorical group variable on the treatment dummy. While the coefficient of categorical group variable is our main interest, we control for other important factors in this regression, including the ability dispersion within a group, the group ability and the trend over time. The ability dispersion within a group is defined as the absolute gap between two group members' performances in the piece rate round. Intuitively, the larger the ability dispersion within a group, the lower the winning probability for the underdog and therefore, underdogs from such a group should be more likely to self-sabotage. The group ability is measured by the average performance of the two members in the piece rate. A higher group ability hints at more competitive and able players. Such a group is more likely to be a Clean group. Since the two-player groups are used as statistically independent observations in our analysis, we cluster standard errors at the group level.

Table 3.5 reports our estimates. At the top we see the impact of the variables on a group being Clean compared to At-One, while the bottom looks at the impact on being Below-One rather than At-One. In the Clean group relative to At-One group model, no significant treatment effects can be found. This means that the leaderboard does not deter self-sabotaging behavior on the group level, which provides evidence against Conjecture 3.5. When we compare the impact on a group to end up Below One rather than At One, we find a positive effect of the LB treatment. The relative probability of being an At-One rather than a Below-One is significantly increased in the LB treatment. This means that if, everything else equal, a group is moved from the NO LB treatment to the LB treatment, the relative probability of being a Below-One group versus being an At-One group decreases by a factor of 0.2709. Put simply, if a group is from the LB treatment, it would be more likely to fall into the "At-One" category as compared to the "Below-One" category.

In summary, these findings reject Conjecture 3.5 and suggest that the leaderboard does not decrease the amount of tanking on the group level. However, the leaderboard has an impact on the degree of self-sabotaging. In the LB treatment, tankers are more likely to sit on the tanking threshold rather than below the threshold. On the other hand, tankers in the NO LB treatment tend to self-sabotage excessively and unnecessarily. Hence, the leaderboard decreases the degree of unnecessary self-sabotaging in the contests. One possible explanation is that when the leaderboard is available, underdogs attempt to climb to the highest possible ranking on the leaderboard without forgoing the consolation prize, which is the threshold. Sitting at the maximum score for the consolation prize could also be interpreted as sending a signal to the public that they understand the game well and deliberately tank rather than being bad at math.

Table 3.5: Multinomial logistic analysis on categorical group types

	Coefficient	Relative Risk Ratio
Clean Group		
Treatment		
LB Treatment	-0.7182	0.4876
	(0.4484)	(0.2187)
Ability Dispersion	-0.3428	0.7098
	(0.3288)	(0.2333)
Group Ability	0.0555	1.0579
	(0.2089)	(0.2209)
Time trend		
Contest 2	-0.2667	0.7659
	(0.4241)	(0.3249)
Contest 3	-0.2551	0.7749
	(0.3935)	(0.3049)
Below One Group		
Treatment		
LB Treatment	-1.3060**	0.2709**
	(0.6367)	(0.1725)
Ability Dispersion	-0.4717	0.6240
	(0.4507)	(0.2812)
Group Ability	-0.4231	0.6550
	(0.3381)	(0.2215)
Time trend		
Contest 2	-0.1744	1.1906
	(0.5623)	(0.6694)
Contest 3	-0.5348	0.5858
	(0.6944)	(0.4068)

"At One" group is the base outcome. *** Sig. at the 1 percent level, **Sig. at the 5 percent level, *Sig. at the 10 percent level

3.5.5 Performance dynamics

On the individual level, the most intuitive qualitative method to analyze performance and self-sabotaging behaviour is through observing individual performance dynamics directly [5]. By visualising individuals' performance patterns, we observe that almost all winners have a similar upward performance trajectory. What is more interesting are the losers' performance patterns. We identify three types of underdog performance patterns. A type 1 underdog tries hard and competes all the way to the end of the game. Type 2 underdogs give up easily and early in a contest. The third type refers to those underdogs who play the game strategically. They try in the first half of the game and consistently "active self-sabotage" in the second half. Out of these three types, the last two types are self-saboteurs, while type one underdogs play clean. We observe far more type 1 and type 2 underdogs than type 3 laggards, which suggests that most of losers do not play optimally.

Consider the two patterns of successful tankers (i.e., underdogs with a final score of one or less) in Figure 3.3. On the left panel, pattern 1 (red line) is a hump-shaped performance curve, indicating a type 3 underdog. On the right panel, pattern 2 (red line) requires underdogs to exhibit consistent "lack of trying" behaviour such that the score value always stays within the threshold. This is typical type 2 loser behaviour. We find that performance pattern 1 is observed much less frequently than pattern 2 in both treatments. In the LB treatment, 7 underdogs exhibit pattern 1 performance paths, while 26 underdogs show pattern 2 dynamics. In the NO LB treatment, 10 losers are consistent with pattern 1, while 18 underdogs adhere to pattern 2. Our qualitative data shows that the "lack of trying" self-sabotaging is more prevalent than the "active self-sabotaging". This observation is consistent with the discouragement effect stated in Conjecture 3.3. Moreover, our data visualisation shows that a substantial amount of successful tankers finishes the task with a final score of exactly one.

[5] In Appendix A, we report all individual performance dynamics for all contest rounds.

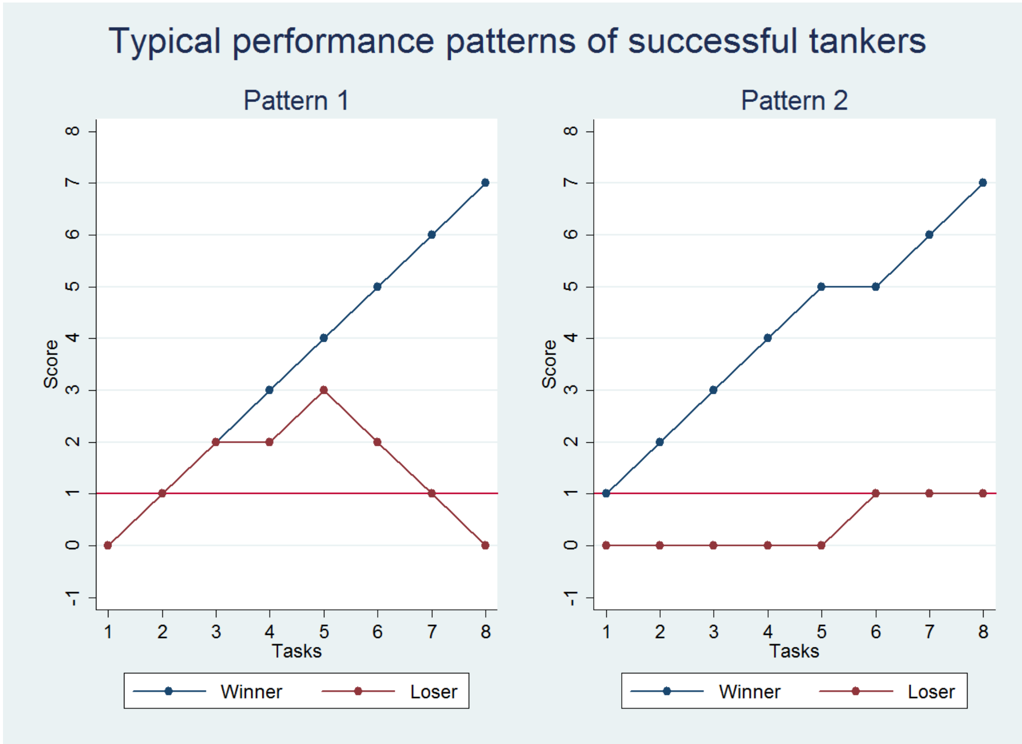


Figure 3.3: Typical performance patterns of successful tankers in contests

3.5.6 Self-sabotaging and the buttons clicked

Deliberate under-performance can be identified if a subject uses the "LEAVE" button and the "CONTINUE" button. Hence, we quantify self-sabotaging behavior by counting the total number of times an individual clicked these two buttons. More specifically, we measure "active self-sabotaging" by using the total number of clicks on the "CONTINUE" button and "lack of trying" by using the total number of clicks on the "LEAVE" button. We then analyze the total number of clicks within each group in every period. Table 3.6 reports the group averages clicks on these two buttons and their standard deviations. We perform sign-rank tests and find that the clicks on the "LEAVE" button are significantly more frequent in the contests than in the piece rate (In the NO LB treatment, $p = 0.043$ for contest 1, $p = 0.0149$ for contest 2 and $p = 0.0981$ for contest 3. In the LB treatment, $p = 0.0145$ for contest 1, $p = 0.0315$ for contest 2 and $p = 0.0031$ for contest 3). Compared to the piece rate, the "CONTINUE" button is clicked significantly more frequently in contest 2 and 3 in the LB

Table 3.6: Average and standard deviation of the number of times the "LEAVE" button and the "CONTINUE" button being clicked

	NO LB		LB	
	LEAVE	CONTINUE	LEAVE	CONTINUE
Piece rate	0.2432	0.2162	0.1563	0.0625
	(0.6414)	(0.5838)	(0.4479)	(0.2459)
Contest 1	0.8108	0.5135	0.8750	0.4375
	(1.6806)	(1.1931)	(1.6801)	(0.9483)
Contest 2	0.8108	0.5405	0.7500	0.2813
	(1.4877)	(1.4258)	(1.5240)	(0.9583)
Contest 3	0.5946	0.4054	1.0313	0.2188
	(1.1416)	(0.9267)	(1.8047)	(0.4908)

treatment ($p = 0.0791$ for contest 2 and $p = 0.0998$ for contest 3), but not in any of the contests in the NO LB treatment.

Within the contests, we find no significant treatment effect on the number of clicks on either buttons. The "CONTINUE" button was clicked by less groups in the LB treatment than in the NO LB treatment, but the difference is not significant ($p\ values > 0.1$ for all three contests). Similarly, the difference in the group average number of clicks on the "LEAVE" button is not significant ($p\ values > 0.1$ for all three contests).

Below, we plot the distributions of the number of clicks on the "LEAVE" button and on the "CONTINUE" button by treatments and types of players (winner or loser) in Figure 3.4 and 3.5, respectively. It is obvious that losers clicked both buttons more frequently than winners. Kolmogorov-Smirnov tests confirms the significant differences in the distributions of the clicks on both buttons between winners and losers ($p = 0.008$ for the "LEAVE" button and $p = 0.008$ for the "CONTINUE" button). Hence, the under-performance of underdogs in the contests is mainly due to actively clicking the "LEAVE" or the "CONTINUE" button rather than more genuine mistakes made under competitive pressure. These findings support Conjecture 3.2.

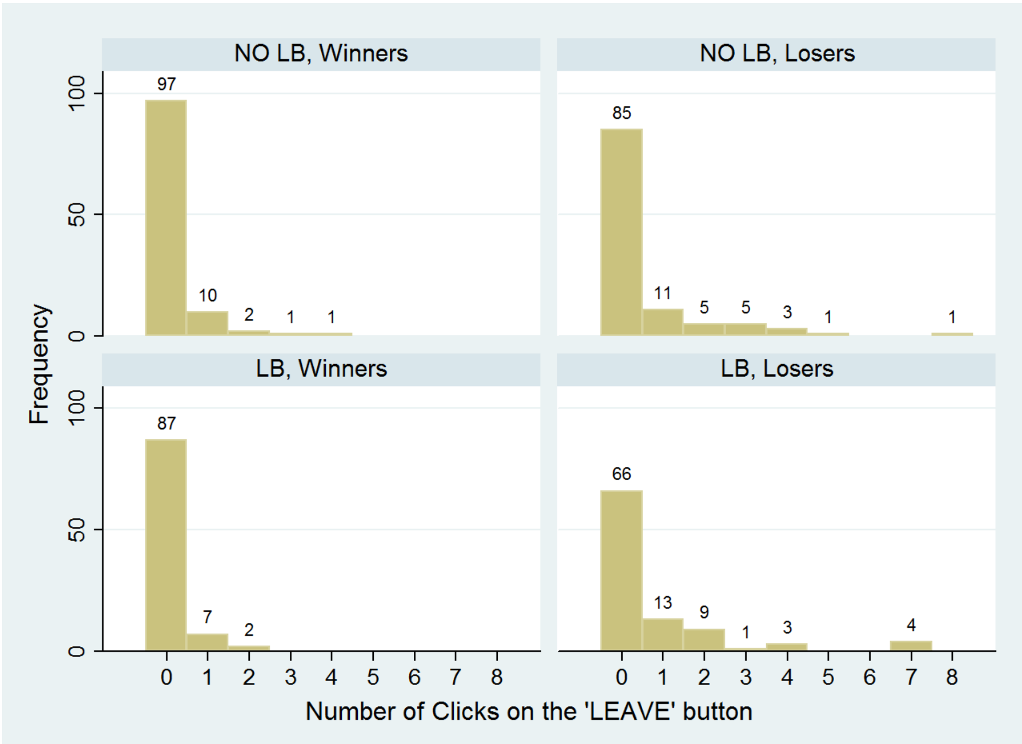


Figure 3.4: Number of clicks on the 'LEAVE' button by treatments and types of players

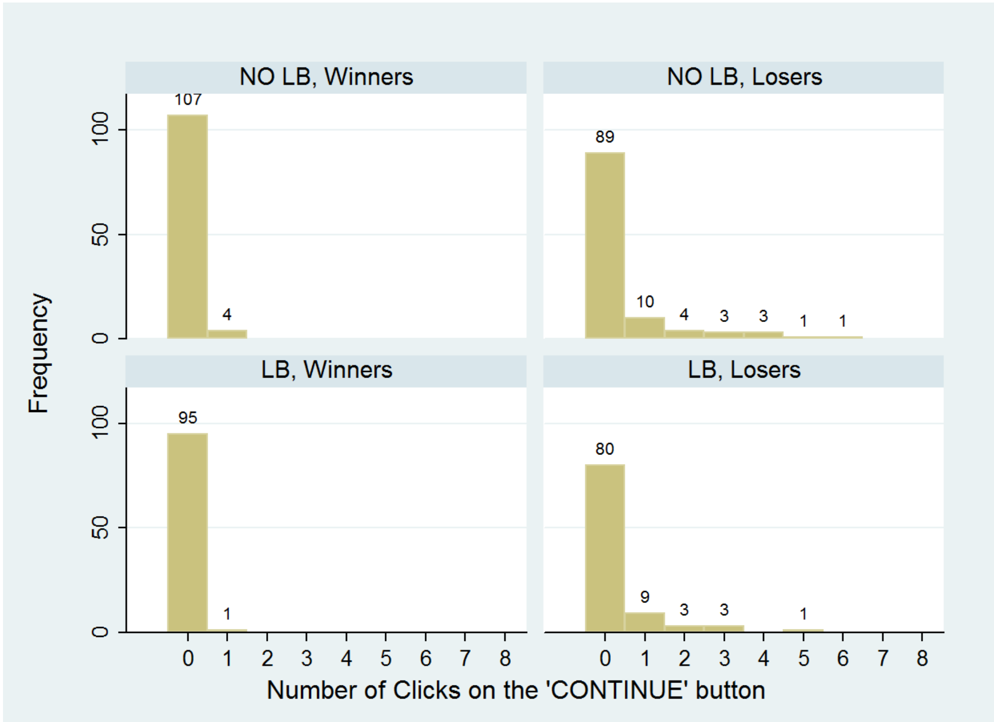


Figure 3.5: Number of clicks on the 'CONTINUE' button by treatments and types of player

To test whether there is a leaderboard effect on different types of tanking we estimate a Zero Inflated Poisson model. This is appropriate as we have count data that represent different types of tanking. That is, "active self-sabotaging" is measured by the number of clicks on the "CONTINUE" button and "lack of trying" is measured by the number of clicks on the "LEAVE" button). Table 3.7 reports estimates from estimating what influences the use of these ways of tanking. In model (1), the dependent variable is "active self-sabotaging" and the explanatory variables are a player type dummy (loser or winner), treatment dummy and time dummies. We find that the player type dummy captures a significant positive effect, suggesting that losers are significantly more likely to use the "CONTINUE" button, which shows that losers exhibit "active self-sabotaging" behaviour. Moreover, subjects from the LB treatment are less likely to self-sabotage actively than those from the NO LB treatment, suggesting that a leaderboard marginally reduces "active self-sabotaging" behaviour. All other factors do not have a significant impact on "active self-sabotaging".

In model (2), the dependent variable is "lack of trying" (i.e., the number of clicks on the "LEAVE" button). We again include a player type dummy, treatment dummy and time dummies as regressors. Our data show that losers tend to skip more questions than winners. No treatment effect can be established in model (2). Overall, our regression results confirms that losers lose the game on purpose by using both "active self-sabotaging" and "lack of trying", rather than by making genuine mistakes.

Table 3.7: Zero Inflated Poisson model on two types of self-sabotaging

Dependent variable Models	ZIP model on "active self-sabotaging" (1)	ZIP model on "lack of trying" (2)
Player type		
Loser	4.042***	0.822***
	(0.560)	(0.494)
Treatment		
LB treatment	-0.456*	-0.274
	(0.260)	(0.413)
Time trend		
Contest 2	0.045	-0.248
	(0.332)	(0.367)
Contest 3	-0.365	0.150
	(0.348)	(0.412)
Demographics	yes	yes

Estimates are conducted with robust standard errors clustered on the group level. *** Sig. at the 1 percent level, **Sig. at the 5 percent level, *Sig. at the 10 percent level.

3.6 Conclusion

This paper develops a contest model that rewards not only the winner with a winning prize but also the poor performing loser with a consolation prize. Such a contest scheme is often used to improve the competitive balance in sports competitions. However, this prize structure provides underdogs with an undesirable incentive to under-perform deliberately, known as self-sabotage. We examine whether underdogs respond to this self-sabotaging incentive in the laboratory. Moreover, we compare two treatments, one with a leaderboard with pictures shown after each round of contests and one without. This treatment variation tests whether status seeking is an efficient deterrence against self-sabotaging behavior. We find that underdogs under-perform through constantly skipping questions ("lack of trying") or by intentionally providing wrong answers ("active self-sabotaging") in the contests. By looking at individual performance dynamics, we observe that a poor performance is mainly driven by "lack of trying" rather than "active self-sabotaging". We propose that this is because the latter strategy requires subjects to think strategically whereas the formal strategy is less sophisticated. Although no significant difference in the amount of tanking can be found across the two treatments, we find evidence that the leaderboard is reduces excessive self-sabotage. In the leaderboard treatment, underdogs who are prepared to self-sabotage in order to obtain the consolation prize are more likely to tank just enough to reach the tanking threshold. Losers that are successfully secure a consolation prize in the treatment without a leaderboard are more likely to excessively self-sabotage. We conjecture that tankers in the leaderboard treatment end up on exactly the score that yields the consolation prize because they want to signal that they are actually not so bad at arithmetic but that they understand the game well and tank to receive the consolation prize.

Statement of Authorship

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Principal Author

Name of Principal Author (Candidate)	Qin Wu
Contribution to the Paper	Theoretical model; Implementation and conducting of experiments; Data analysis; writing
Overall percentage (%)	80%
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.
Signature	Date 04/06/2019

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Name of Co-Author	R. Bayer
Contribution to the Paper	Helped with conceptual idea. made sure that design in accordance with sponsors interest
Signature	Date 4/06/2019

Name of Co-Author	
Contribution to the Paper	
Signature	Date

Please cut and paste additional co-author panels here as required.

Chapter 4

Does joint liability reduce cheating in contests with agency problems? Theory and experimental evidence

4.1 Introduction

Contests can incentivise participants to cheat. The negative consequences are usually designed to deter contestants from cheating. Matters become much more complicated if other agents directly or indirectly benefit from cheating and have an influence on whether a contestant cheats or not. A natural example of such a situation is sports, where often a coach, an official or a doctor can influence the decision to dope. In some instances athletes might not even know that they are being administered illegal substances.[1] However, there are many other environments, where such an agency problem exists. Think of the recent scandal in the automotive industry, where engine developers, who competed against other firms' development teams, installed illegal software that reduced the measured emissions of their engines. It became apparent that company executives had influence over the decision to

[1]Examples are the state organised doping programs in the German Democratic Republic or more recently the doping scandal at the Essendon Football Club in the Australian Football League.

implement the software. In the Enron scandal, CEO Jeffrey Skillings, and to a certain degree Anderson Consulting, were involved in decision making, when the CFO Andrew Fastow and other executives illegally hid billions of dollars of debt (Watkins, 2003).

An intuitive remedy for such agency problems is to extend the liability for sanctions to non-contestants involved in the cheating decision. This paper investigates if such a move necessarily yields expected reduction in cheating. We show in a simple contest model with agency that extending the liability from contestants to managers does not always decrease over-all cheating. In some cases it can even increase the rate of cheating. Joint liability decreases the cheating incentive of non-contestants while at the same time increases the contestant's incentive. Non-aligned preferences of contestants and managers that result from managers not exerting any contest effort and complex equilibrium effects are driving the result that the magnitude of fines is crucial on whether joint liability reduces or increases cheating. In order to test theoretical predictions we take our model to the laboratory. In a two-by-two design we vary the sanctioning rule (individual liability[2] versus joint liability) and the sanction level (high versus low). Theory predicts that joint liability only reduces cheating if fines are high but backfires if fines are low. While our results confirm most qualitative implications of the theory, we do not observe crisp equilibrium play. In particular we find that joint liability has the predicted cheating-reduction effect if fines are high, while it does not backfire under low fines.

There is some theoretical literature that investigates cheating in contests. Berentsen (2002) analyzes cheating in a simple contest model between two asymmetric players, who simultaneously choose whether to cheat or not and finds that in the resulting mixed-strategy equilibrium the more talented player is more likely to cheat. Surprisingly, for a given set of parameter values, the favourite has a smaller winning probability with cheating opportunities than without. Gilpatric (2011) studies cheating behavior in a symmetric rank-order tournament, where two players make effort and cheating decisions. Beyond some

[2] individual liability refers to the scheme that only contestant bears the consequence of cheating

intuitive results, such as that cheating decreases with the probability of being audited and increases with the gain from cheating, the main focus lies on the comparison of two different audit systems – correlated audits where either all or none of the contestants are audited, versus uncorrelated audits where audits follow a random draw. He finds that correlated audits are more effective in deterring cheating. Stowe and Gilpatric (2007) extend Gilpatric (2011)'s rank-order tournament model to discuss the impact of asymmetries among the contestants. They demonstrate that whether the leading player or the trailing player has a stronger incentive to cheat depends on the probability of an audit. When the audit probability is high (low), the trailing (leading) player is more likely to cheat. Kräkel (2007) studies cheating determinants in a two-stage cheating game between two heterogenous players. By concentrating on the conditions required for an equilibrium without cheating, he identifies three effects that jointly determine the attractiveness of cheating: the likelihood effect (i.e., cheating increases likelihood of winning), the cost effect (i.e., cheating affects effort, which in turns affects effort costs), and the base-salary effect (i.e., a cheating player would reduce his expected base salary since there is a chance that he will be caught).

Due to the fact that cheating is often concealed in reality and it is generally impossible to identify how much cheating goes undetected, a substantial body of empirical work concerning cheating is experimental. Faravelli et al. (2015) employ a real effort matrix task to investigate the impact of the tournament incentives on cheating and find that cheating is more likely to occur in a tournament while effort (and output) is higher under an individual piece payment. The authors allow subjects to select between these two payment schemes and find that dishonest people are more likely to self-select into competition. By using a maze-game, Schwieren and Weichselbaumer (2010) again demonstrate that competitive pressure induces cheating and find that in a tournament, those individuals who under-perform tends to cheat more, since for them the gain from cheating is larger. Aligned with prior work, Pettit et al. (2016) point out that people cheat more to prevent a negative status change rather than to gain a positive status in competition. Unlike the mentioned studies, which compare cheating in competitive and non-competitive environments, Cartwright and Menezes (2014) investigate the impact of different levels of intensity of competition on cheating in the workplace. They find that high and low levels of competition can lead to less cheating. The existence of competition only increases cheating propensities, if the level of competition is intermediate.

All the theoretical and experimental studies mentioned above have individuals compete and at the same time make the cheating decision. As mentioned earlier, in reality often other agents have an interest in and an influence on cheating. Just like contestants themselves, managers who benefit from outcomes of their contestants are not immune to unethical behaviors such as cheating. A coach could tell an athlete to use performance enhancing drugs to win a game (Dodge and Robertson, 2004). In an educational context, a teacher might inflate students' grades to improve their chance of getting into a good university (Jacob and Levitt, 2003b,a). In a financial company, a senior manager might suggest a financial advisor to misadvise for a higher commission to be promoted. As the largest corporate financial fraud and the biggest audit failure in American history, the collapse of the Enron Corporation suggests that there are major systemic problems in corporations governance. Under the former top levels of management's instructions, Enron's accountants inflated earnings, hid debts and concealed massive losses to manipulate the profit and its share price. Although its former employee, Sherron Watkins, has explicitly warned the chairman and CEO about accounting scandals, nothing has been done to deal with the company's highly questionable practices. It is clear that far more employees may have contributed, including not only the low level employees but also the top management level. To capture this form of cheating, we distribute the contestant's cheating decision to the manager and allow them both to implement cheating collaboratively.

Cheating in teams has so far only been investigated in non-competitive settings (Soraperra et al., 2017). One possible factor that leads to more cheating when people work together is the exposure to other peoples' unethical behaviors through communication (Kocher et al.,

2017) and observation (Gino et al., 2009). Furthermore, Wiltermuth (2011) finds that people are more likely to over-report their performance when the reward of cheating is shared with another stranger than when it is completely captured by the actor alone. The increased cheating in this case is caused by discounted moral concerns when benefits of cheating are shared. People are averse to cheating (Abeler et al., 2016; Gneezy, 2005; Lundquist et al., 2009; Hurkens and Kartik, 2009). However, when cheating benefits another person in addition to oneself, people tend to discount the immorality of cheating and see themselves as less unethical and therefore, more cheating occurs (Schweitzer and Hsee, 2002; Gino and Pierce, 2010). Conrads et al. (2013) employ a simple die-rolling experimental design which is borrowed from Fischbacher and Föllmi-Heusi (2013) and confirm that there is a positive impact of the team incentive on cheating behavior. They argue that the diffusion of responsibility could be another explanation for more observed cheating in team settings, since the observability of one's actions is decreased within a team. Additionally, Gino et al. (2013) point out that people genuinely care about the social utility of others to the extent that they would cheat even if cheating only benefits another person but not themselves. Other researchers investigate the relationship between group identity and cheating. Cadsby et al. (2016) show that people display in-group favoritism and tend to cheat more on behalf of an in-group member to increase the payoff of an in-group at the expense of an out-group member. Danilov et al. (2013) find that when group affiliation is strong, the problem of a financial adviser deliberately recommending low quality products to customers is more severe under a team compensation scheme. In spite of the apparent existence of the more pervasive cheating in collaborative settings, there is little theoretical and empirical guidance as to the impact of competitive settings on collaborative cheating with agency problems.

In competitions, the incentives of the manager to engage in cheating are affected by the nature of her remuneration. A manager's payoff often directly depends on the contestant's performance which can be improved artificially by cheating. In fact, an agency problem arises in competitions because a non-liable manager always has the incentive to implement cheating on behalf of the contestant even if cheating hurts the contestant. The reason for this is simple. Whenever unethical behavior is detected in competition, the contestants are the ones that are penalized, whereas managers can escape punishment easily due to the fact that their actions are difficult to observe and verify by the anti-cheating authorities. In what follows, we will call a penalty system where only the contestant is sanctioned individual liability. An agency problem occurs, because the incentives of the manager and the contestant are not aligned. In order to align incentives of managers and the contestants, it may be appropriate to extend the punishment to the manager if the contestant is caught cheating. That is to say, the penalties incurred due to detected cheating contestant should be imposed on both the contestant and the manager. We will call such a system joint liability. This practice is common in situations where the identity of the offender is uncertain but the group that he or she belongs to is well defined, which captures the characteristic of our model as it is difficult for the authority to verify whether a cheating contestant is affected by his or her manager or not. In September 2015, Volkswagen has been caught cheating in emission tests by fitting its diesel vehicles with "defeat devices". At first, only the VW engineer, James Liang pleaded guilty to cheat on emissions tests. He was the first person criminally convicted in relation to this corporation fraud. In August 2017, the ex-top emissions compliance manager, Oliver Schmidt, was accused of deceiving federal regulators and sentenced to 7 years in prison. The justice has not yet been served after the lower level employees face prison sentences and fines. A new lawsuit against the former CEO, Martin Winterkorn alleges that several parties were involved in this massive fraud– from their employees like engines experts and emissions specialists to senior management like CEO and other officers. The court case is still ongoing today.

Previous legal, psychological and sociological research was particularly interested in collective punishment as a mechanism to obtain compliance from others. Most studies confirm that it is an efficient method when compared to individual punishment (Heckathorn, 1990; Miceli and Segerson, 2007; Pereira et al., 2015). The most closely related theory paper looking at the impact of joint liability on cheating under agency problems is Crocker and Slemrod (2005). The authors develop a standard principal-agent model to study cheating behaviour in the context of corporate tax evasion. In their setting, it is not the shareholders of the firm, but their agent, a CFO who makes decisions about tax declarations. The CFO possesses private information regarding the allowable deduction in taxable income and might claim illegal deductions which incur penalties. Shareholders incentivise the CFO to lower the company's tax burden by designing his compensation contract in the way that the CFO's salary is inversely related to the effective tax rate. The paper then looks at the efficacy of penalties levied on either the shareholders or the CFO alone and compare the incentives to those under a joint liability regime. They find that penalties imposed on the tax manager are more effective in reducing evasion than are those imposed on shareholders. Our work differs from this study in three key elements of the model we present below. Firstly, our paper focuses on a top manager-contestant relationship. Second, in our model both parties can influence the final cheating decision. Lastly, interesting equilibrium effects come from the competition against other teams rather than from changes in the contract between the parties. To the best of our knowledge, this paper is the first attempt to model and test whether joint liability is more efficient in deterring people from cheating in contests with agency problems.

We develop a game-theoretic model of a two-player contest and solve for equilibrium. In our model, each contestant is paired with a manager to form a team. Our model has two stages. In the first stage, a contestant and a manager propose whether the contestant should cheat or not in the upcoming competition. If both parties agree, then the agreed decision is implemented. Otherwise the decision is determined randomly using a coin toss. If the implemented decision is cheating, then the contestant's performance is enhanced. There is a positive probability of being caught and receiving a fixed fine. In the second stage, two contestants simultaneously exert costly effort to fight for a share of a prize. We study this contest model under individual and joint liability. Under individual liability, contestants bear the fine alone, whereas the same fine is shared by both the contestant and the manager under joint liability. Our model provides a first description of the impact of joint liability on cheating and effort in contests. It shows that theoretically joint liability is not always a better punishment regime. In fact, it can backfire and encourage cheating instead if the original punishment is not severe enough. More specifically, when a fine imposed on cheating is low, joint liability is ineffective in preventing the manager from cheating at all. What made it worse is that it induces more cheating behaviors of contestants. We show that joint liability only reduces cheating when punishment is sufficiently severe. Our model also suggests that optimal effort exertion of a contestant depends on the implemented cheating decisions of both teams but not on the punishment regime.

We then implement our model in the laboratory via a 2×2 design with the aim to test the model predictions and underlying mechanisms. We vary the punishment regime (i.e., individual liability or joint liability). On the other dimension, we vary the size of the fine (low versus high). Our main result corresponds with findings of the theoretical model that the amount of cheating decreases with joint liability when the fine is high. We also find, as predicted, that when a fine is low, joint liability has a significantly positive effect on the contestant's cheating incentive. In contrast to the model prediction, a low shared fine under joint liability is still relatively effective in discouraging managers from cheating. Hence, contradicting the theoretical predictions, the size of the fine does not affect the manager's cheating incentive significantly. Overall, joint liability performs similarly as individual liability when the fine is low but it out-performs individual liability when the fine is high. Generally, no differences of effort exertion can be observed across different treatments. However, a noticeable increase in contest effort and over-dissipation is observed if the own team is cheating. This tendency, in contrast to theoretical predictions, is independent of the opponent's implemented cheating decision. With these findings, our experiments contribute to the very limited literature that examines the interaction between distributed cheating decisions and contests.

The remainder of the paper is organized as follows. Section 4.2 lays out the theoretical framework and derives the equilibrium predictions. In section 4.3, we introduce the experimental design, hypotheses and procedures. Section 4.4 presents the results from the data analysis, and the last section concludes.

4.2 Theoretical Model

We use a simple share contest model allowing for the possibility of cheating and a fine if detected. Subsequently, we extend the model to a setting where the cheating decision does not only depend on the contestant but also on the action of another player, which we will call manager. For example, in sports contests with doping this could be a coach, sports doctor or an official. There we study the average equilibrium cheating frequency under two punishment schemes, the individual liability scheme and the joint liability scheme.

4.2.1 A two-player contest with cheating and audits

We have two contestants $i, j \in \{1, 2\}$. In stage 1 both contestants simultaneously choose to cheat or not. Denote contestant $i's$ cheating decision as $d_i \in 0, 1$,where a value of one indicates cheating. In stage 2, after observing the competitor's cheating decision, both contestants simultaneously exert effort in order to determine the outcome of the contest. The effort of contestant i is denoted by e_i. In stage 3 random audits determine if cheating that has occurred. Audits are individual and detect cheating if it happened with probability p. If cheating is detected a contestant pays a fine. Further assume that the contestants only receive a fraction r of their winnings S and have to give the remainder to somebody else (e.g. manager, coach, or association).[3] We express contestant $i's$ expected payoff as

[3]This assumption does not play an important role yet but paves the way for the introduction of the manager playing an active role later on.

$$\pi_i(e_i, e_j; d_i, d_j) = rS_i(e_i, e_j, d_i, d_j) - e_i - d_i pf, \tag{4.1}$$

where S_i is contestant $i's$ prize share and $d_i pf$ is the expected fine. This setup implies that we are normalizing the total prize to unity. This is without loss of generality. The fine factor $f < 1$,measures the size of the fine as a fraction of the total prize. The prize share S_i is determined by a standard Tullock contest function, where efforts are augmented by an effectiveness factor θ, which depends on the cheating decision. Cheating makes effort more effective at delivering a share of the prize (i.e. $\theta(d_i = 1) > \theta(d_i = 0)$). For simplicity we assume

$$\theta(d_i) = \begin{cases} 1 & if\ d_i = 0 \\ \delta & if\ d_i = 1, \end{cases} \tag{4.2}$$

where $\delta > 1$. Under these assumptions contestant $i's$ share becomes:

$$S_i(e_i, e_j, d_i, d_j) = \begin{cases} \frac{\theta(d_i)e_i}{\theta(d_i)e_i + \theta(d_j)e_j} & if\ e_i + e_j > 0 \\ \frac{\theta(d_i)}{\theta(d_i) + \theta(d_j)} & if\ e_i + e_j = 0. \end{cases}$$

Player j receives a share of $S_j = 1 - S_i$, pays effort cost of e_j and is fined an amount $d_j pf$ in expectation. This setup is the most tractable of the possible setups that do not assume separability of cheating and effort decisions. Alternative ways of modeling the impact of cheating, such as the reduction of marginal effort cost, yield similar equilibrium predictions but are less tractable.

Optimal efforts

In the search for subgame-perfect Nash equilibrium, we start solving the model by first determining the equilibrium efforts conditional on the cheating decision. The Lemma below describes the equilibrium efforts.

Lemma 4.1. *In equilibrium, regardless of the cheating decisions, effort levels are identical with*

$$e_i^* = e_j^* = \frac{r\theta(d_i)\theta(d_j)}{(\theta(d_i) + \theta(d_j))^2}. \tag{4.3}$$

Proof. To see this take the first-order condition for contestant i, which is

$$\frac{\partial \pi_i}{\partial e_i} = \frac{r\theta(d_i)\theta(d_j)e_j}{(\theta(d_i)e_i + \theta(d_j)e_j)^2} - 1 = 0,$$

which implies

$$e_j = \frac{(\theta(d_i)e_i + \theta(d_j)e_j)^2}{r\theta(d_i)\theta(d_j)}. \tag{4.4}$$

Note that the right-hand side is invariant to a swap of indices, which implies that in equilibrium $e_i^* = e_j^*$. Substituting e_i^* for e_j^* in (4.4) and solving yields

$$e_i^* = \frac{r\theta(d_i)\theta(d_j)}{(\theta(d_i) + \theta(d_j))^2}.$$

□

Optimal efforts show an interesting dependence on the cheating decision. The contestants exert the highest efforts when the contest is even. So if both either cheat or both abstain from cheating, then nobody has an advantage in the contest and equilibrium efforts are those a standard Tullock contest would produce. In the case of an unequal contest, where one contestant has an advantage because he cheats while the competitor does not, efforts are lower:

$$e_i^*(d_i, d_j) = \begin{cases} \frac{r}{4} & if\ d_i = d_j \\ \frac{r\delta}{(1+\delta)^2} & if\ d_i \neq d_j. \end{cases} \tag{4.5}$$

The intuition for efforts being lower in an uneven contest is as follows. Compared to somebody in an even contest, the contestant with an advantage has an incentive to reduce efforts for low and medium efforts of the opponent, since this saves resources without reducing the share too much. For a high effort of the opponent it is optimal for the contestant to exert higher efforts than in the even contest. Here the lower marginal cost of grabbing some more of the prize dominates. On the other hand, the contestant with a disadvantage has an incentive to increase efforts (compared to those in an even contest) for very low efforts of the competitor in order to make up some of the disadvantage. For a medium or high effort of the competitor, a lower effort than in the balanced contest is optimal, as increasing the share of the prize has become to expensive. In equilibrium we end up in the medium range of efforts, where both have lower best-response efforts in an uneven contestant than in an even contest. This has interesting implications for the question of efforts and cheating being strategic complements or substitutes. Cheating and efforts are complements if the competitor cheats and substitutes if the competitor does not cheat.

Note that we assume the implemented cheating decisions are common knowledge to both contestants before they choose efforts. In reality, however, one's cheating decision is usually private information. If we relax this assumption, our two-stage game is equivalent to a one-stage game where each contestant i simultaneously decides on the pair $(d_i,\ e_i)$. An analysis of bayesian equilibrium is the natural solution concept. In Tullock contest settings, however, incomplete information has received limited attention because of analytical difficulty. Fey (2008) shows the existence of equilibria in rent-seeking contests where player's cost of effort is private information for two players. In his model, both players choose efforts only and the effort cost is drawn independently from a distribution before the game is played. Kräkel (2007) investigates a rank-order tournament where cheating and effort decisions are available between a favourite and an underdog. Moreover, cheating decisions are modelled as incomplete information. In order to keep his model tractable, he focuses on the no-cheating equilibrium and discusses whether one of the players has incentives to deviate in this equilibrium. Gilpatric (2011) considers a rank-order tournament model where the degree of cheating is common knowledge and demonstrates that the extent of cheating can be reduced by using two enforcements, the "re-awarding" system (i.e., the prize of the top-ranked contestant is re-awarded to to the second-ranked contestant if the winner is caught cheating) and the correlated audits (i.e., all contestants are checked for cheating or none are). Given our contest model allows players to choose effort and cheating and it will be extended to a contest among four players later on, with a focus on solving for all equilibria, we retain the analytical tractability of Tullock's model by assuming it is a complete information game.

Equilibrium cheating decisions

We now turn to the cheating decisions. In order to determine the equilibrium cheating decisions, we calculate the continuation payoffs for the four possible combinations of cheating decisions. The continuation payoff is:

$$\pi_i^*(d_i, d_j, e_i^*, e_j^*) = r\left(\frac{\theta(d_i)}{\theta(d_i)+\theta(d_j)}\right)^2 - d_i p f.$$

Using our assumption on cheating effectiveness from Equation (4.2) in Table 4.1 we derive a normal-form game with the payoffs that results from equilibrium continuation.

		Player 2	
		$d_2 = 1$	$d_2 = 0$
Player 1	$d_1 = 1$	$\frac{r}{4} - pf,\ \frac{r}{4} - pf$	$r\left(\frac{\delta}{1+\delta}\right)^2 - pf,\ r\left(\frac{1}{1+\delta}\right)^2$
	$d_1 = 0$	$r\left(\frac{1}{1+\delta}\right)^2, r\left(\frac{\delta}{1+\delta}\right)^2 - pf$	$\frac{r}{4}, \frac{r}{4}$

Table 4.1: Normal-form first stage of the two-player game given optimal continuation

Denoting the continuation payoff of contestant i as $\pi_i(d_i, d_j)$, we now look for different kinds of equilibira. Cheating is a dominant strategy and the cheating game is a prisoners' dilemma if $\pi_i(1, d_j) > \pi_i(0, d_j)$ for all $d_j \in \{0, 1\}$. Checking the two resulting inequalities reveals that the condition for such an equilibrium is a high cheating efficiency.[4] For a moderate cheating efficiency that makes cheating only a best-response if the other person does not cheat, which implies $\pi_i(1, 0) > \pi_i(0, 0)$ but $\pi_i(1, 1) < \pi_i(0, 1)$, we have a chicken game, with asymmetric equilibria, where one contestant cheats, while the other one does not. For a very low cheating efficiency, not to cheat is a dominant strategy and the unique equilibrium implements the socially efficient outcome of both contestants not cheating. This is summarised in Proporsition 4.1.

Proposition 4.1. *The equilibrium cheating decisions in pure-strategy subgame-perfect Nash equilibria depend on the cheating efficiency. Define*

$$\begin{aligned} \bar{\delta} &= \frac{1}{\sqrt{\frac{1}{4} - \frac{pf}{r}}} - 1 \\ \underline{\delta} &= \frac{\sqrt{\frac{1}{4} + \frac{pf}{r}}}{1 - \sqrt{\frac{1}{4} + \frac{pf}{r}}}. \end{aligned}$$

Then we have

1. $(d_1^*, d_2^*) = (1, 1)$ *iff* $\delta \geq \bar{\delta}$
2. $(d_1^*, d_2^*) = (1, 0)$ *or* $(d_1^*, d_2^*) = (0, 1)$ *iff* $\delta \in [\underline{\delta}, \bar{\delta}]$
3. $(d_1^*, d_2^*) = (0, 0)$ *iff* $\delta \leq \underline{\delta}$.

Proof. It is straight-forward to check the inequalities. For (1) we require $\pi_i(1, 0) \geq \pi_i(0, 0)$ and $\pi_i(1, 1) \geq \pi_i(0, 1)$. For (2) $\pi_i(1, 0) \geq \pi_i(0, 0)$ but $\pi_i(1, 1) \leq \pi_i(0, 1)$ are required, while for (3) $\pi_i(1, 0) \leq \pi_i(0, 0)$ and $\pi_i(1, 1) \leq \pi_i(0, 1)$ is necessary. □

As expected, the advantage cheating brings is the driving factor for how much cheating we observe in a pure strategy equilibrium. For low δs, cheating does not occur. For intermediate

[4] We implicitly assume that the expected fine is not prohibitive ($pf < r/4$).

values of δ, half of the players cheat and if the effectiveness of cheating is very high, then everybody cheats. The expected fine pf, just as intuition suggests, has the opposite effect on cheating. Similarly, the lower the fraction r of the prize retained by the contestant, the higher the effectiveness of cheating has to be such that one ore both contestants cheat in equilibrium.

There obviously exists a mixed-strategy equilibrium for $\delta \in \left[\underline{\delta}, \bar{\delta}\right]$, when the the underlying structure is that of a game of chicken with two asymmetric equilibria.

Proposition 4.2. *Define the probability of contestant i cheating when playing a mixed strategy as σ_i, then for $\delta \in \left[\underline{\delta}, \bar{\delta}\right]$ there also exists a mixed strategy equilibrium $\left(\sigma_1^*, \sigma_2^*\right)$,with*

$$\sigma_i^* = \frac{\left(\frac{\delta}{1+\delta}\right)^2 - \frac{1}{4} - \frac{pf}{r}}{\frac{1+\delta^2}{(1+\delta)^2} - \frac{1}{2}} \; \forall i \in \{1,2\}.$$

Proof. For contestant 1 to be willing to randomise indifference is necessary and $\sigma_2 \pi_1(1,1) + (1-\sigma_2)\pi_1(1,0) = \sigma_2 \pi_1(0,1) + (1-\sigma_2)\pi_1(0,0)$ must hold. Solving for σ_2 yields σ_2^*. Symmetry implies $\sigma_1^* = \sigma_2^*$. □

The equilibrium cheating probability in the mixed-strategy equilibrium increases with the effectiveness of cheating from zero at $\delta = \underline{\delta}$ to one at $\delta = \bar{\delta}$. This observation is in line with general intuition. Similarly, the cheating probability increases with the retention fraction r and decreases with the expected fine.

It will prove useful for future comparison to reduce the dimensionality of the parameter space by defining a constant h.

Definition. Define h as the opponent's cheating probability that solves $h\pi_i(1,1) + (1-h)\pi_i(1,0) = h\pi_i(0,1) + (1-h)\pi_i(0,0)$:

$$h := \frac{\left(\frac{\delta}{1+\delta}\right)^2 - \frac{1}{4} - \frac{pf}{r}}{\frac{1+\delta^2}{(1+\delta)^2} - \frac{1}{2}}.$$

Note that h can be interpreted as the opponent's cheating probability that makes a contestant indifferent between cheating and not cheating. This implies that for a cheating probability of the opponent smaller (greater) than h (not) cheating is optimal.

Then we can replace the conditions in the Propositions above. For example, $\delta \geq \bar{\delta}$ becomes $h \geq 1$, $\delta \in [\underline{\delta}, \bar{\delta}]$ becomes $h \in [0,1]$ and $\delta \leq \underline{\delta}$ becomes $h \leq 1$. Also the equilibrium mixing strategy can be expressed as $\sigma_i^* = h$.

Figure 4.1 plots the average cheating probability in the equilibria depending on h. The average cheating probability, g, is calculated as $(\sigma_1^* + \sigma_2^*)/2$. According to the Proposition 4.1, when $h \geq 1$, both competitors play cheating as a pure strategy at equilibrium (i.e., $(\sigma_1^*, \sigma_2^*) = (1,1)$) and therefore, $g = 1$. This relationship is captured by the flat line segment PSE_1 in Figure 4.1. When $h \leq 0$, there only exists a non-cheating pure strategy equilibrium (i.e., $(\sigma_1^*, \sigma_2^*) = (0,0)$), which yields $g = 0$. This is indicated by the flat line segment PSE_2. When $h \in [0,1]$, in an asymmetric pure strategy equilibrium of $(\sigma_1^*, \sigma_2^*) = (1,0)$ or $(\sigma_1^*, \sigma_2^*) = (0,1)$, g is found to be $1/2$ (i.e., see the flat line segment PSE_3). In addition, there also exists a mixed strategy equilibrium where $(\sigma_1^*, \sigma_2^*) = (h,h)$, $g = h$ (i.e., see the upward sloping line segment MSE). As expected the equilibrium cheating probability (weakly) increases with h. Recall that a high value of h signifies an environment that is cheating friendly, because cheating is very effective at improving the outcome in the contest (i.e. a high δ or a low expected fine pf).

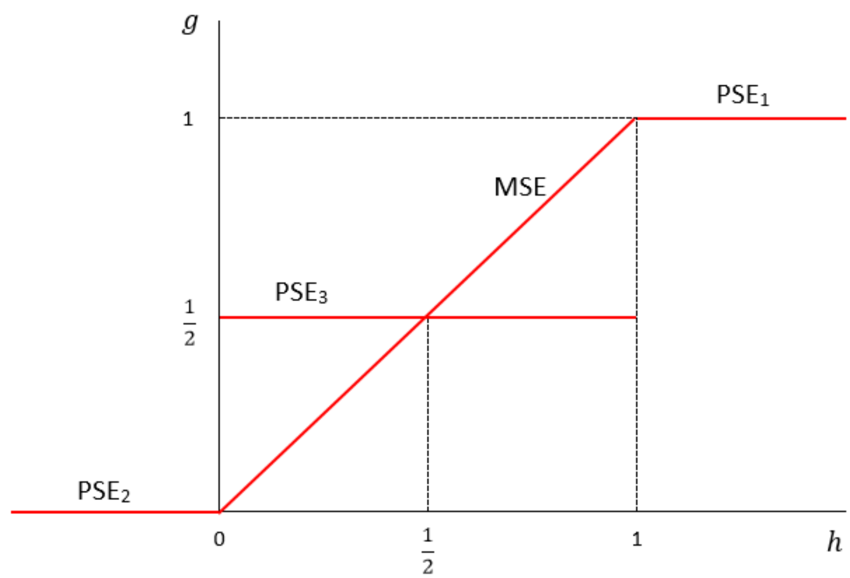


Figure 4.1: Equilibrium cheating probabilities for individual cheating decisions

4.2.2 Non-liable manager with influence on cheating

Let us now introduce the manager. We start with a scenario where the manager receives a fraction $(1-r)$ of the prize-share S_i the contestant secures. The manager has an influence on the contestant's cheating decision but is not liable for it if the contestant is caught cheating. Our new game now has four players, two contestants and two non-contestants that have an input into the cheating decision and receive a share of the prize their contestants receive. For simplicity we call the the non-contestants managers. Denote the four players as $\{a1, m1, a2, m2\}$, where for example $a1$ stands for the contestant of team one, while $m2$ is the manager of team two. A player can now be referred to as ri, where $r \in a, m$ denotes the role and $i \in 1, 2$ the team. The timing is as follows.

1. All four players choose their cheating intention $d_{ri} \in \{0, 1\}$.

2. For each team Nature picks one player at random with equal probability, whose cheating intention is implemented. Denote the implemented decision for the contestant i by d_i.

3. Both contestants a_i, $i \in 1, 2$, learn (d_i, d_j) , $i, j \in \{1, 2\}$, $i \neq j$ and choose efforts e_i.

4. Payoffs are realised.

We model the distributed cheating decision as a random dictator mechanism. The random dictator mechanism is chosen as a reduced-form description of an otherwise very complex negotiation process. For a purely theoretical contribution, a more detailed modeling of the intra-team bargaining would be preferable. Our choice is made with the experimental implementation in mind, where simplicity is important in order to keep confusion and the noise in behaviour resulting from it to a minimum. Our simple reduced-form mechanism captures the salient feature of bargaining by ensuring that the likelihood of a contestant's cheating increases with each team member's intention to cheat.

We, as usual, proceed backwards when solving the game for subgame-perfect equilibria. When the contestants choose their efforts, the cheating decisions (d_1, d_2) have been implemented. So the contestants' continuation payoffs are identical to those in the game without an active involvement of a manager, as defined in Equation (4.1). This implies that Lemma 4.1 applies, and equilibrium efforts are given by Equation (4.5). Again, we assume the implemented cheating decisions are common knowledge to both teams before contestants choose their efforts. If we relax this assumption, our two-stage game is equivalent to a one-stage game where each contestant i simultaneously decides on the pair $(d_{ai},\ e_i)$ while each manager i decides on d_{mi}.

Now consider the choice of cheating intentions of the managers d_{mi}, $i \in 1, 2$. It is easy to see that the lack of liability for detected cheating leads to $d_{mi} = 1$ being a dominant strategy in the game that takes the equilibrium efforts as given. Regardless of the cheating decisions of the other team the manager prefers his own team to cheat, since we have:

$$\pi_{mi}(1,1) = \frac{(1-r)}{2} > \pi_{mi}(0,1) = \frac{(1-r)}{1+\delta}$$
$$\pi_{mi}(1,0) = \frac{(1-r)\,\delta}{(1+\delta)} > \pi_{mi}\,(0,0) = \frac{(1-r)}{2}.$$

The observation that the probability of the own team cheating increases by 1/2 if the manager's intention is to cheat, in equilibrium she will always choose $d_{mi} = 1$. This yields the following proposition.

Proposition 4.3. *Non-liable managers will always choose to cheat, i.e.* $d^*_{mi} = 1 \, \forall i \in 1, 2$.

The payoffs for the contestants depending on the implemented cheating decisions are identical to those in the individual choice problem laid out in Table 4.1. It turns out that the conditions on parameters for contestants to have a dominant strategy in choosing d_{ai} in the reduced normal-form game are identical to the individual case. The intuition behind this is simple. Choosing $d_{ai} = 1$ increases the likelihood that cheating is implemented. Then a contestant who prefers cheating regardless of the likelihood of the manager cheating will choose $d_{ai} = 1$. Similarly, a contestant who prefers not to cheat to be implemented will always choose $d_{ai} = 0$. Since the payoffs for the contestants are the same as in the individual case, the conditions on parameters are also the same. We will formalize this now.

Proposition 4.4. *Defining*

$$h^I := \frac{\left(\frac{\delta}{1+\delta}\right)^2 - \frac{1}{4} - \frac{pf}{r}}{\frac{1+\delta^2}{(1+\delta)^2} - \frac{1}{2}}, \tag{4.6}$$

we obtain the following pure-strategy equilibria in weakly dominating strategies in the reduced game where future equilibrium efforts are taken into account:

1. $(d^*_{m1}, d^*_{a1}; d^*_{m2}, d^*_{a2})$=$(1, 1; 1, 1)$ *if* $h^I \geq 1$.

2. $(d^*_{m1}, d^*_{a1}; d^*_{m2}, d^*_{i2})$=$(1, 0; 1, 0)$ *if* $h^I \leq 1$.

Proof. Denote the probability that the opponent implements cheating as μ_j. Then player $ai's$ expected payoff from choosing $d_{ai} = 1$ is given by

$$\pi_{ai}\left(1, d^*_{mi}; \mu_j\right) = \mu_j \pi_{ai}\left(1, 1\right) + \left(1 - \mu_j\right) \pi_{ai}\left(1, 0\right).$$

Similarly, the payoff form choosing $d_{ai} = 0$ calculates as

$$\pi_{ai}\left(0, d^*_{mi}; \mu_j\right) = \mu_j \pi_{ai}\left(0,1\right) + \left(1-\mu_j\right)\pi_{ai}\left(0,0\right).$$

Note that the $d^*_{mi} = d^*_{mj} = 1$ from the proposition above.

$$\mu_j \pi_{ai}\left(1,1\right) + \left(1-\mu_j\right)\pi_{ai}\left(1,0\right) \gtreqless \mu_j \pi_{ai}\left(0,1\right) + \left(1-\mu_j\right)\pi_{ai}\left(0,0\right).$$

Since we are looking for weak dominance this has to hold for all μ_j, which implies that

$$\begin{aligned}\pi_{ai}\left(1, d^*_{mi}; \mu_j\right) \geq \pi_{ai}\left(0, d^*_{mi}; d_{aj}, d^*_{mj}\right) \forall \mu_j \in [0,1] \\ \Longleftrightarrow & \pi_{ai}\left(1,1\right) \geq \pi_{ai}\left(0,1\right) \wedge \pi_{ai}\left(1,0\right) \geq \pi_{ai}\left(0,0\right) \\ \Longrightarrow & h^I \geq 1.\end{aligned}$$

Similarly,

$$\begin{aligned}\pi_{ai}\left(1, d^*_{mi}; \mu_j\right) \leq \pi_{ai}\left(0, d^*_{mi}; d_{aj}, d^*_{mj}\right) \forall \mu_j \in [0,1] \\ \Longleftrightarrow & \pi_{ai}\left(1,1\right) \leq \pi_{ai}\left(0,1\right) \wedge \pi_{ai}\left(1,0\right) q \pi_{ai}\left(0,0\right) \\ \Longrightarrow & h^I \leq 0.\end{aligned}$$

□

Recall that the constant h^I is the probability of the opponent to implement cheating that makes a contestant indifferent between cheating an not cheating. The actual cheating probability of the opponent (contestant aj) to implement cheating is calculated as $(d_{aj} + d_{mj})/2$. If this actual cheating probability is greater than h^I, then not cheating is optimal for contestant ai. Now suppose contestant aj does not cheat (i.e. $d_{aj} = 0$), then the expected probability of the opponent to implement cheating is equal to $\mu_j = (1+0)/2 = 1/2$. In this case, for $h^I \leq 1/2$, any contestant ai's best response is not to cheat. By symmetry, not cheating for both contestants becomes an equilibrium. Similarly, suppose that contestant aj cheats (i.e. $d_{aj} = 1$). It follows that $\mu_j = (1+1)/2 = 1$, which implies that for $h^I \leq 1$, not cheating is a best response for contestant ai (i.e. $d_{ai} = 0$). Now we have to check if cheating for contestant aj is a best response to contestant ai not cheating. The actual implemented cheating probability of contestant ai is $\mu_i = 1/2$. So for $h^I \geq 1/2$ $d_{aj} = 1$ is a best response to $d_{ai} = 0$. So for $h^I \in [1/2, 1]$ we have two pure-strategy equilibria, where – additionally to the two managers cheating – one of two contestants also cheats. Finally, in the same region there exists a mixed-strategy equilibrium, where $\mu_1 = \mu_2 = h^I$ has to hold. Since $\mu_i = \frac{\sigma_{ai}+1}{2}$, it follows that $\sigma^*_{ai} = 2h^I - 1$ for $i = 1, 2$. We summarise the findings in the following proposition.

Proposition 4.5. *for intermediate h^I we obtain the following equilibria*

1. $(d^*_{m1}, d^*_{a1}; d^*_{m2}, d^*_{a2})$=$(1, 0; 1, 0)$ *if* $h^I \in [0, 1/2]$.

2. $(d^*_{m1}, d^*_{a1}; d^*_{m2}, d^*_{a2})$=$(1, 1; 1, 0)$ *or* $(1, 0; 1, 1)$, *or* $(d^*_{m1}, \sigma^*_{a1}; d^*_{m2}, \sigma^*_{a2}) = \left(1, h^I; 1, h^I\right)$ *if* $h^I \in [1/2, 1]$.

To examine the overall amount of cheating at equilibrium when managers can influence cheating decisions, we define the average cheating probability as

$$g = \left(\sigma^*_{m1} + \sigma^*_{a1} + \sigma^*_{m2} + a^*_{a2}\right)/4.$$

For each equilibrium identified in Propositions 4.4 and 4.5, g can be calculated accordingly:

1. When $h^I \geq 1$, in the cheating equilibrium, $g = 1$.[5]

2. When $h^I \leq 1/2$, in the equilibrium where contestants do not cheat $(1, 0; 1, 0)$, $g = 1/2$. [6]

[5] See the flat dashed line segment PSE^I_1 in Figure 4.2.
[6] See the flat dashed line segment PSE^I_2 in Figure 4.2.

3. When $h^I \in [1/2, 1]$, $g = 3/4$ in the asymmetric pure strategy equilibrium $(1, 1; 1, 0)$ or $(1, 0; 1, 1)$, [7]or $g = h$ in the mixed strategy equilibrium $(1, 2h - 1; 1, 2h - 1)$.[8]

Figure 4.2 shows the plot of the average cheating probabilities for individual decision making case (solid line) and compares it to the cheating probabilities under distributed decision making where the contestant is fully liable for cheating (dashed line). Both correspondences are increasing in h^I, as one would expect. Recall that the manager always cheats in the distributed decision-making case. This leads to weakly higher maximum and minimum cheating probabilities for all levels of h^I. In equilibria where the contestant can adjust his own behaviour, such that he prefers the manager to cheat, there the cheating probabilities are the same as in the individual decision case. In equilibria, where at least one contestant cannot adjust her own behaviour such that she prefers the manager to not cheat, we have a higher cheating probability in the joint decision making case. The cases where this leads to strictly higher cheating probabilities in the joint decision case are for $h^I < 0$and for $h^I \in(1/2, 3/4)$.

[7] See the flat dashed line segment PSE_3^I in Figure 4.2.
[8] See the upward sloping dashed line segment MSE^I in Figure 4.2.

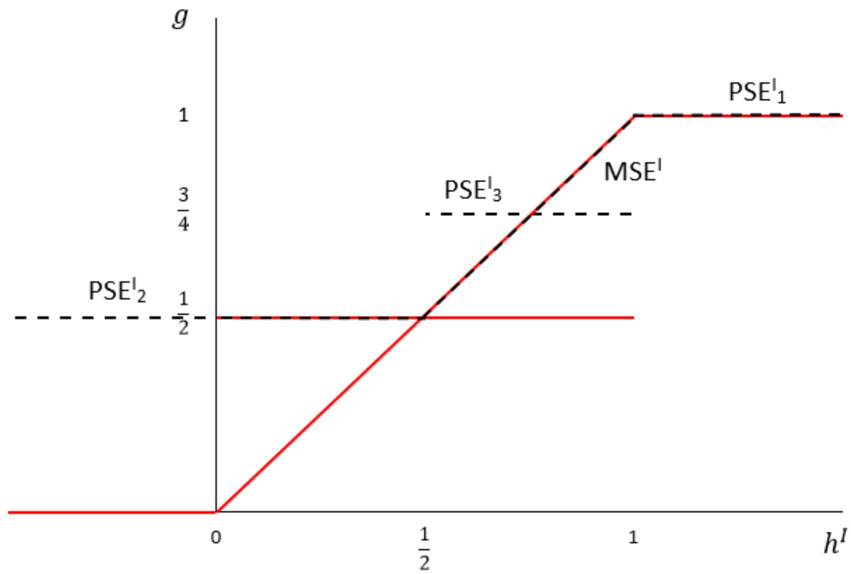


Figure 4.2: Comparison of the average cheating probability between contestants only and distributed decision regimes

Suppose that all equilibiria in a given regime at a given value of $h^I$are all equally likely, then the resulting expected cheating probability is higher under distributed decision making for all values up to $h^I = 1$ where cheating becomes a dominant strategy for the contestant in both environments and everybody involved cheats with certainty. In summary, the addition of a manager who is not liable for detected cheating to the cheating decision tends to lead to an agency problem in teams, which tends to increase the prevalence of cheating.

4.2.3 Jointly liable manager with impact on cheating

We now turn to a regime, which only differs from the distributed cheating decision environment described above by the payoffs. We want to see if making the manager liable for detected cheating can overcome the problem that adding a non-competing agent with an influence on the cheating decision to the mix, tends to increase the equilibrium cheating frequency. In this environment, the manager does not only receive a share $1 - r$ of the prize money but also has to pay his share of the fine if cheating is detected. Ideally, one would like to align the manager's and the contestant's incentives, such that the strategic situation reduces to the case without an agency problem. However, even imposing joint liability does not achieve this, since the manager cannot be forced to share the cost for the contestant's effort in the contest. So introducing joint liability for fines, does not totally eliminate the agency problem. The immediate consequence of joint liability is that the manager does not have an incentive to cheat all the time anymore, as it was the case when the fine was solely levied on the contestant. This deterrence effect has a negative effect on the equilibrium cheating rate. However, there is also a countervailing effect. The contestant will now only pay a fraction r of the fine if caught, which reduces the disincentive the fine has on her cheating behaviour. So ex-ante the over-all effect of the shift in liability is unclear.

The expected payoff for the contestants are now given by:

$$\pi_{ai} = rS_i(e_i, e_j, d_i, d_j) - e_i - rd_ipf.$$

Note that the difference to the individual liability case is that now the contestant only pays her share r of the expected fine if she is caught cheating. Our first observation is that this difference does not impact the equilibrium efforts since this changes neither the marginal benefit nor the marginal cost of efforts. This implies again that Lemma 4.1 applies, and the equilibrium efforts are given by Equation (4.5). The continuation payoffs for the contestants who are anticipating optimal efforts are given in Table 4.2.

		Contestant aj	
		$d_j = 1$	$d_j = 0$
Contestant ai	$d_i = 1$	$\frac{1}{4}r - pfr,\ \frac{1}{4}r - pfr$	$\left(\frac{\delta}{\delta+1}\right)^2 r - pfr,\ \left(\frac{1}{1+\delta}\right)^2 r$
	$d_i = 0$	$\left(\frac{1}{1+\delta}\right)^2 r,\ \left(\frac{\delta}{\delta+1}\right)^2 r - pfr$	$\frac{1}{4}r,\ \frac{1}{4}r$

Table 4.2: Contestants' continuation payoffs under joint liability

As in the other regimes, we can again calculate the probability of the opponent to implement cheating as a function of the parameters that makes the contestant indifferent between cheating and not cheating.

Definition. Define h^J that solves $h^J \pi_i(1,1) + \left(1 - h^J\right)\pi_i(1,0) = h^J \pi_i(0,1) + \left(1 - h^J\right)\pi_i(0,0)$, where the continuation payoffs are taken form Table 4.2:

$$h^J := \frac{\left(\frac{\delta}{1+\delta}\right)^2 - \frac{1}{4} - pf}{\frac{1+\delta^2}{(1+\delta)^2} - \frac{1}{2}}. \tag{4.7}$$

we can now compare the resulting critical constant h in the individual liability systems, which we denote by $h^I$from now on, to the critical constant h^J under joint liability. The only difference is that under the joint liability regime the negative impact of the expected fine in not divided by the share r. It is easy to see that h^J is greater than h^I for all $r \in (0,1)$. This has the important implication that the doping incentives are stronger for the contestant in the joint liability case, which we establish formally in the following proposition.

Proposition 4.6. *Denote the different regimes as I for individual liability and J for joint liability. Denote the optimal probability of cheating for contestant ai in regime $K \in I, J$ for given parameters δ, p and r and for a given implemented cheating probability of the opponent*

μ_j *as* $\sigma^*_{K,ai}$, *then we have*

$$\sigma^*_{J,ai} \geq \sigma^*_{I,ai} \forall \delta > 1, p \in (0,1), r \in (0,1). \tag{4.8}$$

Proof. Recall that

$$\sigma^*_{K,ai} = \begin{cases} 0 & \text{if } h^K < \mu_j \\ \in [0,1] & \text{if } h^K = \mu_j \\ 1 & \text{if } h^K > \mu_j. \end{cases}$$

Observe that for given μ_j, $\sigma^*_{K,ai}$ is increasing in h^K. Combining this with the fact $h^J > h^I$ for given parameters implies inequality (4.8). □

The proposition above documents the increased cheating incentive for the contestants, which occurs since now the expected fine for cheating is shared with the manager. The share of the fine borne by the manager causes a reduction in the managers' incentive to cheat. Table 4.3 shows the managers' continuation payoffs depending on the team cheating or not under the assumption that efforts will follow equilibrium.

		Manager mj	
		$d_j = 1$	$d_j = 0$
Manager mi	$d_i = 1$	$(1-r)\left(\frac{1}{2} - pf\right)$, $(1-r)\left(\frac{1}{2} - pf\right)$	$(1-r)\left(\frac{\delta}{1+\delta} - pf\right)$, $\left(\frac{1-r}{1+\delta}\right)$
	$d_i = 0$	$\left(\frac{1-r}{1+\delta}\right)$, $(1-r)\left(\frac{\delta}{\delta+1} - pf\right)$	$\frac{1-r}{2}$, $\frac{1-r}{2}$

Table 4.3: Managers' continuation payoffs under joint liability

It turns out that depending on parameter values the managers either has a dominant strategy to cheat or not to cheat.

Lemma 4.2. *In the joint liability regime, the optimal decision of the manager is*[9]

$$\sigma^*_{mi} = \begin{cases} 0 & \text{if } h^J < 1/2 \\ \in [0,1] & \text{if } h^J = 1/2 \\ 1 & \text{if } h^J > 1/2 \end{cases} \tag{4.9}$$

Proof. Checking the conditions for $\pi_{mi}(1,1) \lesseqgtr \pi_{mi}(0,1)$ and $\pi_{mi}(1,0) \lesseqgtr \pi_{mi}(0,0)$ reveals that the sufficient condition for both to hold is identical with

$$pf \lesseqgtr \frac{1}{2} - \frac{1}{1+\delta}.$$

Solving equation (4.7), which defines $h^J$for pf and substituting into the equality above yields $h^J \lesseqgtr 1/2$. □

According to the proposition above, joint liability over-all weakly reduces the cheating incentive of the manager. For the case that the cheating effectiveness δ is low or the expected fine for cheating pf is high, a manager does not any longer prefer to cheat if she is jointly liable. The joint liability does not prevent the managers from cheating if the environment is very favourable for cheating, though.

Interestingly, joint liability does not perfectly align the incentives of the contestants and their managers. This stems from the fact that only the contestants have to bear the effort cost from the competition. So there is still room for equilibrium cheating probabilities to be distorted by the agency problem within manager-contestant teams. The question of interest here is if joint liability, as simple intuition might suggest, always reduces the cheating prevalence compared to the case where only the contestant is liable. The answer is no. As we will show below, the equilibrium cheating probabilities with joint liability are lower for

[9]For notational ease, we drop the index for the regime in places where there is no risk of confusion.

some parameter constellations, but equal or even greater than under individual liability for other parameter constellations.

In what follows we will derive and describe the equilibria for different values for μ_j. It is easy to see that for $h^J < 0$ all four players in the reduced game have a dominant strategy not to cheat, which leads to an equilibrium without cheating. For $h^J \in [0, 1/2]$ it is still a best response for the managers not to cheat. Hence, the probability of the opponent to implement cheating is $\mu_j = (\sigma_{mj} + \sigma_{aj})/2 = \sigma_{aj}/2$. Recall that any contestant ai has a best response to cheat whenever μ_j is weakly below h^J. Suppose that the other contestant does not cheat, which implies $\mu_j = 0$. Then for contestant ai, it is a best response to cheat, since $h^J > \mu_j$ given $\mu_j = 0$ and $h^J \geq 0$. With $\sigma_{ai} = 1$ we obtain $\mu_i = 1/2$, which in turn makes the conjectured $\sigma_{aj} = 0$ a best response. Hence, for $h^J \in [0, 1/2]$ there exist two asymmetric equilibria, where one contestant cheats, while the other three players do not. In the corresponding mixed strategy equilibrium we must have $\mu_i = \mu_j = h^J$,which implies that both contestants cheat with probability $\sigma^*_{ai} = \sigma^*_{ai} = 2h^J$,since the managers do not cheat. For the knife-edge case where $h^J = 1/2$, there exists a continuum of mixed-strategy equilibria, where all four players are indifferent and mix with probabilities, such that the implemented cheating probability d_i is equal to 1/2. Any strategy profile $(\sigma_{m1}, \sigma_{a1}; \sigma_{m2}, \sigma_{a2})$ that satisfies $\sigma_{mi} + \sigma_{ai} = 1 \forall i \in 1, 2$ is an equilibrium.

If the environment is more favourable for cheating, i.e. $h^J \in [1/2, 1]$, then the managers have dominant strategies to cheat $(d_{mi} = d_{mj} = 1)$. Now suppose that the contestant aj does not cheat, $d_{aj} = 0$. Then $\mu_j = 1/2$,which now implies that cheating is a best response for contestant ai,since $h^J \geq \mu_j$. It remains to check if the assumption that contestant aj does not want to cheat is actually true. With both team members of team i cheating, we have $\mu_i = 1$. Not to cheat is indeed a best response, since $h^J \leq 1$. In this equilibrium we can see that joint liability does not totally align the incentives of the two team members. In one of the teams the manager and the contestant choose different actions. The contestant would prefer if the manager did not cheat. In addition to the two asymmetric pure-strategy equilibria, a hybrid equilibrium exists where the managers cheat and the contestants mix. Mixing is optimal for contestant ai if $\mu_j = h^J$,which pins down the cheating probabilities $\sigma^*_{ai} = \sigma^*_{ai} = 2h^J - 1$. Finally for $h^J \geq 1$, all four players have a dominant strategy to cheat, which results in a cheating equilibrium. The following proposition summarises the equilibria.

Proposition 4.7. *In the joint-liability regime we obtain the following equilibria*

1. $(\sigma^*_{m1}, \sigma^*_{a1}; \sigma^*_{m2}, \sigma^*_{a2})$=$(1, 1; 1, 1)$ *and* $g = 1$ *if* $h^J \geq 1$.[10]

2. $(\sigma^*_{m1}, \sigma^*_{a1}; \sigma^*_{m2}, \sigma^*_{a2})$=$(0, 0; 0, 0)$ *and* $g = 0$ *if* $h^J \leq 0$.[11]

3. $(\sigma^*_{m1}, \sigma^*_{a1}; \sigma^*_{m2}, \sigma^*_{a2})$=$(0, 1; 0, 0)$, $(0, 0; 0, 1)$ *and* $g = 1/4$,[12] *or* $\left(0, 2h^J; 0, 2h^J\right)$ *and* $g = h^J$ *if* $h^J \in [0, 1/2]$. [13]

4. $(\sigma^*_{m1}, \sigma^*_{a1}; \sigma^*_{m2}, \sigma^*_{a2})$, such that $\sigma^*_{mi} + \sigma^*_{ai} = 1 \forall i \in 1, 2$ and $g = 1/2$ *if* $h^J = 1/2$.

5. $(\sigma^*_{m1}, \sigma^*_{a1}; \sigma^*_{m2}, \sigma^*_{a2})$=$(1, 1; 1, 0)$, $(1, 0; 1, 1)$*;* $g = 3/4$ *or* $\left(1, 2h^J - 1; 1, 2h^J - 1\right)$*;* $g = h^J$ *if* $h^J \in [1/2, 1]$.[14]

4.2.4 Comparison of equilibrium cheating rates in the two regimes

Characterising the equilibria under both liability regimes, allows us to answer the question, which regime yields lower predicted cheating rates. Figure 4.3 overlays the average cheating probabilities in the two regimes. The solid line depicts the equilibrium average cheating probability in the joint liability scheme, while the dashed line does the same for the individual liability case. Note that the position of the dashed line depends on r. To see this take the definitions of $h^I$and h^Jin equations (4.6) and (4.7). We see that h^Iconverges to $h^J$when r goes to one. For positive shares of the manager (i.e. $1 - r < 0$), we have $h^I < h^J$. Hence, in Figure 4.3 the dashed line shifts to the the right when r decreases. On the other hand,

[10] See the flat line segment PSE^J_1 in Figure 4.3.
[11] See the flat line segment PSE^J_2 in Figure 4.3.
[12] See the flat line segment PSE^J_3 in Figure 4.3.
[13] See the flat line segment MSE^J_1 in Figure 4.3.
[14] See the flat line segment MSE^J_2 in Figure 4.3.

when r goes to one, then the equilibrium cheating graph in the individual liability regime converges to that under joint liability for $h^J > 1/2$. From the graph we can see that for $h^J < 1/2$ the average equilibrium cheating probability is strictly higher under individual liability. The incentive of the manager to cheat dominates. For higher values of h^Jindicating an environment that is more conducive to cheating, then the cheating probability tends to be lower in the individual liability case. This is driven by the contestants reduced deterrence in the joint liability case dominating the increased deterrence the joint liability regime has on the manager.

Define the maximum equilibrium cheating probability in regime K for parameter values h^Jas $\bar{g}^K\left(h^J\right)$. Similarly define the minimum as $\underline{g}^K\left(h^J\right)$. Then we can more precisely summarise the results of our comparison.

Proposition 4.8. *The following comparisons of equilibrium cheating rates hold:*

1. $\bar{g}^J\left(h^J\right) < \underline{g}^I\left(h^J\right)$ if $h^J < 1/2$.

2. $\bar{g}^J\left(h^J\right) \geq \bar{g}^I\left(h^J\right)$ and $\underline{g}^J\left(h^J\right) \geq \underline{g}^I\left(h^J\right)$ if $h^J > 1/2$.

Proof. This follows directly from propositions 4.4, 4.5 and 4.7. □

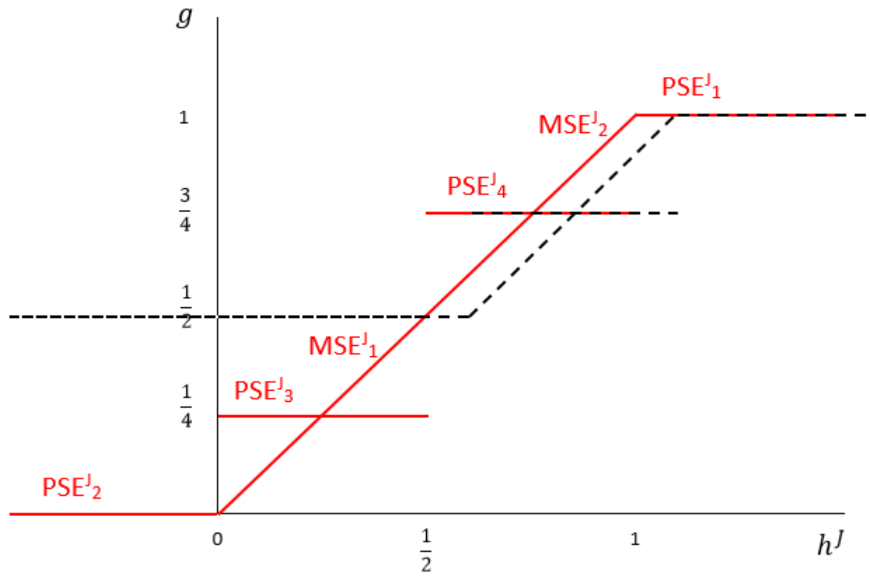


Figure 4.3: Comparison of cheating rates under individual and joint liability

Corollary 4.1. *For any $r < 1$ there exists an $h^J > 1/2$ such that* $\underline{g}^J\left(h^J\right) > \bar{g}^I\left(h^J\right)$.

Proof. First define an arbitrary small constant $\epsilon < pf\left(\frac{1}{r} - 1\right)$,which always exist since $r < 1$. Then fix $\tilde{h}^J = 1/2 + \epsilon$. Since $h^I = h^J - pf\left(\frac{1}{r} - 1\right)$ it follows that $h^I < 1/2$ if $h^J = \tilde{h}^J$. Now check in propositions 4.5 and 4.7 for the equilibria and in the two regimes at $\tilde{h^J}$. We find that $\underline{g}^J\left(h^J\right) = 1/2 + \epsilon > \bar{g}^I\left(\hat{h}^J\right) = 1/2$. □

With the previous proposition and and corollary we have shown that for any r there exist parameter regions, where either the joint or the individual liability regime leads to a strictly lower cheating probability. In environments with lower cheating incentives (i.e. low cheating effectiveness δ,or high expected fines pf), joint liability is preferable due to the less equilibrium cheating. In environments that are more favourable for cheating, individual liability is preferred. In the next Section, we bring our model to the laboratory and check if human behaviour is consistent with our model and if the policy implication from the model are likely to be valid in reality.

4.3 Experimental Design and Hypotheses

In what follows we will present an experimental design, which will be used to test if the general result from our model, that joint liability tends to lead to lower cheating rates in environments with low cheating incentives, while putting all liability on the contestant is theoretically preferred in environments where cheating incentives are strong. In our 2×2 design we vary the cheating incentives by employing two different fine levels f_l and f_h, as increasing the fine reduces the cheating incentives. The other dimension is the liability regime. In the individual-liability regime I the fine for caught cheating is borne by the contestant alone. Under joint-liability J the manager and the contestant share not only the revenue from the contest but also the fine if cheating is detected. We end up with the four treatments If_l, If_h, Jf_l, and Jf_h. For the four treatments we choose the parameters such that we obtain clear predictions on cheating. In the individual liability case for both fines levels in equilibrium both managers cheat, while both contestants do not. This leads for both If_l and If_h to a predicted cheating probability of 50%. In the joint-liability treatments the equilibria differ. Here with a high fine in If_h in equilibrium on average one contestant cheats, while both managers do not cheat, which results in a cheating probability of 25%. For the high-fine treatment Jf_l in equilibrium on average still one contestant cheats. Now the lower fine renders it optimal for both managers to cheat, which increases the average cheating probability to 75%. Figure 4.4 shows the location of the treatment on the equilibrium map, where the dark line captures the individual liability regime, while the lighter (red) lines correspond to joint liability.

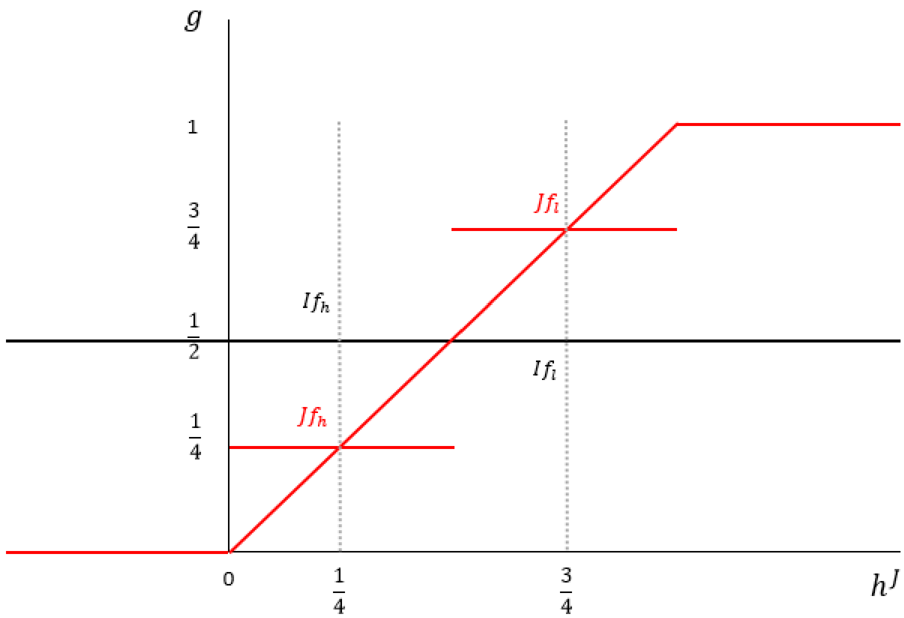


Figure 4.4: Equilibria in the four treatments

The parameter values we use in order to obtain these equilibria are as follows. The cheating efficiency δ is set to 2. This means that if both contestants choose the same effort and don't cheat, then switching to cheating unilaterally increases the prize share from 1/2 to 2/3. The contestant's share r is set to 2/3. This leads to equilibrium payoffs that are similar between the manager and the contestant. In order to obtain payoffs in experimental currency units that are of a reasonable size we choose a prize V of 90. [15] The probability of getting caught cheating p is equal to 25 percent. The fines for the two treatments are set to $f_l = 55$ and $f_h = 65$. The parameter values and the predictions are summarized in Table 4.4.

[15] In the model section we normalized the prize to unity. The prize V just scales contest revenue and therefore equilibrium efforts and enters h^J and h^I in an obvious way: pf becomes pf/V and pf/r becomes pf/rV, respectively.

	If_l	If_h	Jf_l	Jf_h
Prize, V	90	90	90	90
Cheating efficiency, δ	2	2	2	2
Probability of getting caught, p	25%	25%	25%	25%
Sharing ratio, r: 1-r	$\frac{2}{3}:\frac{1}{3}$	$\frac{2}{3}:\frac{1}{3}$	$\frac{2}{3}:\frac{1}{3}$	$\frac{2}{3}:\frac{1}{3}$
Fixed fine, f	55	65	55	65
Cheating rate of contestants	$\sigma_{ai}=0$ $\sigma_{aj}=0$	$\sigma_{ai}=0$ $\sigma_{aj}=0$	$\sigma_{ai}=1$, $\sigma_{aj}=0$ or $\sigma_{ai},\sigma_{aj}=0.5$	$\sigma_{ai}=1$, $\sigma_{aj}=0$ or $\sigma_{ai},\sigma_{aj}=0.5$
Cheating rate of managers	$\sigma_{mi},\sigma_{mj}=1$	$\sigma_{mi},\sigma_{mj}=1$	$\sigma_{mi},\sigma_{mj}=1$	$\sigma_{mi},\sigma_{mj}=0$
Predicted cheating rate, g	$\frac{1}{2}$	$\frac{1}{2}$	$\frac{3}{4}$	$\frac{1}{4}$

Table 4.4: A summary of values of parameters by treatment

Based on the parameters chosen, we then can derive the important theoretical predictions on how players should behave in our experiment. Firstly, comparing predicted average cheating probability across four treatments, shows that the Jf_l treatment produces that highest rate of cheating of 3/4, followed by the If_l and the If_h treatments where a cheating rate of 1/2 is predicted. The Jf_h yields the lowest predicted cheating probability of 1/4. This can be summarised in Conjecture 4.1.

Conjecture 4.1. *Theoretically, the average cheating probabilities across four treatments follows a relationship of* $Jf_h < If_h = If_l < Jf_l$.

From Equation (4.5) , we find that effort is higher if symmetric implemented cheating decisions are reached. Given contestant's and manager's cheating incentives at equilibrium, the probability of having same cheating decisions implemented is the same between the If_h and the If_l treatments, at 1/4. This probability is higher, at 5/8, in both the Jf_h and the Jf_l treatments. This means average effort is predicted to be higher in the joint liability treatments than in the individual liability treatments. Hence, we summarize this in Conjecture 4.2.

Conjecture 4.2. *Induced by optimal cheating decisions of both teams, equilibrium efforts across the four treatments follow a relationship of* $If_h = If_l < Jf_h = Jf_l$.

A corollary to the above Conjecture, efforts should only depend on actually implemented cheating decisions but not on treatments, once the cheating conditions are controlled for. By design, in the If_l and If_h treatments, the size of the fine does not affect manager's and contestant's cheating incentives. Therefore, under individual liability, contestants should not cheat whereas managers should always cheat, which yields the following Conjecture:

Conjecture 4.3. *Under the individual liability scheme (*If_l *and* If_h*), contestants never cheat while managers always do.*

Under joint liability, however, the magnitude of the fine plays an important role. While a shared low fine is ineffective in deterring managers from cheating, a shared high fine eliminates manager's cheating incentive completely. The contestant's equilibrium cheating incentive is not affected by the fine size. That is,

Conjecture 4.4. *Under joint liability, managers are more likely to cheat in the* Jf_l *treatment, while the size of the fine does not impact the cheating behavior of contestants.*

The experiment took place at the Adelaide Laboratory for Experimental Economics (AdLab) at the University of Adelaide. For each treatment we ran three sessions. All 12 sessions were programmed and implemented using Z-tree (Fischbacher, 2007). 248 subjects were recruited using the online recruitment system ORSEE (Greiner, 2015). Each subject participated in one session only.

Upon arrival the subjects were randomly assigned to a computer. The instructions were distributed and read aloud by the experimenter. Subjects then were required to answer test questions correctly to proceed to the actual experiment. In each session, subjects were placed into teams of two. We randomly assigned roles (one contestant and manager per team), which stayed the same for the whole experiment. Then two teams were randomly matched to compete against each other. Matched teams competed in 20 identical rounds of the two-stage contest game with cheating. In the first stage both players, contestant and manager, made their individual cheating decision. One of the decisions was randomly selected and implemented as the team's decision for this round. Thereafter, all individual and implemented cheating decisions were displayed to the contestants. In the second stage contestants had to decide on how much effort to exert. To help them with their decisions, competitors were provided a profit calculator on screen, which calculated the resulting prize share and the manager's and contestant's profits (not including potential fines) for hypothetical efforts the contestants entered. The managers who could not influence their contestant's effort choice observed all actions (including the hypothetical profit calculations) of their contestant on their screens. At the end of each round, all subjects were informed if their team was caught cheating and learned the efforts of both contestants and the resulting prize shares. Furthermore, both manager and contestants learned their and the their team member's payoff for the round. All payments were in ECU, which were converted into AUD at an exchange rate of 10:1 (10 ECUs for 1 AUD). A session lasted on average 1 hour and 20 minutes, during which participants earned 26.23 AUD on average, which included a show-up fee of 5 AUD.

4.4 Results

In this section, we present the main results. We first present summary statistics on the prevalence of cheating and on effort levels. After that we investigate the aggregate dynamics of cheating. Next, we conduct regression analysis on the individual level in order to gain an insight on the drivers behind the aggregates. Finally, we take a closer look on the impact of treatments on individual effort exertion and competitiveness.

4.4.1 Aggregate cheating

Table 4.5 reports the average proportion of cheating subjects by treatment and role. Initially, we report raw proportions and make no judgments on statistical significance. In later sections we will use panel data analysis for this purpose. [16] On average, we observe similar proportions of cheating subjects, slightly over 60%, in three treatments (If_h, If_l and Jf_l). In the Jf_h treatment, however, this proportion is noticeably lower at 53%. Given a certain punishment regime (individual liability or joint liability), average cheating tends to be somewhat higher when the fine is low than when the fine is high. On the other dimension, we observe that for a high fine joint liability seems to outperform individual liability (Jf_h has lower cheating rates than If_h). The difference between the regimes is negligible when fines are low.

Next we break the overall cheating proportions into two components: the proportion of cheating decisions made by contestants and by managers. The highest and lowest fraction of cheating contestants is found of occur in the Jf_l (62.3 and the If_h(41.7 treatments. Moreover, contestants are more inclined to cheat under joint liability (Jf (h and l)) than under individual liability (If (h and l)). This shows that the joint liability regime causes unwanted increased cheating incentives for contestants, as suggested by theory.

We now consider the data of cheating managers. A similar proportion of cheating managers, slightly over 80%, is observed in the If (h and l) treatments. The fraction of cheating is approximately 18% and 24% lower in the Jf_l and the Jf_h treatments. This

[16] The appropriate level of an individual observation for a non-parametric test is a that of a matching group of two teams, which leaves us with too few observations (about 15 per treatment) for meaningful statistical tests.

implies that that managers respond to joint liability (Jf (h and l)) with reduced the cheating.

Treatments	N Obs.	Proportion of cheating subjects		Proportion of cheating con.		Proportion of cheating mana.	
		Mean	St.dev.	Mean	St.dev.	Mean	St.dev.
Jf_l	1120	0.621	0.485	0.623	0.485	0.620	0.486
Jf_h	1200	0.53	0.499	0.500	0.500	0.560	0.497
If_l	1360	0.624	0.485	0.446	0.497	0.801	0.399
If_h	1280	0.610	0.488	0.417	0.493	0.803	0.398

Table 4.5: Averages and standard deviations of total cheating, cheating contestants and cheating managers

In a first summary, we do not observe crisp equilibrium behaviour. However, the data reveal regularities that qualitatively agree with theory. On aggregate the fine matters for cheating under joint liability but not under individual liability. Managers cheat more under individual liability, while contestants cheat more under joint liability. The clearest deviation from theory is that managers are not as reactive to the fine level under joint liability as theory suggests. Note that in theory conditional on subgame-perfect efforts managers have dominant strategies to cheat in the Jf_l and not to cheat in Jf_h, while in the experiment the cheating fractions for the two treatments only differ by 0.06 percentage points.

4.4.2 Overall cheating dynamics and cheating patterns by role

The environment is quite complex and strategically rich. Therefore, learning to play the game might play an important role. Figure 4.5 plots the proportion of cheating subjects per period and per phase (a phase consists of four periods). As expected, there is quite some across-period variation. The highest and the lowest fractions of cheaters are observed most frequently in the Jf_l and the Jf_h treatments. From the right panel where we smooth out some of the short-term variation by aggregating four periods, we observe more clearly that the Jf_l, If_h and If_l treatments yield similar proportions of cheating subjects, while the Jf_h treatment results in a smaller fraction of cheaters over time. Moreover, we observe a downward trend of the average cheating probability over phases in the Jf_h treatment, while no clear time-trend can be established in other three treatments.

Figure 4.5: Proportion of cheating subjects over time by treatment

In order to understand which type of players causes the overall cheating rate to be lower in the Jf_h treatment, we compare the evolution of cheating behaviour by roles and treatments. Figure 4.6 illustrates the proportion of cheating contestants per period in the upper left panel. The smoothed cheating fractions of contestants per phase is depicted below in the lower left panel. The proportion of cheating managers by period and phase can be seen in the two panels on the right.

First consider the cheating dynamics of contestants on the left two panels. Among the four treatments, the Jf_l treatment has the highest fraction of 60% cheating contestants per phase. In the Jf_h treatment, approximately 60% contestants cheat in the first two phases and this fraction decreases noticeably in the next three phases. In both the If_h and the If_l treatments, between 40% to 50% cheating contestants per phase is observed. This is in strict contrast to Conjecture 4.3, which states that the equilibrium prediction of cheating contestants should be zero in these treatments.

When analysing the proportion of cheating managers over time, our data tells a different story. Not surprisingly, the highest rate of 80% over phases is observed under individual liability, which is still lower than the model prediction of 100% and therefore violates Conjecture 4.3. The lack of a time-trend towards higher levels of cheating is suggestive evidence against confusion driving compliance in this case. A possible explanation for non-cheating managers, who do not have to fear a penalty can be social preferences. A large body of existing researches shows that people do not only care about their own payoffs, but also payoffs of others when their actions affect others' payoffs (Charness and Rabin, 2002; Fehr and Schmidt, 1999; Chen and Li, 2009). Comparing to joint liability treatments, payoffs in individual liability treatments are more likely to be unequal between a manager and her contestant. Hence, managers who care about fairness and the payoff equality with their contestants could show concern for their contestants, who suffer from managers cheating and therefore, choose to not cheat even though the non-cheating decision does not maximise their own monetary payoffs. Moreover, we observe that managers do not respond to the fine level under joint liability. Theory predicts that managers always cheat if the fine is low and never do so if the fine is high. Given subgame-perfect continuation efforts managers have dominant strategies. Taking into account of social preferences, managers could be more likely to cheat. This is because when managers share the fine with their contestants, they might find it easier to justify their cheating action than when they do not share the fine at all. However, social preferences fail to explain managers under-cheating in the Jf_l treatment and over-cheating in the Jf_h treatment. In contrast, contestants should not react to the fine level under joint liability. This is an equilibrium prediction though and therefore depends on the behaviour of the managers. Given the very similar behaviour of the managers in the two join liability treatments, contestants have a higher cheating incentive in the low fine environment. In this light the observation that contestants cheat more in Jf_l than in Jf_h becomes rationaliseable.

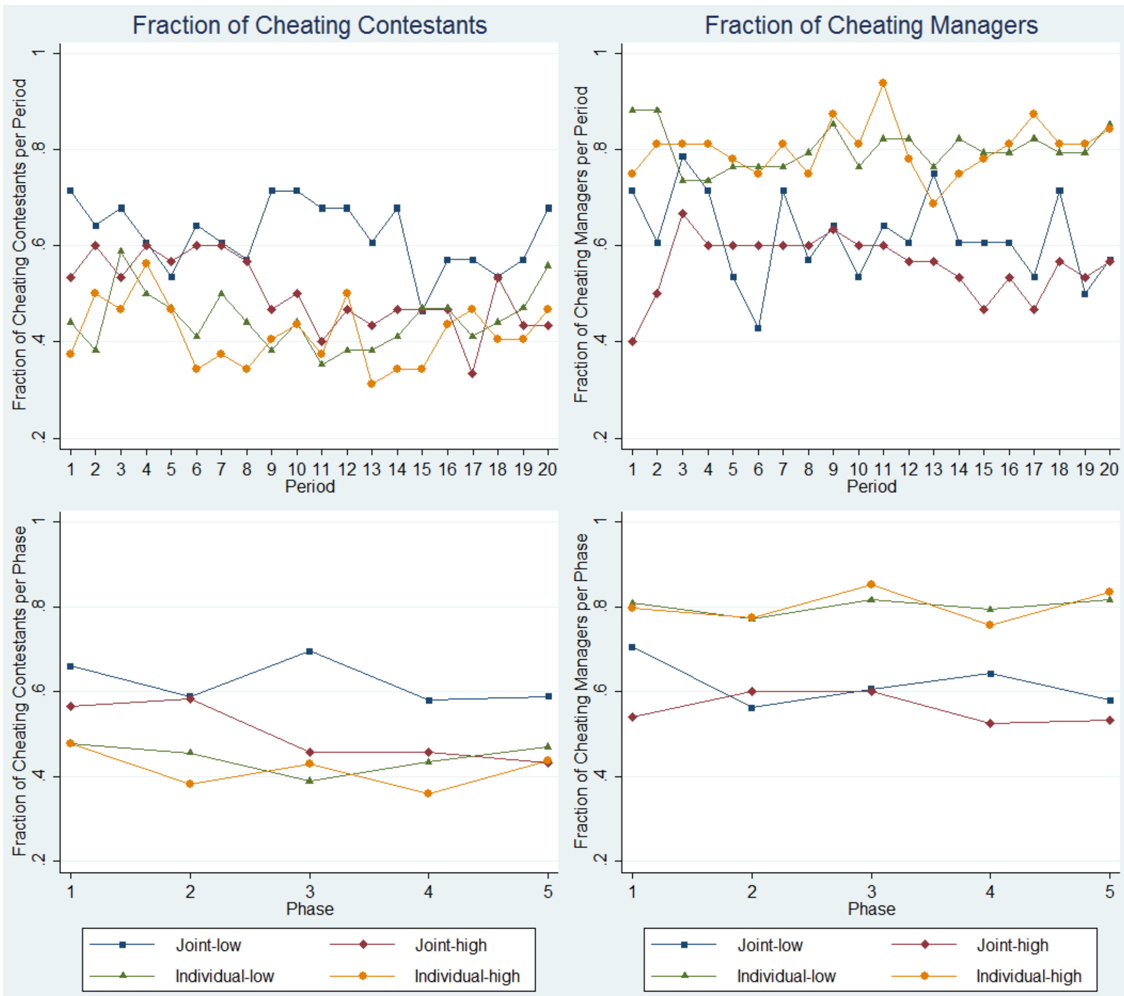


Figure 4.6: Proportion of cheating subjects over time by role and treatment

Given these observations we can assess, where the two main deviations from theory with respect to the comparative statics of cheating result from. First of all the, the best performance of the joint liability regime with high fines Jf_h with respect to cheating prevention, does not stem from the different behaviour of managers when fines rise but result from the reaction of contestants to the changed cheating incentives given that managers do not react to it. Similarly, the observation that joint liability with low fines does not backfire and lead to the highest cheating incidence also stems from the fact that managers do not react to fines. Instead of switching between cheating and not cheating if the fine changes, they cheat under both fine levels about 60% of the time.

A further illustration for the observation that fines have no effect on cheating behaviour in the individual liability regime, while they do under joint liability. For this we classify each team choice into one of the four natural categories: “no one cheats”, “only manager cheats”, “only contestant cheats” and “both cheat.” For further reference denote these categories as “no”, “man”, “con” and “both”, respectively. We then plot the distributions of the team type by treatment in Figure 4.7. Clearly, the distributions are virtually identical under individual liability (in the If (h and l) treatments) but differ under joint liability. There we observe more “no one cheats” and less “both cheat” teams in the Jf_h treatment than in the Jf_l treatment.

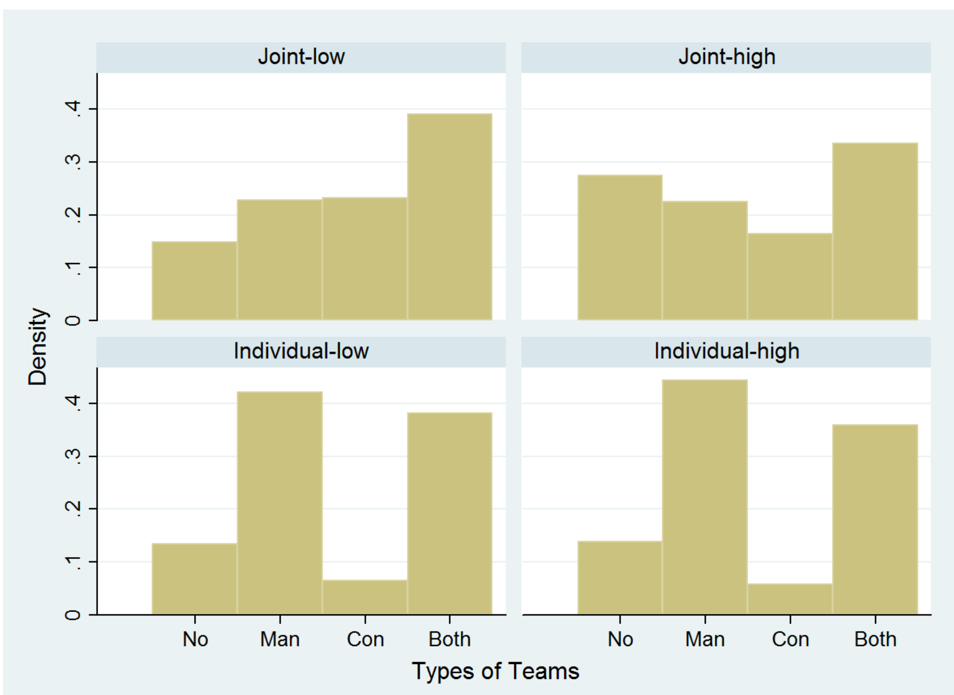


Figure 4.7: Histogram of types of teams by treatment

4.4.3 Treatment effect on cheating

After the descriptive aggregate analysis, we will use panel-data models to further investigate the determinants of cheating behaviour. Conditional on the validity of the underlying statistical assumptions, we will also establish the statistical significance of our results. We start by running a random-effects logistic regression on the team's final cheating decision and use treatment dummies as the explanatory variable [17]. Since subjects are learning in early periods, the choice made early are typically noisy. Therefore, we run the regression twice. The first model considers all periods, while the second model covers the last three phases (periods 9 to 20), where we expect less noise, since subjects are familiar with the game. In Table 4.6, we report both the estimated coefficients and the corresponding marginal effects of both models. In the full model, teams tend to be less likely to cheat in the Jf_h treatment than in the other treatment ($p = 0.076$ for Jf_h versus Jf_l; $p = 0.1496$ for Jf_h versus If_l; $p = 0.1731$ for Jf_h versus If_h). The marginal effect differences are between 0.08 and 0.11. The result that joint liability with high fines is best at deterring cheating becomes stronger in the last three phases, where teams are less likely to cheat in the Jf_h treatment than all other three treatments ($p = 0.053$ for Jf_h versus J_l; $p = 0.0858$ for Jf_h versus If_l; $p = 0.0806$ for Jf_h versus If_h). The marginal effect difference are now between 0.12 and 0.14. On the team level, we observe that the Jf_h treatment is performing best as Conjecture 4.1 suggests. Contrary to the expectations, the Jf_l treatment is not the worst performing treatment, violating Conjecture 4.1.

[17] Recall that team's cheating decision is randomly chosen from the manager's and the contestant's cheating decisions

Cheating Team	All phases		Last three phases	
	Coefficient	Marginal Effect	Coefficient	Marginal Effect
Treatment (Base: Jf_l)				
Jf_h	-0.5634*	-0.1103*	-0.7844*	-0.1425*
	(0.3208)	(0.0616)	(0.4057)	(0.0726)
If_l	-0.1270	-0.0241	-0.1185	-0.0209
	(0.3081)	(0.0585)	(0.3938)	(0.0693)
If_h	-0.1460	-0.0278	-0.1014	-0.0178
	(0.3115)	(0.0593)	(0.3973)	(0.0698)
Intercept	0.7003***		0.7059**	
	(0.2282)		(0.2916)	

*** Sig. at the 1 percent level, **Sig. at the 5 percent level, *Sig. at the 10 percent level

Table 4.6: Logistic regression on individual cheating decision with clustered standard errors

Next, we analyze cheating determinants on the individual level. To allow for the correlation between subject's cheating decisions across 20 periods and the correlation between two team member's cheating decisions, we use a multilevel mixed-effects logistic regression model with a random intercept for individuals and a random intercept for teams. The dependent variable is the individual's cheating decision, with 0 and 1 corresponding to "not cheating" and "cheating", respectively. The independent variables of major interest are treatment dummies, role dummies and the interaction term between the two. We further include time dummies and subject's characteristics as additional explanatory variables. Table 4.7 presents the estimated coefficients and the corresponding marginal effects of the full model and that of the model with the last three phases.

The full model regression reveals that the likelihood of a contestant cheating is significantly higher in the Jf_l treatment than in the If_l and the If_h treatments with a p value of 0.011 and 0.003, respectively. However, the propensity of contestants to cheat is not significantly different between the Jf_h and the If_l treatment ($p = 0.4220$) and between the Jf_h and the If_h treatments ($p = 0.2276$). This shows that the counterproductive incentive of joint liability on contestants who now bear less of the fine is only triggered if the fine is low. The manager's cheating probability is significantly higher under individual liability, i.e. in the If (h and l) treatments than in the Jf (h and l) treatments (both significant on the 1% level). Significant time effects are found between the first phase and three later phases, indicating a noisy environment in earlier periods. Our main results on cheating behaviour of contestants and managers are robust to the use of just the last three periods. Additionally, under the joint liability schemes, now managers are not affected by the size of the fine whereas contestants are significantly less likely to cheat in the Jf_h treatment than in the Jf_l treatment ($p = 0.026$). This finding agrees with descriptive findings from above and are in conflict with Conjecture 4.4.

In short, we confirm what our descriptive analysis already revealed. Managers and contestants behave similarly in the individual liability treatments (If_h and the If_l) . The Jf_l treatment has a positive impact on the compliance of contestants but a negative impact on that of managers when compared to both the If_h and the If_l treatments. These two effects offset each other, erasing part of the theoretical treatment effect on total cheating. Therefore, the Jf_l treatment performs similarly to the If_h and the If_l treatments. Consequently, the Jf_h treatment is the only treatment that yields a different level of over-all cheating because it has no significant impact on contestants while its negative impact on managers is persistent, when we compare it to the If_h and the If_l treatments. If we compare it to the low Jf_l treatment, then in contrast to theory the behaviour of the contestants rather than that of the manager makes the difference. In summary, in contrast to the theoretical prediction, we do not find the highest rate of cheating in the Jf_l treatment. The potential of joint liability backfiring if fines are low, which is predicted by theory, does not occur. However, the Jf_h treatment results in a significant reduction in the average cheating rates, as predicted in the model but driven by the reaction of contestants to managers that are non reactive to fine levels rather than by managers who reduce their cheating if fines are high. This implies that the joint liability scheme performs at least as well as the individual liability scheme empirically.

Cheat	All phases Coefficient	All phases Marginal Effect	Last three phases Coefficient	Last three phases Marginal Effect
Treatment interacted with Role (Base: Jf_l#Contestant)				
Jf_l#Manager	-0.2010	-0.0436	-0.3583	-0.0718
	(0.4712)	(0.1022)	(0.6347)	(0.1272)
Jf_h#Contestant	-0.8073	-0.1882	-1.7150**	-0.3882**
	(0.5213)	(0.1189)	(0.7712)	(0.1579)
Jf_h#Manager	-0.5674	-0.1295	-0.7940	-0.1705
	(0.5198)	(0.1174)	(0.7597)	(0.1609)
If_l#Contestant	-1.2014**	-0.2844**	-1.7272**	-0.3909**
	(0.5041)	(0.1124)	(0.7441)	(0.1511)
If_l#Manager	1.3363**	0.2005	1.6834**	0.1938*
	(0.5184)	(0.0850)	(0.7659)	(0.1056)
If_h#Contestant	-1.4164***	-0.3346***	-2.009***	-0.4504***
	(0.5107)	(0.1111)	(0.7500)	(0.1441)
If_h#Manager	1.1190**	0.1860	1.6332**	0.1909*
	(0.5175)	(0.0865)	(0.7678)	(0.1059)
Phases (Base: 1st Phase; 3rd Phase)				
2nd Phase	-0.2671**	-0.0520**		
	(0.1187)	(0.0231)		
3rd Phase	-0.1627	-0.0314		
	(0.1190)	(0.0230)		
4th Phase	-0.4115***	-0.0809***	-0.3101**	-0.0535**
	(0.1185)	(0.0233)	(0.1316)	(0.0229)
5th Phase	-0.2740**	-0.0534**	-0.1390	-0.0239
	(0.1187)	(0.0231)	(0.1319)	(0.0227)
Controls (periods, age, gender, math, degree) not significant				
Intercept	1.5770***	0.6210**	2.0191**	0.6088***
	(0.5617)	(0.0278)	(0.8137)	(0.0382)

*** Sig. at the 1 percent level, **Sig. at the 5 percent level, *Sig. at the 10 percent level

Table 4.7: Mixed effects logistic regression on individual cheating decision

4.4.4 Average effort and over-dissipation

Moving to the second stage of the game, we analyze the effort decisions. Table 4.8 reports the average efforts and the average deviation from of optimality. The deviation from optimality is calculated by taking the difference between the effort and the optimal effort conditional on the effort of the competitor. A positive deviation from optimality implies over-exertion of effort, while a negative value implies under-exertion. The average efforts are very similar across four treatments with a minimum of 16.5 in the Jf_l treatment and a maximum of 18.88 in the If_h treatment. The mean values for average deviation from optimality in all treatments are positive, suggesting an over-exertion of efforts in contests. This finding is consistent with the literature (Chaudhuri, 2011; Choi and Bowles, 2007; Sheremeta, 2018).

Treatments	N Obs.	Average Effort		Average Dev. f. Optimality	
		Mean	St. dev.	Mean	St. dev.
Jf_l	560	16.500	7.950	2.1964	7.9346
Jf_h	600	18.870	15.510	4.5367	15.5178
If_l	680	17.794	13.183	3.5049	13.1840
If_h	640	18.880	13.942	4.6089	13.8229

Table 4.8: Averages and standard deviations of efforts, optimality and over-dissipation

4.4.5 Dynamics of effort

We now examine the dynamics of effort exerted by contestants over time. Figure 4.8 depicts the average effort per period in different treatments in the left panel and the average per phase in the right panel. In the first period, the average efforts all start at about 22 to 27 and in all treatments decrease dramatically over the next five to seven periods. The extremely high efforts in early periods, especially the first period, are due to strategic confusion among subjects at the beginning of the experiment. Once they receive payoff feedback and realize that over-exertion leads to low or even negative profits, most subjects drastically reduce efforts in the following periods. From the second phase onward, the effort slowly trends upwards again in all treatments except for the Jf_l treatment, where it gradually declines further until the end. The upward trend suggests a more competitive environment in later periods. Moreover, according to the theoretical model, the optimal efforts are 15 if the two teams have the same final cheating decisions and 13.5 if they have different final cheating decisions. We observe that the actual efforts are consistently above the optimal levels in all treatments, which reveals that our subjects, on average, do not play subgame-perfect continuation efforts. Overall, the efforts are very similar across treatments, though.

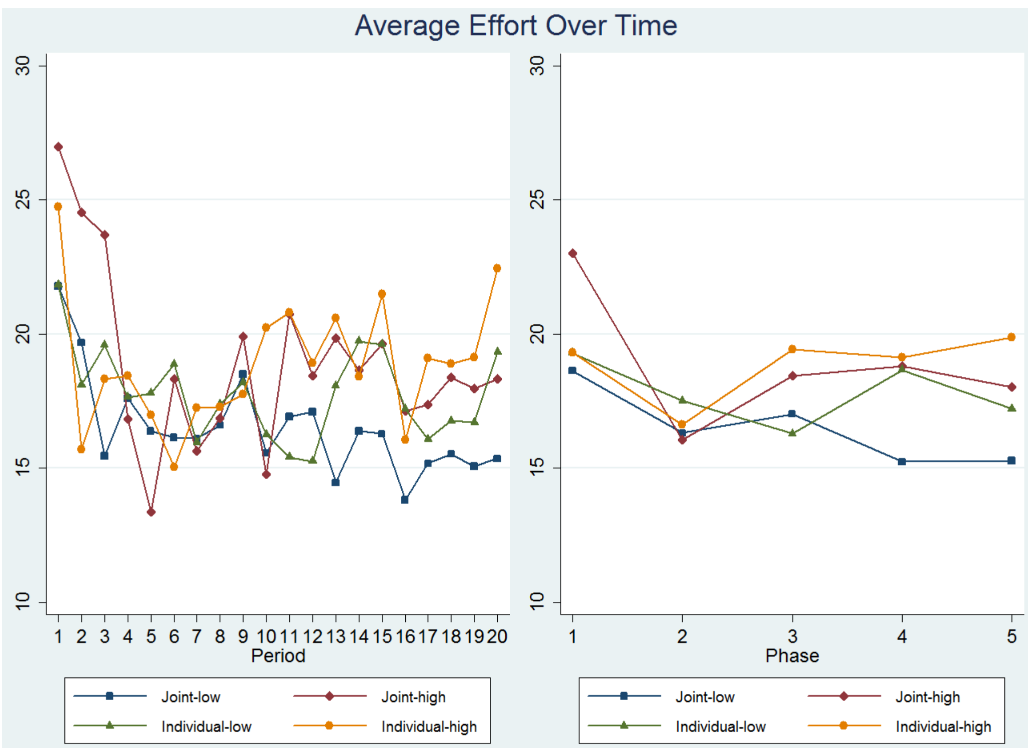


Figure 4.8: Average effort by treatment over time

4.4.6 Over-dissipation

Noticing that average effort are consistently higher than the equilibrium effort, we next analyze over-dissipation of contestants. Figure 4.9 depicts actual efforts of contestants against the best response to their competitor's effort. We overlay this by a quadratic fitting line. We calculate the best response effort by substituting the opponent's actual effort and implemented cheating decisions of both teams into the best response equation 4.4.

In all treatments, the quadratic prediction is above the 45-degree line, confirming a consistent over-dissipation across treatments. Moreover, we observe that when the best response effort approaches zero, the deviation of one's own effort from the optimal level is larger, as shown by the wider gap between the quadratic prediction and the 45-degree line for low values. This implies that when the opponent of a contestant exerts an extremely high effort, the contestant on average also puts in an effort well above the optimal level, suggesting that contestants become more irrationally competitive if their rivals are irrationally over-competitive. Some of these extremely over-competitive periods are repeated between rivals across periods and become feuds. The problem of over-dissipation becomes less severe when both contestants exert a reasonable effort. This can be seen as actual efforts cluster around the equilibirum-effort levels of 13.5 and 15. Our result shows that when an opponent's deviation from the equilibrium effort is large, the contestant is more likely to act irrationally and therefore, over-dissipation of effort becomes more severe. However, when both contestants are not engaging in feuds, then average effort decisions are close to the best response efforts as predicted by theory. Quite a bit of noise remains though.

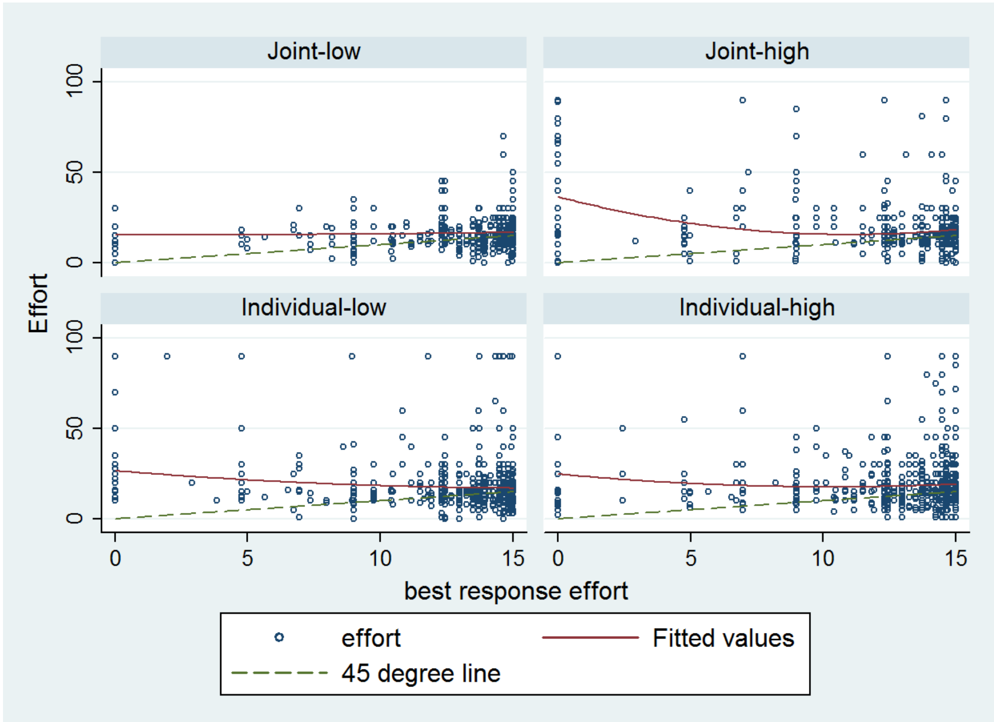


Figure 4.9: Effort versus best response effort by treatment

We are now interested in which factors can explain the over-dissipation of effort. For this we employ a random-effects interval-data regression. The dependent variable, over-dissipation, is point data which is left- and right-censored. This is accounted for by the use of an interval regression. The covariates include treatment dummies, interaction terms between the own team's and the rival team's cheating decision, time dummies as well as subject characteristics.

The estimated coefficients are presented in Table 4.9. First, over-dissipation is significant and positive in all treatments in the full model ($p-values$ of 0.015 for the Jf_l, 0.000 for the Jf_h, 0.001 for the If_l and 0.000 for the If_h treatments). In the model containing only last three phases, over-dissipation of effort persists in the Jf_h ($p = 0.009$), the If_l ($p = 0.05$) and the If_h ($p = 0.010$) treatments while it is no longer significantly different from zero in the Jf_l treatment ($p = 0.164$). In addition, given that over-dissipation is a function of implemented cheating decisions and efforts, the result shows that as predicted by theory and a corollary to Conjecture 4.2, controlling for the cheating decisions, treatments have no impact on over-dissipation. Moreover, inspecting the coefficients on the interaction term between two team's cheating decisions, we observe that over-dissipation is significantly higher when one's own team is cheating, given the opponent team's cheating decision. We obtain a p value of 0.024 for "Not cheat$\times$ Not cheat" teams versus "Cheat$\times$Not cheat" teams and a p value of 0.0424 for "Not cheat$\times$Cheat" teams versus "Cheat$\times$Cheat" teams in the full model. This shows that it is mainly one's own cheating decision that has an impact on the effort rather than whether the contest is symmetric or not. It seems as if contestants have the feeling that they need to make it count when they cheat. The same positive effects of the team's implemented cheating on over-dissipation is persistent in the model that includes only the last three phases. Finally, over-dissipation is significantly more prevalent in the first phase when subjects are most confused and are still figuring out how to play the game. This time effect on over-dissipation disappears after the first phase.

Over-dissipation	All phases	Last three phases
Treatment (Base: Jf_l)		
Jf_h	3.8626*	4.1077
	(2.2772)	(2.7946)
If_l	1.4850	1.5437
	(2.2772)	(2.7060)
If_h	2.5535	3.4830
	(2.2219)	(2.7263)
Own team cheat interacted with opponent team cheat (Base: Not cheat×Not cheat)		
Not cheat×Cheat	0.7547	0.5419
	(0.8050)	(0.8743)
Cheat×Not cheat	1.8097**	1.8311**
	(0.8045)	(0.8737)
Cheat×Cheat	2.0914***	1.8953**
	(0.7662)	(0.8514)
Phases (Base: 1st Phase; 3rd Phase)		
2nd Phase	-3.8831***	
	(0.7183)	
3rd Phase	-2.8413***	
	(0.7209)	
4th Phase	-2.4425***	-0.3975
	(0.7207)	(0.6040)
5th Phase	-3.1179***	-0.2724
	(0.7190)	(0.6043)
Controls not significant[18]		
Intercept	6.5149**	4.2057
	(3.0603)	(3.6998)

*** Sig. at the 1 percent level, **Sig. at the 5 percent level, *Sig. at the 10 percent level

Table 4.9: Random-effects interval-data regression on over-dissipation

[18] *Except for gender effect which is siginificant at 8% level in the full model*

4.5 Conclusion

Individual contestants often interact with other agents and work as a team in competitions. The agency problem that agents have incentives to cheat on behalf of their contestants, since they are not bearing the negative consequences if caught has received insufficient attention by economists. A natural remedy for such a moral hazard model is to extend the liability to the agent. We have shown in theory that this can backfire if fines are low, as now the deterrence effect for the acting contestants are reduced. In order to get a clearer picture if a) the joint liability can really backfire for low fines and b) if joint liability really reduces over-all cheating if fines are high we developed a two-player share-prize contest experiment with four treatments. We vary the the enforcement regime between individual liability and joint liability as well as the severeness of the fine. We calibrate the experiments such that we get a crisp ordering of predicted cheating frequencies. Joint liability is theoretically effective in reducing cheating if fines are high but is less effective than individual liability if the fines are low.

The robust finding in our data shows that managers and contestants respond differently to the joint liability schemes, than to individual liability schemes. The cooperative statics of individual agent and contestant behaviours across regimes are roughly in line with theoretical predictions. We do not observed crisp equilibrium behaviour though. The comparative statics in our data with respect to changes in the fine are off under the joint liability regime. Agents do not react to changes in the fine level as predicted by theory. Contestants who are not expected to react in equilibrium do react though. Under a high fine there is less cheating among contestants under a joint liability regime. This is a reasonable reaction to incentives and out of equilibrium behaviour of the agents. This very specific deviation from equilibrium play implies that joint liability still delivers the expected reduction in cheating if fines are high, without suffering from the reverse effect if fines are low. Hence, imposing joint liability for cheating on agents is shown to be a beneficial policy despite the theoretical potential to backfire. Joint liability under high fines has the additional benefit of potentially being able to reduce over-dissipation of rents in contests with cheating, as our analysis of efforts has shown that contestants over-exert more efforts when their teams are cheating.

Appendix A

Additional Information on Chapter 3

A.1 Performance dynamics by groups in contests

Figure A.1 to A.6 show performance dynamics of individuals by groups in each contest.

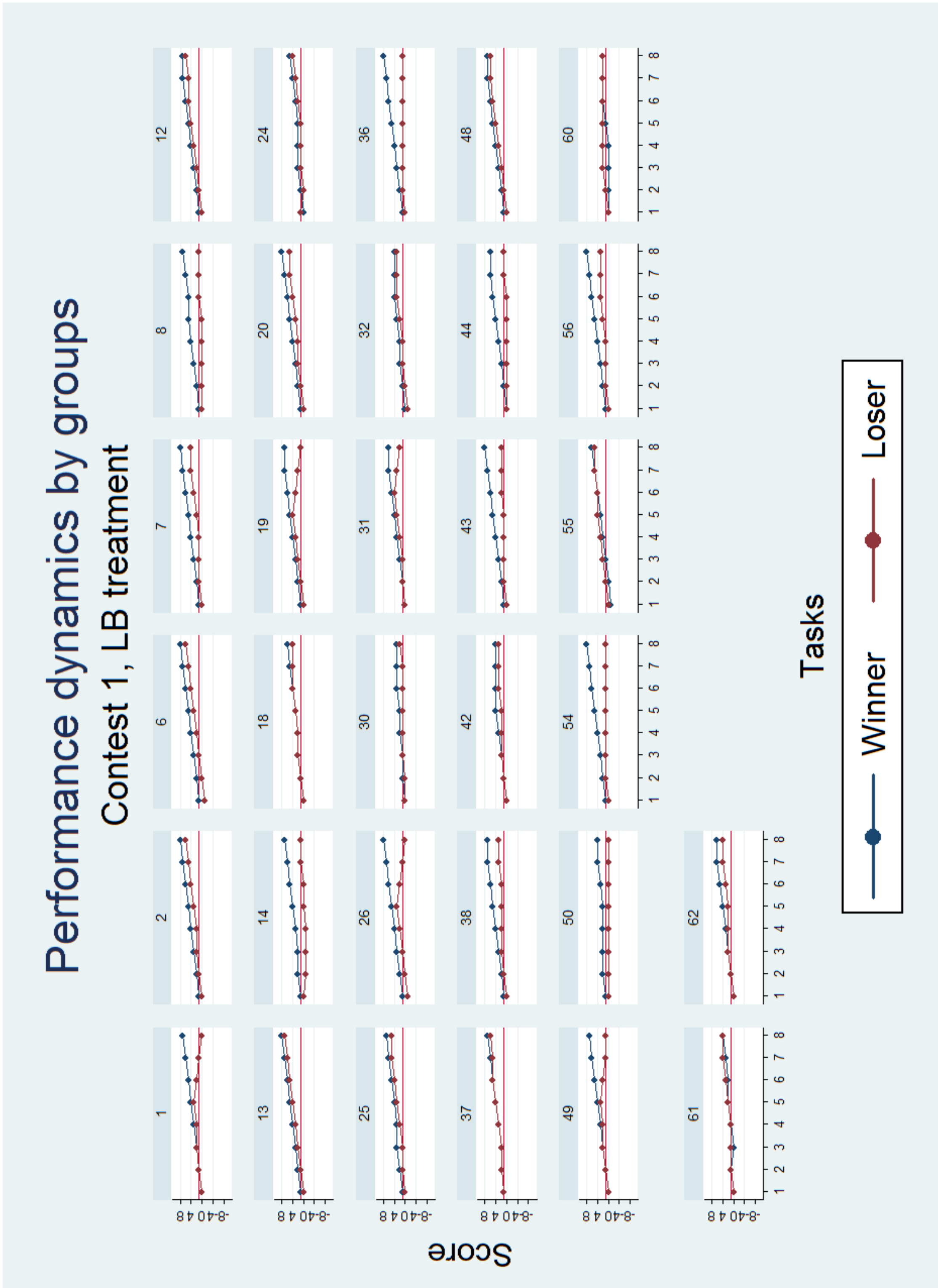


Figure A.1: Performance dynamics by groups over contest 1 in the LB treatment

Figure A.2: Performance dynamics by groups over contest 2 in the LB treatment

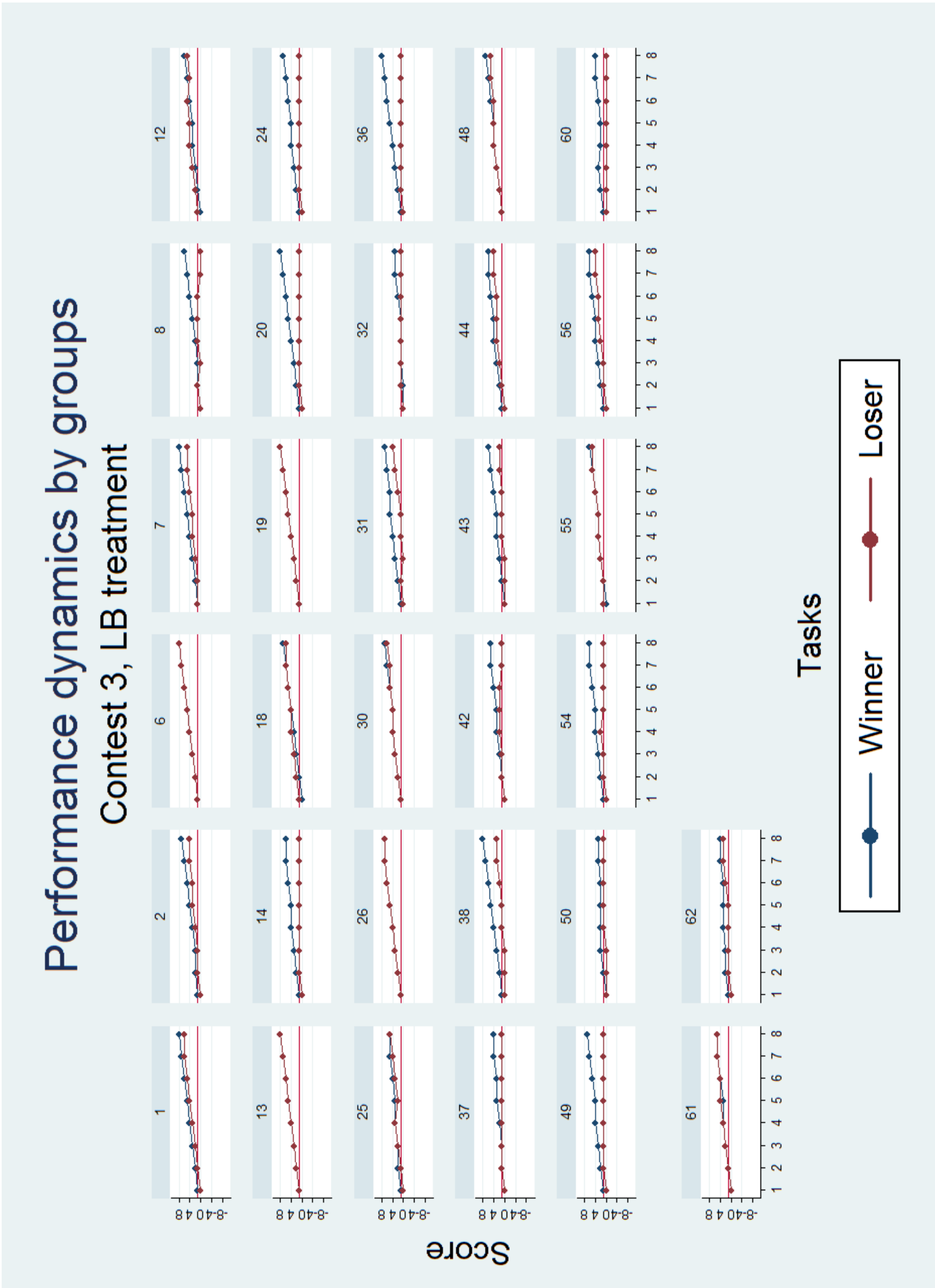


Figure A.3: Performance dynamics by groups over contest 3 in the LB treatment

Figure A.4: Performance dynamics by groups over contest 1 in the NO LB treatment

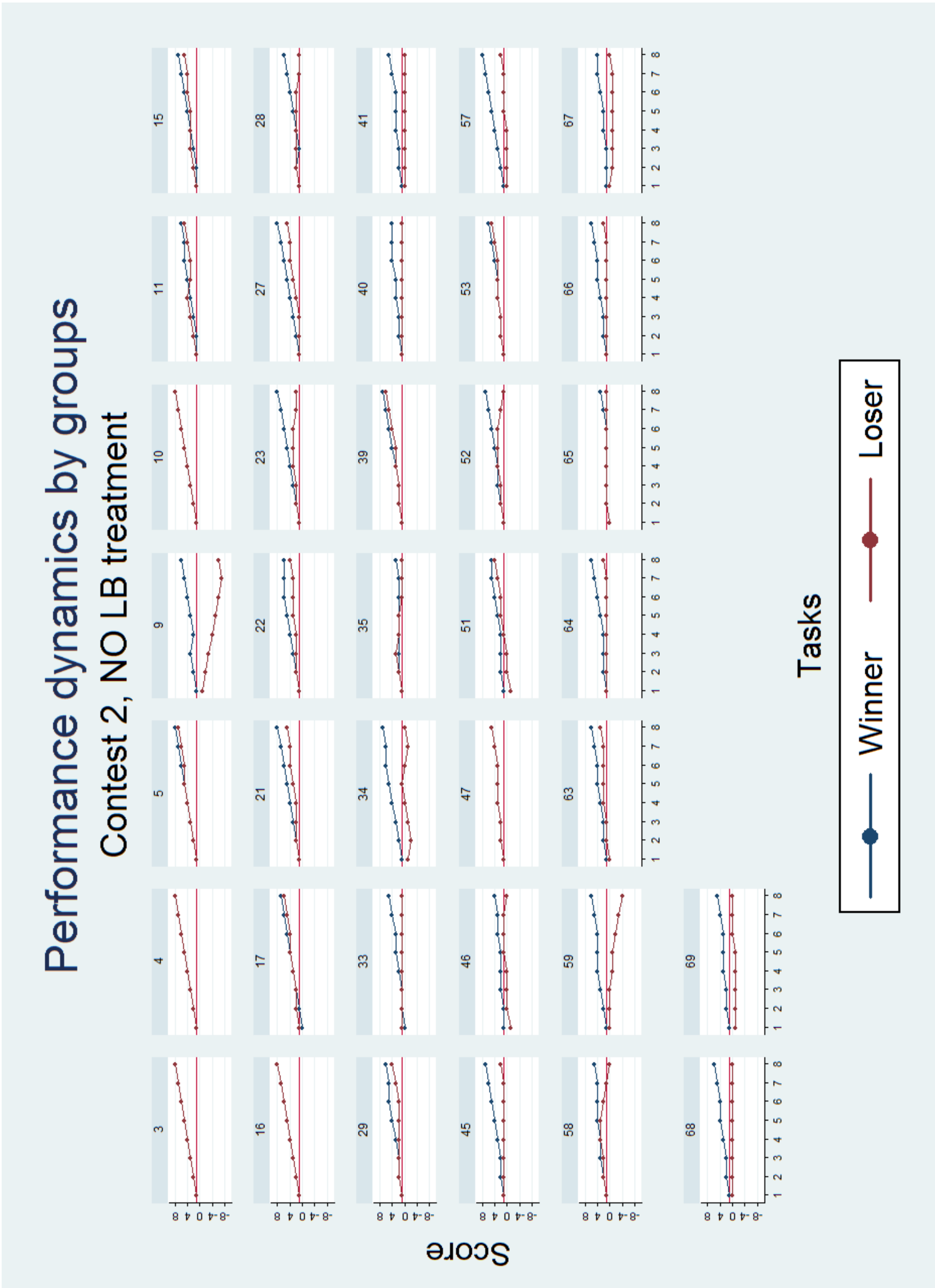


Figure A.5: Performance dynamics by groups in contest 2 in the NO LB treatment

Figure A.6: Performance dynamics by groups over contest 3 in the NO LB treatment

A.2 Correction for the coding error

Due to the coding error made in the first three sessions, subjects who lose the competition with a score of two receive the consolation prize. This mistake affects seven subjects. The first time that the player finish the game with a score of two does not count since they have not received the incorrect feedback from the program yet. It is only in the following contests, their behaviors might be changed. To correct this mistake in the following tests, we identify the first time that subjects lose the game with a score of two in these three sessions. Then, we mark the following two contests as “being affected”.

In Table A.1, we report the proportion of successful tanking subjects after taking into consideration of the coding error. For subjects who are not affected by the error, successful self-saboteurs are those who finish the tasks with a score of one or less. For those who are marked as “being affected”, however, successful tanking means to achieve a final score of two or less. McNemar’s tests report a consistent result as the previous case where the coding error is omitted. The defeated players are more likely to have a poor performance in contests than in the piece rate ($p - values$ of 0.0027, 0.0002 and 0.0043 for the first, second and third contest, as compared to the piece rate round). Within each contest, no significant proportion difference can be found between two treatments based on the Kolmogorov-Smirnov tests ($p > 0.1$).

Table A.1: Proportion of successful tanking subjects after correction of the coding error

	N Participants	Proportion of Successful Tanking Subjects[1]
Piece Rate		
NO LB Treatment	74	5.405%
LB Treatment	64	7.813%
Contest 1		
NO LB Treatment	74	13.514%
LB Treatment	64	15.625%
Contest 2		
NO LB Treatment	74	20.270%
LB Treatment	64	15.625%
Contest 3		
NO LB Treatment	74	14.865%
LB Treatment	64	20.313%

Taking into account of the coding error, we need to redefine At-One and Below-One groups. At-One groups now include groups with two kinds of losers. First, for those who are not affected by the error, groups of losers who finish with a score of one are identified as At-One groups. Additionally, for losers who are affected by the error, when they have a final score of two, their groups are classified into the "At-One" category. In terms of the Below-One groups, if a loser is not affected by the error and finishes the task with a score less than one, his or her group is referred to as a Below-One group. For a loser who is affected by the error, his or her group is still Below-One if he or she finishes the task with a score

[1] In the piece rate, this is the proportion of subjects with a score of one or less

less than two. As shown in Figure A.7, we find consistent results as before. There are more At-One than Below-One groups when the leaderboard is shown. On the other hand, there are more Below-One than At-One groups when there is no leaderboad. With new types of groups, we then run multinomial logistic regression on group types. Again, the result is consistent.

Figure A.7: Fractions of three different types of groups in two treatments after correction for the coding error

Table A.2: Multinomial logistic analysis on categorical group types

	Coefficient	Relative Risk Ratio
Clean Group		
Treatment		
LB Treatment	-0.7103	0.4915
	(0.4472)	(0.2198)
Ability Dispersion	-0.2980	0.7423
	(0.3202)	(0.2377)
Group Ability	0.08947	1.0936
	(0.2092)	(0.2288)
Time trend		
Contest 2	-0.2676	0.7652
	(0.4230)	(0.3237)
Contest 3	-0.3176	0.7279
	(0.3900)	(0.2839)
Below One Group		
Treatment		
LB Treatment	-1.2916**	0.2738**
	(0.5891)	(0.1619)
Ability Dispersion	-0.2992	0.7414
	(0.4157)	(0.3082)
Group Ability	-0.3001	0.7407
	(0.2935)	(0.2174)
Time trend		
Contest 2	0.1719	1.1876
	(0.5565)	(0.6609)
Contest 3	-0.1106	0.8953
	(0.6575)	(0.5887)

"At One" group is the base outcome. *** Significant at the 1 percent level; **Significant at the 5 percent level; *Significant at the 10 percent level.

Appendix B

Experimental Instructions

B.1 Experiment 1

B.1.1 Piece rate

General Information

The experiment is about solving a series of arithmetic tasks. The number of tasks you solve correctly and the time you spend on solving tasks will determine your final payment. Your payment will increase with the number of task you solve. However, there is a cost associated with doing tasks. The longer the time you spend on completing tasks, the more costly it is. In this experiment, your earning will be measured in Experimental Currency Units (ECUs). The ECUs you have earned will be converted into real money at the exchange rate of 70:1 (70ECUs for 1 dollar).

Tasks and Effort

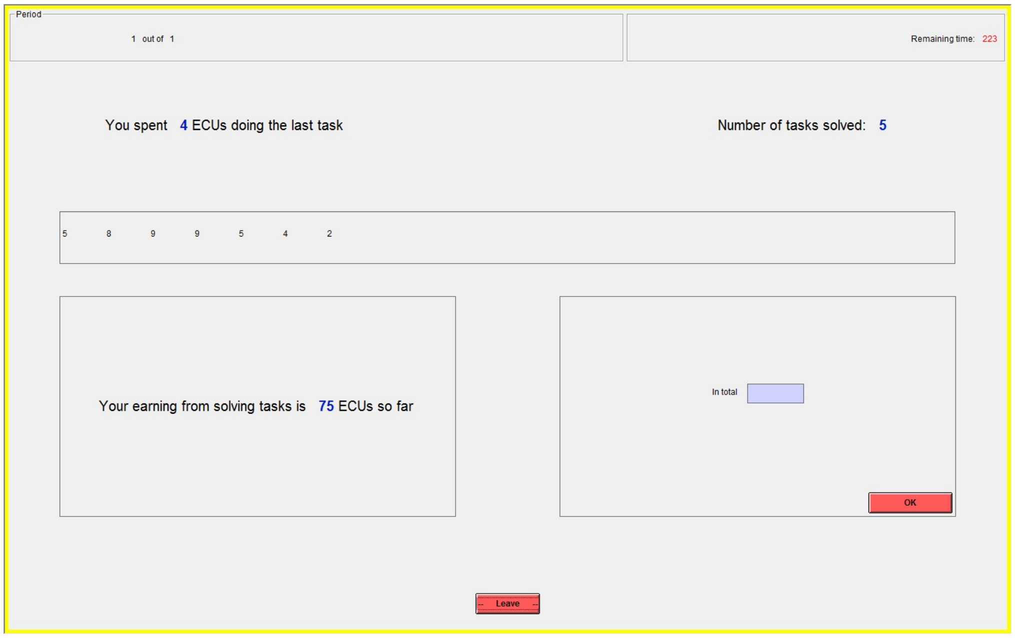
In this experiment, you will be given 240 seconds. You may choose to complete up to a maximum of 20 tasks in total. The first task involves adding two single-digit numbers together. To solve this task, you must enter your answer in the "in total" box and then click the “OK” button. If your answer is correct, you will move on to the next task which has three new single-digit numbers for you to add together. If the answer is incorrect, you have to try again until you enter the correct answer. After you enter a correct response for this task and click the “OK” button again, it will take you to the third task which has four numbers to be added up and so on, until you reach the point you want to stop (See the screenshot attached on the next page).

Payment

It is important for you to choose how to allocate and optimise the 240 seconds.
The payoff of this experiment is as such:

1. If you allocate time to do tasks, you will earn 15 ECUs per task solved.
2. For every second that is left of the initial 240 seconds when you click the “Leave” button you will receive one ECU per second.

For example, if you click “Leave” after spending 40 seconds, where you managed to solve 6 tasks, then you receive 6 x 15= 90 ECUs as a payment for solving the tasks and 200 ECUs for the remaining time, which would be 290 ECU in total.
Here is an example of how the screen will look:



In this example the player has solved 5 tasks already and has 223 seconds left. To solve the sixth task, she would have to add up the seven numbers, 5, 8, 9, 9, 5, 4 and 2. After finding the right solution, she enters it in the "in-total" box and clicks the OK button. On the top left of the screen it is shown how much money the player has forgone for solving the last task. Recall that the player will be paid one ECU for every second not used for solving tasks. So the money equivalent spent on solving a particular task is the time it takes to solve it times one ECU.

On the bottom there is the "Leave" button. As soon as you decide that it is not worthwhile anymore to spend more time on solving sums anymore. When you hit the leave button you will be paid 15 ECUs per task solved so far plus one ECU per second still remaining on the clock in the top right corner.

Please raise your arm if you have any questions.

B.1.2 Penalty free treatment

General Information

The experiment you are about to participate in consists of 3 periods. At the beginning of the first period, you will be placed in a group of three (you and two unidentified competitors). You will play all three periods with the same two competitors.

In this experiment we will use the task you have just played to simulate a competition. Now the payoff from solving tasks will not be a certain amount per task solved. Your payment will depend on the number of tasks you solve and the numbers of tasks two competitors solve.

Your earnings will be measured in Experimental Currency Units (ECUs). At the conclusion of the third period, the ECUs you have earned will be converted into real money at the exchange rate of 70:1 (70 ECUs for 1 Dollar).

Competition

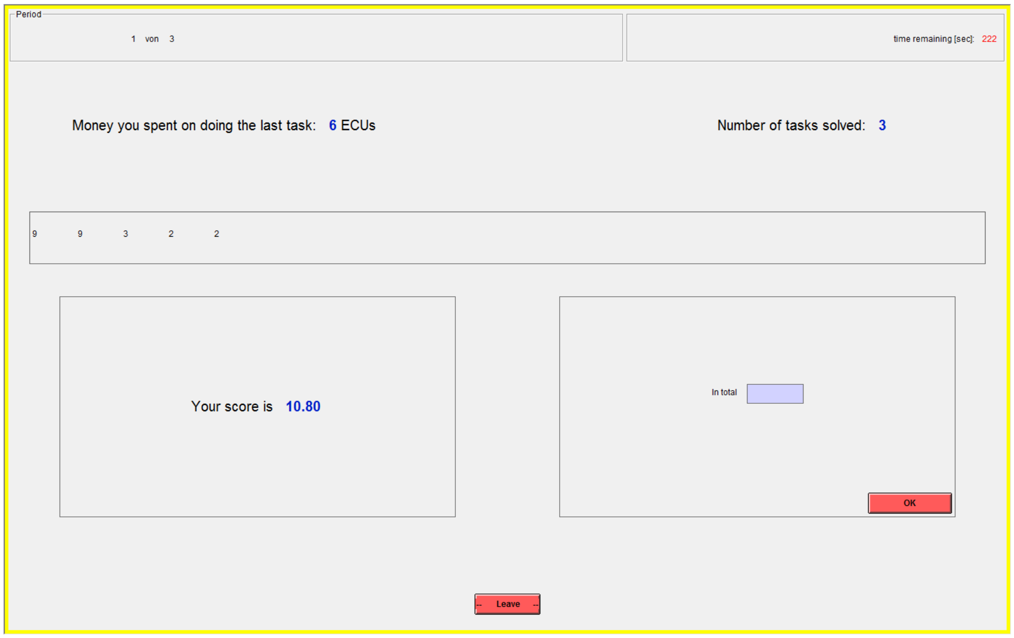
In each competition round, there is a 600 ECUs prize money awarded to each group. You can increase your share by solving tasks, where you again have to decide when to stop solving tasks. As before, the maximum time given is 240 seconds. For each second not used to solve tasks, you will be given one ECU.

It is important for you to choose the right time to stop doing the summation tasks:

1. If you spend time doing tasks, your score increases with the number of tasks you solve. The higher your score, given the scores of other two group members, the greater is your share of the prize of 600 ECUs.

2. On the other hand, you will lose one ECU for every second while you are working on the task. Again, you will be paid one ECU for every second remaining (of the initial 240) when you click "Leave" on the task screen.

Here is an example of how the screen will look:



Score, Number of Tasks Solved, Multiplier and Cheating

The score for a given period is calculated as the number of tasks a player solved times a multiplier (which can be 2, 3, or 4). In each period there is one player in the group with a multiplier of 2, one with 3 and one with 4. You will be shown which multiplier you will have in the three periods before the first period and you will be reminded in the subsequent periods.

At the beginning of each period you will be asked if you want to cheat in the contest. If you decide to cheat then you will get a 20 percent bonus.

For example, for any participants, if you are assigned a multiplier of 3 and you solve 10 tasks in total, your score will be 3×10=30. If you accept the 20% cheating bonus, then the final score will be 30+20 percent bonus=36.

Payment

Your final money payment consists of two parts:

1. Fixed payment, 1 ECU per second of remaining time from effort stage
2. Share of the prize

Your share of the prize is calculated as follows. If everybody has the same score then the prize is shared equally. So everybody gets 200 ECUs, which is one third of the total prize of 600. If your score is higher than the average score of the other two players you receive 6 ECUs for every unit that your score is higher than the average of competitors' score. For example if your score is 10 units higher than the average score of the other two competitors, then you will receive 200+60=260 ECUs as prize money.
On the other hand, if your score is lower than the average, then for every unit your score is lower than the average of the others, 6 ECUs are deducted from 200 ECUs. So if your score is, e.g. 10 units lower than the average, then you receive 200-60=140 ECUs as prize money.
Recall that at the effort stage, you are given 240 seconds to do tasks. You get paid 1 ECU per second for the remaining time on the clock after you leave the stage.
So your prize money is calculated as:

$$Prize\ money\ in\ ECU = 200 + 6 \times (your\ score - average\ score\ of\ others)$$

Your total earnings per period are calculated as:

$$Total\ earnings\ in\ ECU = Prize\ money + time\ not\ spent\ solving\ tasks$$

Note that the payoffs for your competitors are calculated in the same manner.

Summary

You are competing in three competitions with the same two other competitors. In order to determine you scores in second and third competitions, we use the same addition tasks as before. The score in a period will be the number of tasks solved times a multiplier. You can decide to cheat and get a 20 percent bonus on your score. Your score relative to the average score of the two competitors determines how much the prize money of 600 ECUs you receive. In addition to the prize money you also receive one ECU per second left on the clock when you leave the summing-up task.

Questions

To make sure you fully understand how the prize money works, you will be given two numerical examples with two questions on the screen. You need to answer both of them correctly before we can start the experiment. Please click OK button once you finish the questions. Please raise your arm if you have any questions.

B.1.3 Fine treatment

General Information

The experiment you are about to participate in consists of 3 periods. At the beginning of the first period, you will be placed in a group of three (you and two unidentified competitors). You will play all three periods with the same two competitors.

In this experiment we will use the task you have just played to simulate a competition. Now the payoff from solving tasks will not be a certain amount per task solved. Your payment will depend on the number of tasks you solve and the numbers of tasks two competitors solve.

Your earnings will be measured in Experimental Currency Units (ECUs). At the conclusion of the third period, the ECUs you have earned will be converted into real money at the exchange rate of 70:1 (70 ECUs for 1 Dollar).

Competition

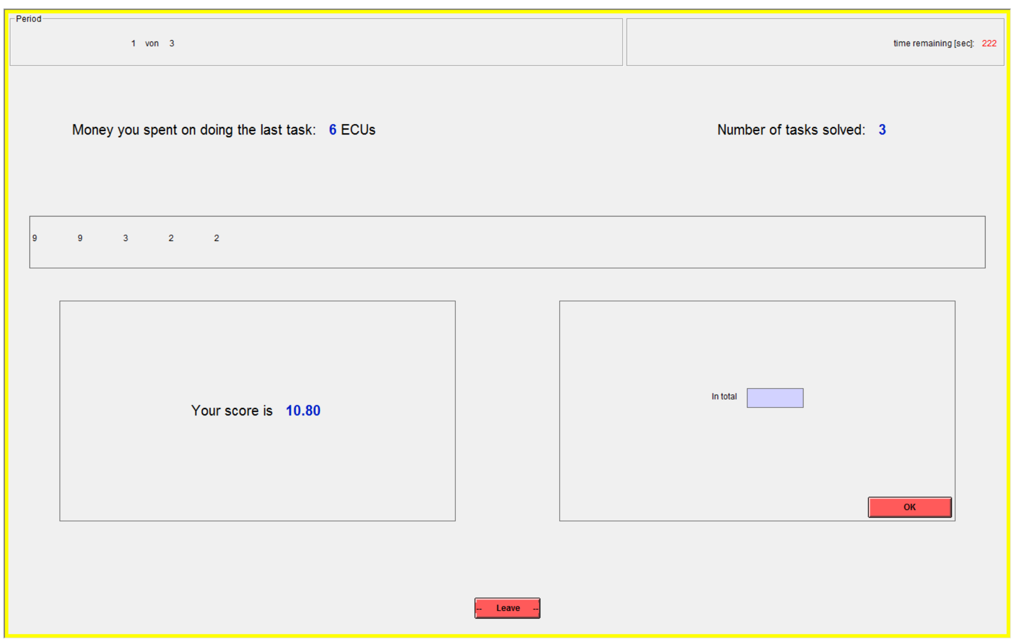
In each competition round, there is a 600 ECUs prize money awarded to each group. You can increase your share by solving tasks, where you again have to decide when to stop solving tasks. As before, the maximum time given is 240 seconds. For each second not used to solve tasks, you will be given one ECU.

It is important for you to choose the right time to stop doing the summation tasks:

1. If you spend time doing tasks, your score increases with the number of tasks you solve. The higher your score, given the scores of other two group members, the greater is your share of the prize of 600 ECUs.

2. On the other hand, you will lose one ECU for every second while you are working on the task. Again, you will be paid one ECU for every second remaining (of the initial 240) when you click "Leave" on the task screen.

Here is an example of how the screen will look:



Score, Number of Tasks Solved, Multiplier, Cheating and Fine

The score for a given period is calculated as the number of tasks a player solved times a multiplier (which can be 2, 3, or 4). In each period there is one player in the group with a multiplier of 2, one with 3 and one with 4. You will be shown which multiplier you will have in the three periods before the first period and you will be reminded in the subsequent periods.

At the beginning of each period you will be asked if you want to cheat in the contest. If you decide to cheat then you will get a 20 percent bonus on your score. However, there is a 30% chance that you will get caught cheating if you choose to cheat. If you get caught, you will lose all your share of the prize in that round. If you choose not to cheat, there is no risk of losing your share of prize.

For example, for any participants, if you are assigned a multiplier of 3 and you solve 10 tasks in total, your score will be 3×10=30. If you accept the 20% cheating bonus, then the final score will be 30+20 percent bonus=36.

Payment

Your final money payment consists of two parts:

1. Fixed payment, 1 ECU per second of remaining time from effort stage
2. Share of the prize

Your share of the prize is calculated as follows. If everybody has the same score then the prize is shared equally. So everybody gets 200 ECUs, which is one third of the total prize of 600. If your score is higher than the average score of the other two players you receive 6 ECUs for every unit that your score is higher than the average of competitors' score. For example if your score is 10 units higher than the average score of the other two competitors, then you will receive 200+60=260 ECUs as prize money.

On the other hand, if your score is lower than the average, then for every unit your score is lower than the average of the others, 6 ECUs are deducted from 200 ECUs. So if your score is, e.g. 10 units lower than the average, then you receive 200-60=140 ECUs as prize money.

Note that after you complete the competition, there is 30% chance that you will lose your prize money if you get caught cheating.

So your prize money is calculated as:

$$Prize\ money\ in\ ECU = 200 + 6 \times (your\ score - average\ score\ of\ others)$$

Remember that your prize money if you get caught is zero.

Recall that at the effort stage, you are given 240 seconds to do tasks. You get paid 1 ECU per second for the remaining time on the clock after you leave the stage.

Your total earnings per period are calculated as:

$$Total\ earnings\ in\ ECU = prize\ money + time\ not\ spent\ solving\ tasks$$

Again, prize money will be zero if you get caught.

Note that the payoffs for your competitors are calculated in the same manner.

Summary

You are competing in three competitions with the same two other competitors. In order to determine you scores in second and third competitions, we use the same addition tasks as before. The score in a period will be the number of tasks solved times a multiplier. You can decide to cheat and get a 20 percent bonus on your score in each round. However, there is a 30% chance that you will be caught and lose all your prize money in each round as well. If you choose not to cheat, there is no risk of losing your prize. Remember that the consequences of cheating in all three periods are independent. For example, if you choose to cheat in period 1 but not cheat in period 2, you will have 30% chance of being caught in period 1 but no risk of being caught in period 2. You will not be punished for cheating in previous periods. Your score relative to the average score of the two competitors determines how much the prize money of 600 ECUs you receive. In addition to the prize money you also receive one ECU per second left on the clock when you leave the summing-up task.

Questions

To make sure you fully understand how the prize money works, you will be given two numerical examples with two questions on the screen. You need to answer both of them correctly before we can start the experiment. Please click OK button once you finish the questions.

Please raise your arm if you have any questions.

B.1.4 Ban treatment

General Information

The experiment you are about to participate in consists of 3 periods. At the beginning of the first period, you will be placed in a group of three (you and two unidentified competitors). You will play all three periods with the same two competitors.

In this experiment we will use the task you have just played to simulate a competition. Now the payoff from solving tasks will not be a certain amount per task solved. Your payment will depend on the number of tasks you solve and the numbers of tasks two competitors solve.

Your earnings will be measured in Experimental Currency Units (ECUs). At the conclusion of the third period, the ECUs you have earned will be converted into real money at the exchange rate of 70:1 (70 ECUs for 1 Dollar).

Competition

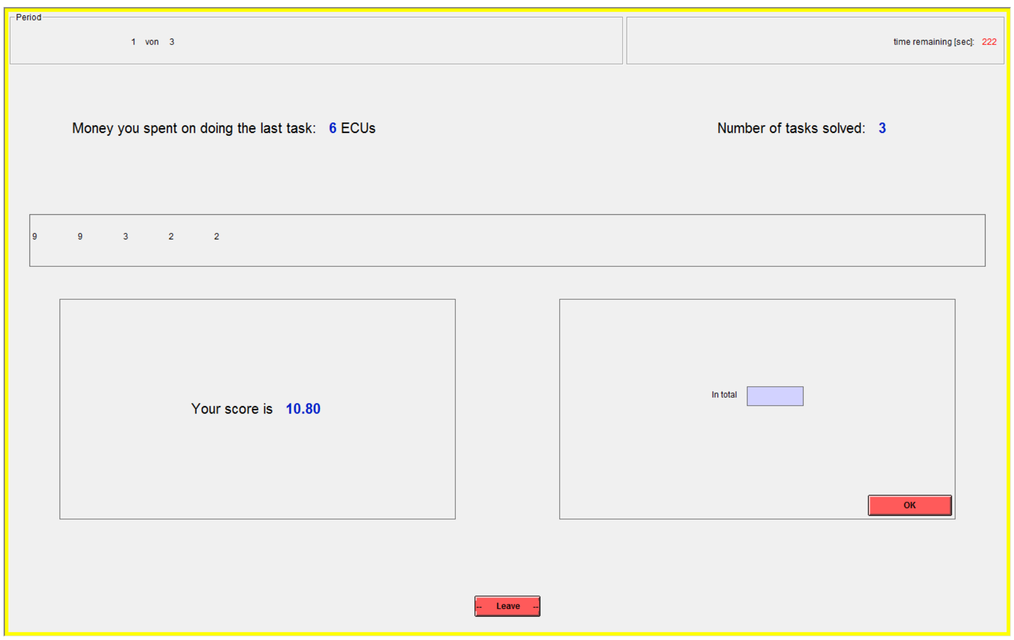
In each competition round, there is a 600 ECUs prize money awarded to each group. You can increase your share by solving tasks, where you again have to decide when to stop solving tasks. As before, the maximum time given is 240 seconds. For each second not used to solve tasks, you will be given one ECU.

It is important for you to choose the right time to stop doing the summation tasks:

1. If you spend time doing tasks, your score increases with the number of tasks you solve. The higher your score, given the scores of other two group members, the greater is your share of the prize of 600 ECUs.

2. On the other hand, you will lose one ECU for every second while you are working on the task. Again, you will be paid one ECU for every second remaining (of the initial 240) when you click "Leave" on the task screen.

Here is an example of how the screen will look:



Score, Number of Tasks Solved, Multiplier, Cheating and Ban

The score for a given period is calculated as the number of tasks a player solved times a multiplier (which can be 2, 3, or 4). In each period there is one player in the group with a multiplier of 2, one with 3 and one with 4. You will be shown which multiplier you will have in the three periods before the first period and you will be reminded in the subsequent periods.

At the beginning of each period you will be asked if you want to cheat in the contest. If you decide to cheat then you will get a 20 percent bonus on your score in that round. However, there is a 30 percent chance that you will get caught cheating in each competition. Recall that there are 3 competitions in total. If you get caught in a certain competition, you will be banned from participating in next competition. Hence, you will not receive a score in next competition where you get banned. If you choose not to cheat, there is no risk of getting banned in the future.

For example, for any participants, if you are assigned a multiplier of 3 and you solve 10 tasks in total, your score will be 3×10=30. If you accept the 20% cheating bonus, then the final score will be 30+20 percent bonus=36.

Payment

- If you are banned, you payment in the banned period is 110 ECUs. There will be no prize money since you are not allowed to participate in the competition.
- If you are not banned, your payment in each competition consists of two parts:

1. Share of the prize money
2. Fixed payment, 1 ECU per second of remaining time from the effort stage.

Your share of the prize is calculated as follows. If everybody has the same score then the prize is shared equally. So everybody gets 200 ECUs, which is one third of the total prize of 600. If your score is higher than the average score of the other two players you receive 6 ECUs for every unit that your score is higher than the average of competitors' score. For example if your score is 10 units higher than the average score of the other two competitors, then you will receive 200+60=260 ECUs as prize money.

On the other hand, if your score is lower than the average, then for every unit your score is lower than the average of the others, 6 ECUs are deducted from 200 ECUs. So if your score is, e.g. 10 units lower than the average, then you receive 200-60=140 ECUs as prize money.

So your prize money if you are not banned is calculated as:

$$Prize\ money\ in\ ECU = 200 + 6 \times (your\ score - average\ score\ of\ others)$$

Notice that if any of your group members are banned in the competition, his or her score will be substituted by the score of another random player in the room with the same ability level as the banned person.

Again, for the 240 seconds you are given, you get paid 1 ECU per second on the time not spent solving tasks.

Your total earnings per period are calculated as:

$$Total\ earnings\ in\ ECU = Prize\ money + Time\ not\ spent\ solving\ tasks$$

Note that the payoffs for your competitors are calculated in the same manner.

Summary

You are competing in three competitions with the same two other competitors. In order to determine you scores in second and third competitions, we use the same addition tasks as before. The score in a period will be the number of tasks solved times a multiplier. You can decide to cheat and get a 20 percent bonus on your score. However, there is a 30% chance that you will be caught and get banned for next competition. If you are banned, you receive a fixed amount of 110 ECUs. If you are not banned, your score relative to the average score of the two competitors determines how much the prize money of 600 ECUs you receive. In addition to the prize money you also receive one ECU per second left on the clock when you leave the summing-up task.

Questions

To make sure you fully understand how the prize money works, you will be asked three questions on the screen. You need to answer all of them correctly before we can start the experiment. Please click OK button once you finish the questions.

Please raise your arm if you have any questions.

B.1.5 Conditional-superannuation treatment

General Information

The experiment you are about to participate in consists of 3 periods. At the beginning of the first period, you will be placed in a group of three (you and two unidentified competitors). You will play all three periods with the same two competitors.

In this experiment we will use the task you have just played to simulate a competition. Now the payoff from solving tasks will not be a certain amount per task solved. Your payment will depend on the number of tasks you solve and the numbers of tasks two competitors solve.

Your earnings will be measured in Experimental Currency Units (ECUs). At the conclusion of the third period, the ECUs you have earned will be converted into real money at the exchange rate of 70:1 (70 ECUs for 1 Dollar).

Competition

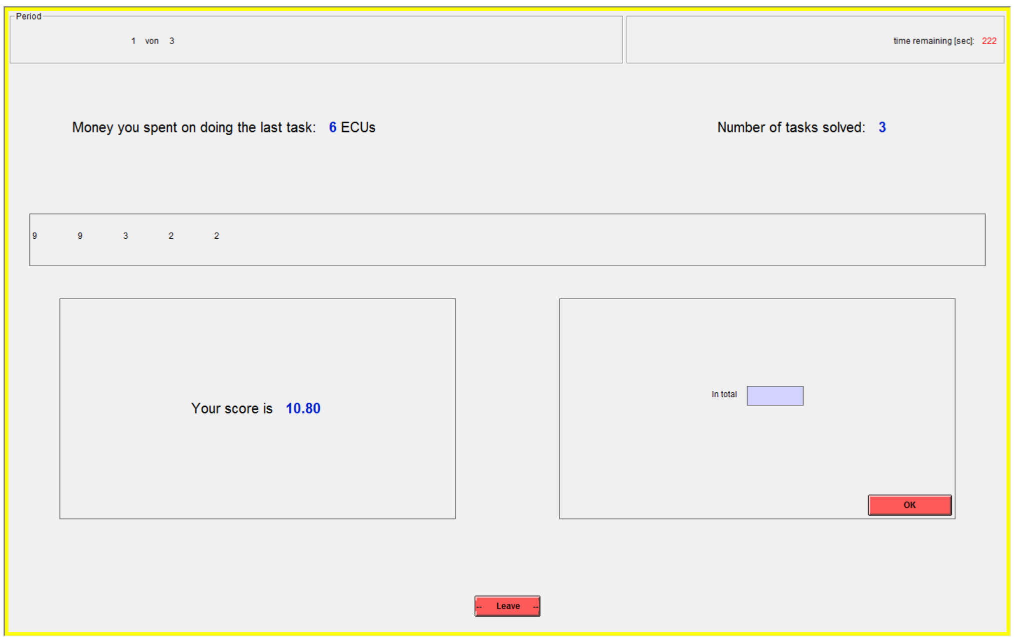
In each competition round, there is a 600 ECUs prize money awarded to each group. You can increase your share by solving tasks, where you again have to decide when to stop solving tasks. As before, the maximum time given is 240 seconds. For each second you are not using to solve tasks, you will be given one ECU.

It is important for you to choose the right time to stop doing the summation tasks:

1. If you spend time doing tasks, your score increases with the number of tasks you solve. The higher your score, given the scores of other two group members, the greater is your share of the prize of 600 ECUs.

2. On the other hand, you will lose one ECU for every second while you are working on the task. Again, you will be paid one ECU for every second remaining (of the initial 240) when you click "Leave" on the task screen.

Here is an example of how the screen will look:



Score, Number of Tasks Solved, Multiplier and Cheating

The score for a given period is calculated as the number of tasks a player solved times a multiplier (which can be 2, 3, or 4). In each period there is one player in the group with a multiplier of 2, one with 3 and one with 4. You will be shown which multiplier you will have for which period in the first period and you will be reminded in the subsequent periods.

At the beginning of each period you will be asked if you want to cheat in the contest. If you decide to cheat, then you will get a 20 percent bonus on your score in that round.

For example, for any participants, if you are assigned a multiplier of 3 and you solve 10 tasks in total, your score will be 3×10=30. If you accept the 20% cheating bonus, then the final score will be 30+20 percent bonus=36.

Cheating, Payment and Superannuation Fund

The period payment you will receive at the end of each period consists of two parts:

1) Your share of the prize money which depends on your score relative to other two competitors' scores.

AND

2) 1 ECU for every second remaining (of the initial 240 seconds).

After each round, 35 percent of your share of the prize money will be put in your superannuation fund. This contribution is compulsory for all three periods.

Remember that you can cheat for higher score value. However, there is a 30 percent chance that you will get caught cheating in each competition. As long as you are caught cheating once, you will lose your entire contribution. Only if you are not caught cheating for all three periods, you will be able to get your total contribution back at the end of the third period. You will be told that if you lose your entire superannuation fund contribution at the end of each period, which indicates whether you are caught cheating or not. If you choose not to cheat, there is no risk of losing your money in superannuation fund.

Payment

Again, your guaranteed final money payment consists of two parts:

1. Share of the prize after contribution to the superannuation fund

2. Fixed payment, 1 ECU per second of remaining time from effort stage

Your share of the prize is calculated as follows. If everybody has the same score then the prize is shared equally. So everybody gets 200 ECUs, which is one third of the total prize of 600. If your score is higher than the average score of the other two players you receive 6 ECUs for every unit that your score is higher than the average of competitors' score. For example if your score is 10 units higher than the average score of the other two competitors, then you will receive 200+60=260 ECUs as prize money.

On the other hand, if your score is lower than the average, then for every unit your score is lower than the average of the others,Sc 6 ECUs are deducted from 200 ECUs. So if your score is, e.g. 10 units lower than the average, then you receive 200-60=140 ECUs as prize money.

So your prize money is calculated as:

$$Prize\ money\ in\ ECU = 200 + 6 \times (your\ score - average\ score\ of\ others)$$

You will have to make a compulsory contribution of 35% of the prize money to your superannuation fund each period:

$$Contribution = 35\%$$

Therefore, your net prize money after contribution is 65% of the total prize money:

$$Net\ prize\ money = 65\%$$

Recall that at the effort stage, you are given 240 seconds to do tasks. You get paid 1 ECU per second for the remaining time on the clock after you leave the stage.

Your guaranteed total earnings per period are calculated as:

$$Gauranteed\ total\ earnings\ in\ ECU = net\ prize\ money + time\ not\ spent\ solving\ tasks$$

If you are not caught cheating for all 3 periods, the contribution you make will be fully paid back to you at the end of the third period.

However, if you are caught cheating once or more, you will not be able to get back your contribution.

Summary

You are competing in three competitions with the same two other competitors. In order to determine you scores in second and third competitions, we use the same addition tasks as before. The score in a period will be the number of tasks solved times a multiplier. You can decide to cheat and get a 20 percent bonus on your score. However, there is a 30% chance that you will be caught and lose your 35% contribution of the prize money for all three periods. Your score relative to the average score of the two competitors determines how much the prize money of 600 ECUs you receive. In addition to the prize money you also receive one ECU per second left on the clock when you leave the summing-up task.

Questions

To make sure you fully understand how the prize money works, you will be given two numerical examples with two questions on the screen. You need to answer both of them correctly before we can start the experiment. Please click OK button once you finish the questions.

Please raise your arm if you have any questions.

B.2 Experiment 2

B.2.1 Piece rate

General Information

The experiment is about solving a series of arithmetic tasks. You will receive a 5-dollar show up fee. The number of tasks you solve correctly will determine your final payment.

- For every task you solve correctly, you will receive 1 point.
- For every task you solve incorrectly, or for every task you skip, you will receive 0 point.

Every point is worth of 1 AUD.

Background

In this experiment, there will be eight different tasks for you to solve. You will have 20 seconds to complete each task and the remaining time is always shown on the top right corner.

The task involves adding a stream of single-digit numbers together within 20 seconds. There are five levels of difficulty:

1. Beginner: adding up 5 single-digit numbers
2. Easy: adding up 7 single-digit numbers
3. Normal: adding up 9 single-digit numbers
4. Hard: adding up 11 single-digit numbers
5. Very hard: adding up 13 single-digit numbers

For each task, the level of difficulty is randomly assigned and everyone face the same difficulty level.

Task

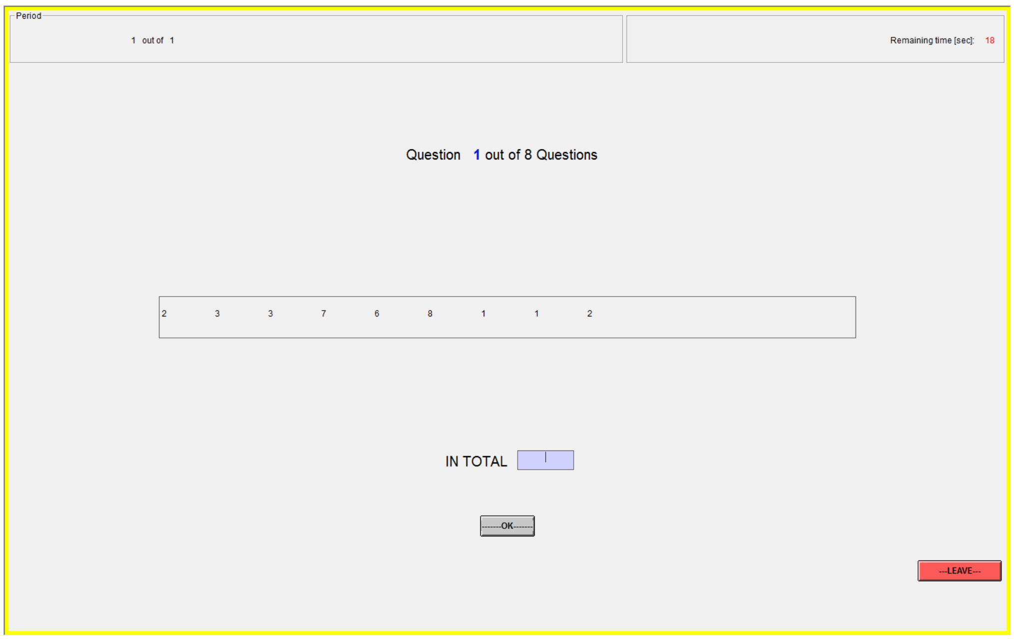
For each task, you have two choices:

- If you wish to skip the task, you can click the "LEAVE" button on the bottom right corner. Then, you will receive nothing and move on to the next task.

Or

- If you wish to solve this task, you must enter your answer in the "IN TOTAL" box and then click the "OK" button.

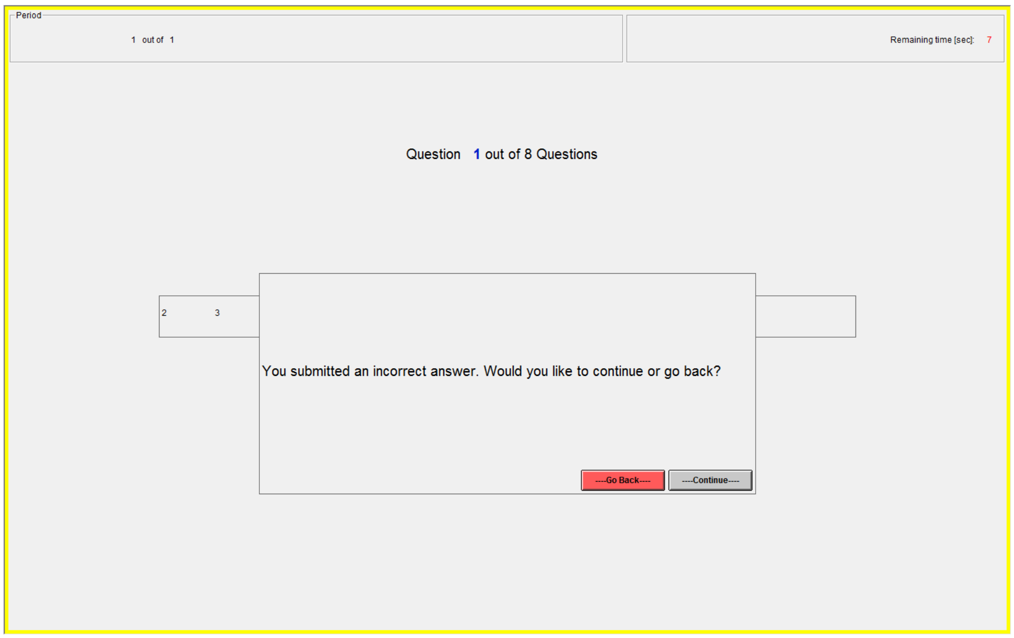
A screenshot is as below:



For example, if you wish to solve this task in the screenshot, you need to add 2, 3, 3, 7, 6, 8, 1, 1 and 2 together. Then, put your answer in the "IN TOTAL" box and click "OK" button.

- If the answer submitted is correct, you will receive 1 point and move on to the next task.
- If the answer submitted is incorrect, for the first time only, you will see a pop-up window with a message saying "You submitted an incorrect answer. Would you like to

Continue or Go Back?" If you would like to keep the incorrect answer as it is, then you should click "Continue" button. If you would like to go back and re-submit an answer, then you should click "Go Back" button (see the screenshot below).



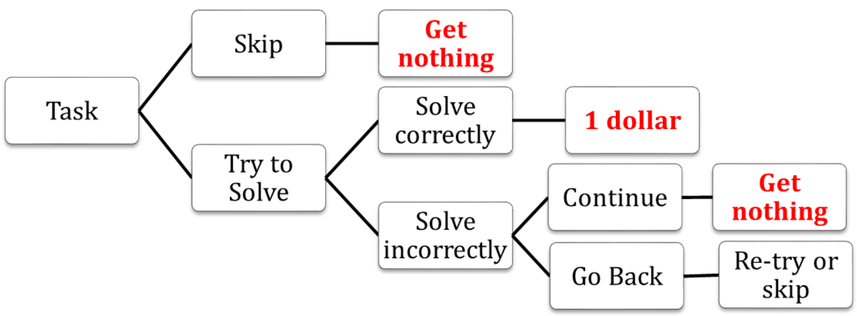
- Once you choose to keep the wrong answer and click the "Continue" button, you will receive nothing and move on to the next task.

- On the other hand, the pop-up window will disappear after you click the "Go Back" button. Just like before, now you can choose to re-submit an answer in the "IN TOTAL" box and click the "OK" button or skip the task by clicking the "Leave" button. Notice that this time, no message will be shown. Whatever answer re-submitted will be treated as the final answer. Hence, if the answer re-submitted is correct, you will receive one dollar. Otherwise, you will receive nothing.

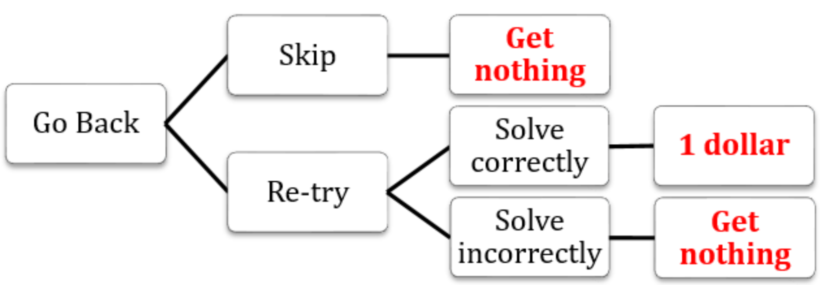
If you failed to submit an answer within 20 seconds, you will be treated as if you skipped the task.

This process is repeated for all eight tasks.

To summarise, for every task, you can choose to skip it and get nothing or try to solve it. You will receive 1 point (equivalent to 1 dollar) if you solve it correctly. You will be reminded if you submitted a wrong answer for the first time. You can then choose between "Continue" and "Go back". To continue, you keep your wrong answer and get nothing.



If you choose to go back, you will have another chance to retry the task. This time, whatever answer submitted will be counted.



At the end, your payment is calculated as:

$$Your\ payment = 5\ dollars\ show\ up\ fee + number\ of\ tasks\ solved\ correctly$$

B.2.2 No leaderboard treatment

General Information

The experiment you are about to participate in consists of three rounds. At the beginning of the first round, you will be placed in a group of two (you and another unidentified competitor). You will play all three rounds with the same competitor.

In this experiment we will use the task you have just played to simulate a competition (such as in sports). Your monetary payment will depend on you and your competitor's performance. Performance is measured in points.

Competition

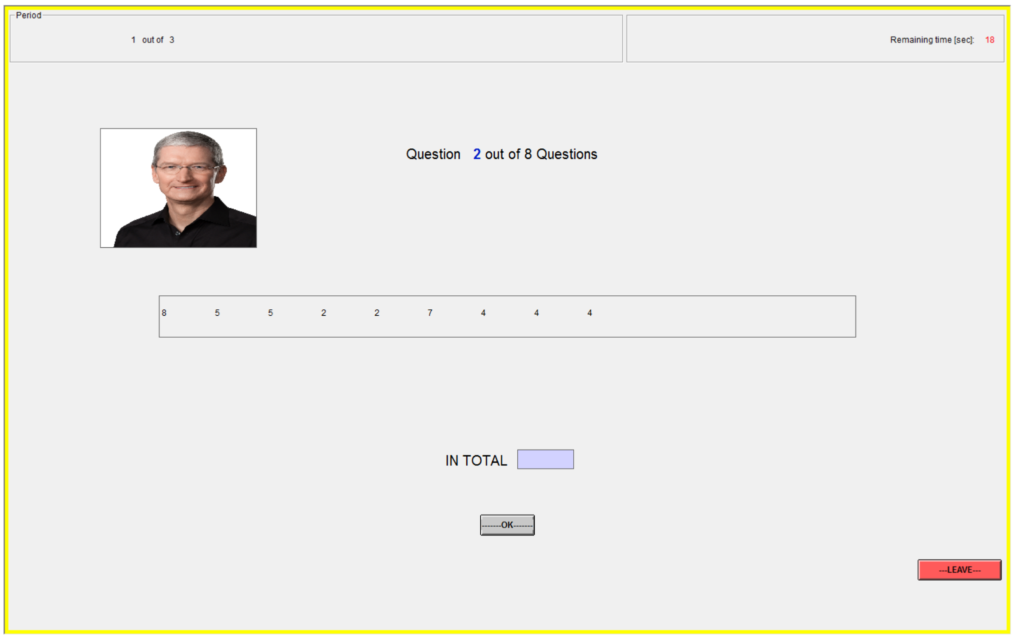
In each round, you and your competitors will be given eight summation tasks. In each of the three competitions, everybody starts with a balance of zero point. You can either choose to submit an answer or not. Scoring works as follows:

- If you submitted a correct answer, one point will be added to your balance.
- If you submitted an incorrect answer, one point will be deducted from your balance
- If you don't submit an answer, your point balance does not change.

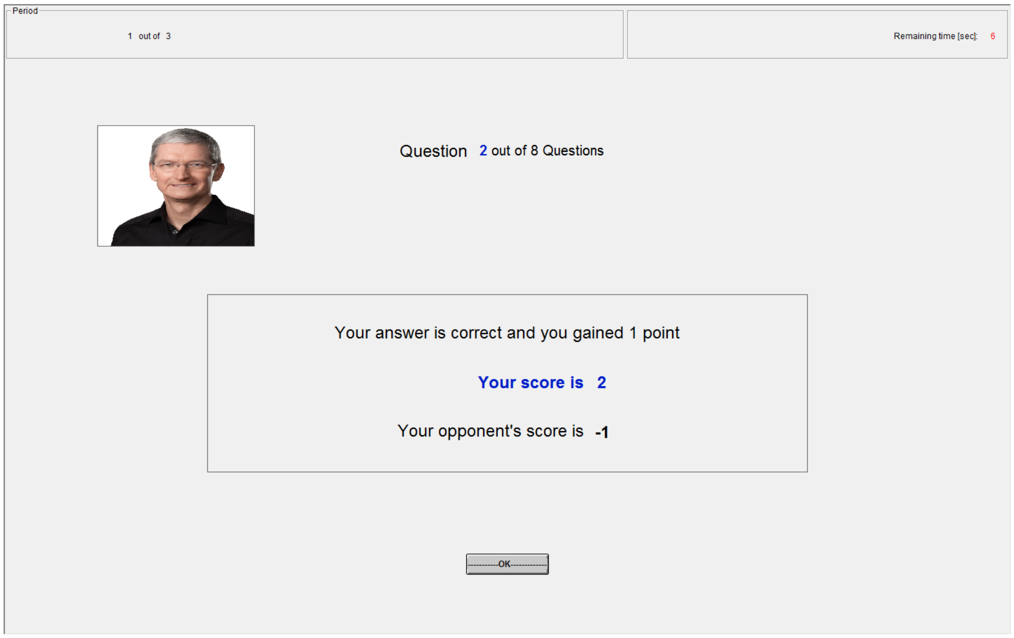
So, at the end of each round, the maximum score one can achieve is 8 and the minimum score is -8.

The summation tasks will have the identical structures to those you played before. You will have 20 seconds to complete each task and the remaining time is always shown on the top right corner. There will be the same five levels of difficulty of the tasks. The higher the level of difficulty, the more single-digit numbers to be added.

For every task, you can choose to submit an answer or not. If you don't submit an answer, you will move to the next task. If you submitted a correct answer, you will move to the next task. However, if you submitted an incorrect answer for the first time, you will see the same pop-up window as before. Then, you will need to make a choice between “Go Back” and “Continue” depending on whether you want to re-submit an answer or not. Your profile picture will be shown in the top left corner on your screen throughout three rounds (See the screenshot below).



Notice that every time when a task is completed, both you and your group member’s scores will be updated and shown. See the screenshot below:



Payment

After you complete all three rounds, ONE of the three competitions will be randomly selected to determine your payment. That is, you will receive a payoff according to the ranking of your score in that one specific round:

- If you won the competition (i.e. having the highest point balance), you will receive 15 AUDs. On the other hand, if you lost the competition, you will receive nothing.
- However, as a compensation for subjects who are not very good at math, a person who lost the competition and finished with one point or less will receive 5 AUDs.

Notice that if you and your competitor have the same score, the computer randomly picks the winner.

Please raise your arm if you have any questions.

B.2.3 Leaderboard treatment

General Information

The experiment you are about to participate in consists of three rounds. At the beginning of the first round, you will be placed in a group of two (you and another unidentified competitor). You will play all three rounds with the same competitor.

In this experiment we will use the task you have just played to simulate a competition (such as in sports). Your monetary payment will depend on you and your competitor's performance. Performance is measured in points.

Competition

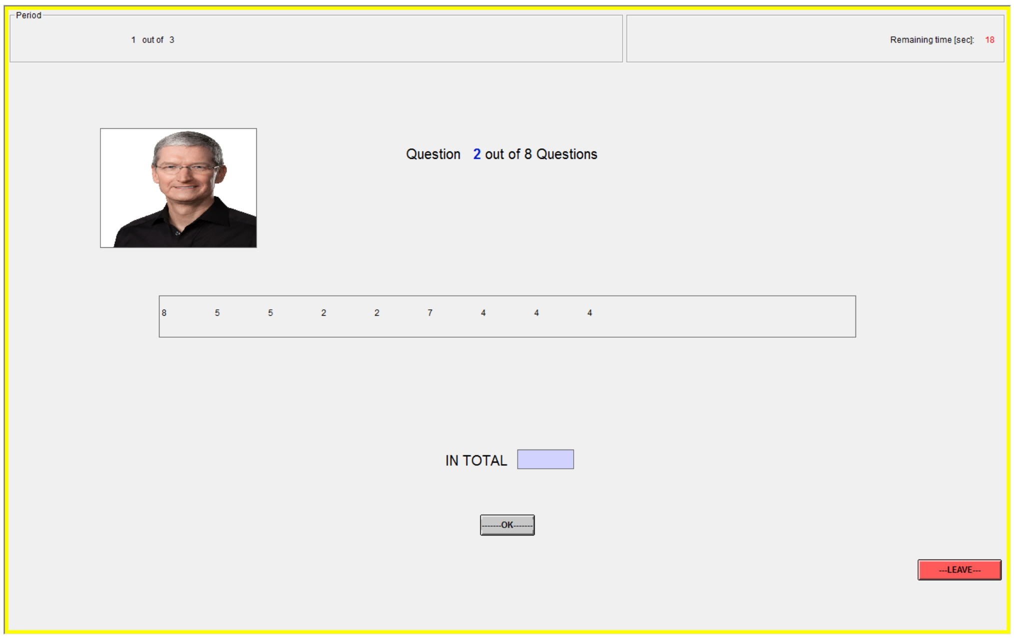
In each round, you and your competitors will be given eight summation tasks. In each of the three competitions, everybody starts with a balance of zero point. You can either choose to submit an answer or not. Scoring works as follows:

- If you submitted a correct answer, one point will be added to your balance.
- If you submitted an incorrect answer, one point will be deducted from your balance
- If you don't submit an answer, your point balance does not change.

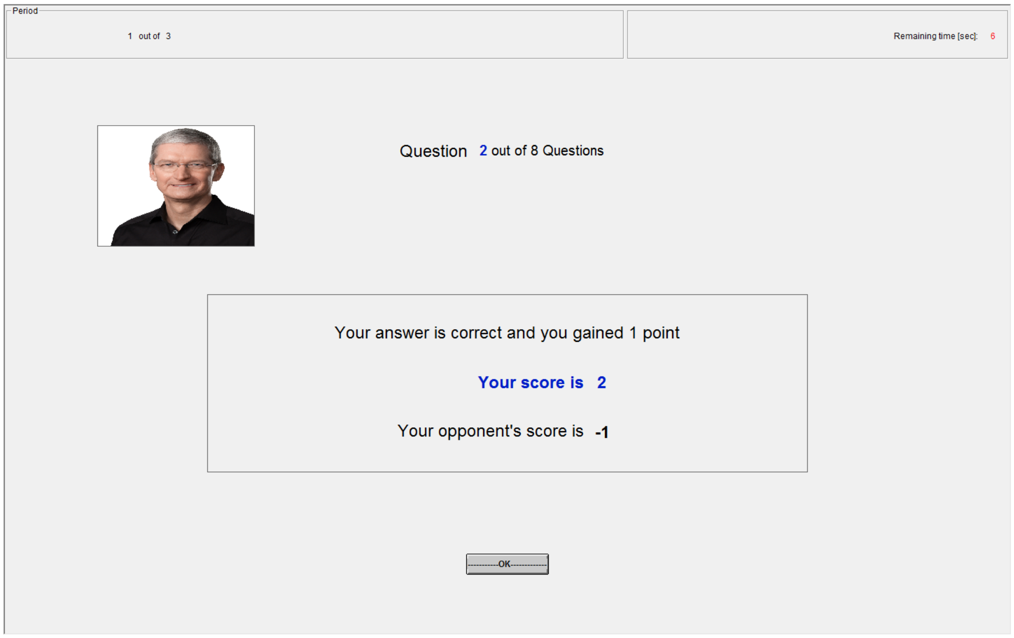
So, at the end of each round, the maximum score one can achieve is 8 and the minimum score is -8.

The summation tasks will have the identical structures to those you played before. You will have 20 seconds to complete each task and the remaining time is always shown on the top right corner. There will be the same five levels of difficulty of the tasks. The higher the level of difficulty, the more single-digit numbers to be added.

For every task, you can choose to submit an answer or not. If you don't submit an answer, you will move to the next task. If you submitted a correct answer, you will move to the next task. However, if you submitted an incorrect answer for the first time, you will see the same pop-up window as before. Then, you will need to make a choice between "Go Back" and "Continue" depending on whether you want to re-submit an answer or not. Your profile picture will be shown in the top left corner on your screen throughout three rounds (See the screenshot below).



Notice that every time when a task is completed, both you and your group member's scores will be updated and shown. See the screenshot below:



Payment

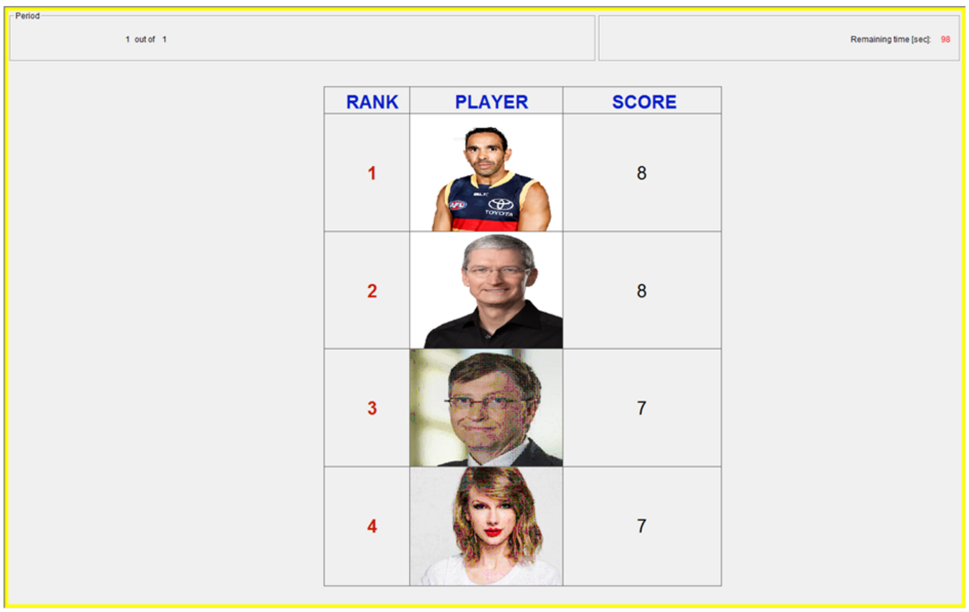
After you complete all three rounds, ONE of the three competitions will be randomly selected to determine your payment. That is, you will receive a payoff according to the ranking of your score in that one specific round:

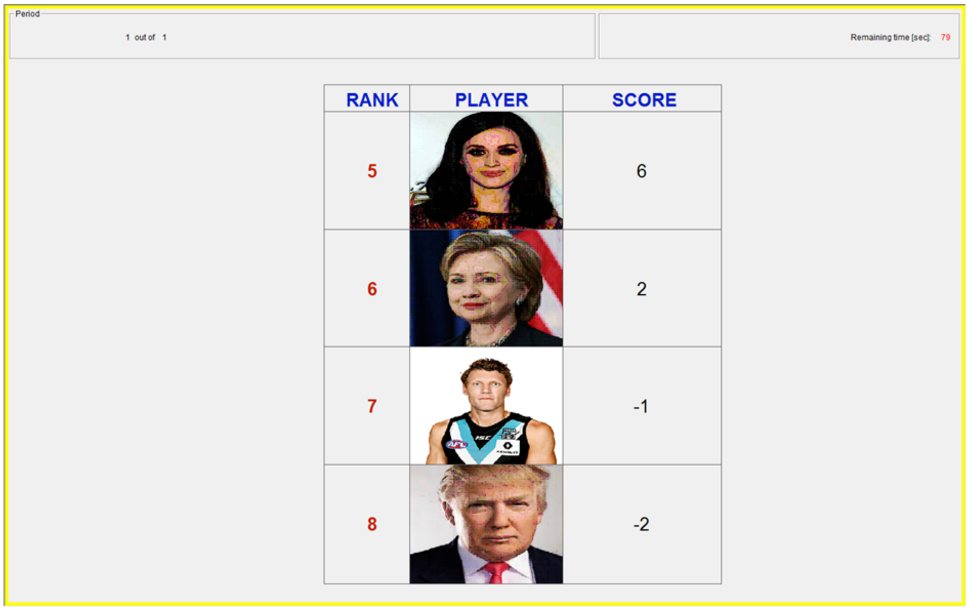
- If you won the competition (i.e. having the highest point balance), you will receive 15 AUDs. On the other hand, if you lost the competition, you will receive nothing.
- However, as a compensation for subjects who are not very good at math, a person who lost the competition and finished with one point or less will receive 5 AUDs.

Notice that if you and your competitor have the same score, the computer randomly picks the winner.

Leaderboard

At the end of each round, you and everyone in this room will be ranked according to your scores. Then, everybody in this room will see a leaderboard showing the ranking from the top player to the bottom player with profile pictures and points balances. Each page of the leaderboard contains four players and each page stays on your screen for 15 seconds before it moves to the next page automatically. After all the players are listed out, you will see an "OK" button. After you click the "OK" button, you will finish that round. An example of the leaderboard is shown below.





Please raise your arm if you have any questions.

B.3 Experiment 3

B.3.1 Individual liability low fine treatment

General Information

The experiment you are about to participate in consists of 20 rounds of team competitions. At the beginning of the first round, you will be placed in a team of two (you and another unidentified team member). Then, you and your team member will compete with another team that also consists of two players. You will compete with the same other team for 20 rounds.

You will receive a show-up fee of 5 Dollars for this experiment. In addition to the show-up fee you can earn money by making smart choices in the contest game. Your earnings will be measured in Experimental Currency Units (ECUs). At the conclusion of the last round, the ECUs you have earned will be converted into real money at an exchange rate of 10:1 (10 ECUs for 1 Dollar).

Competition

At the beginning of the first round you will be randomly assigned a role in your team. Each team will consist of one manager and one player. You will keep the assigned role throughout the 20 rounds of the experiment. In each round, your team will compete with your opponent team for a share of a prize of 90 ECUs. How much of the share your team gets will depend on your team's performance relative to that of the competitor. Your team performance will be determined by the choice of costly effort by the player and by the team's decision to cheat or not to cheat. The part of the prize your team wins will be shared between the player, who receives 2/3 of wining share and the manager, who receives the remaining 1/3.

Your team share of the prize is calculated as:

$$\frac{Your\ team\ performance}{Your\ team\ performance + Your\ competitor's\ performance} \times 90 ECUs$$

Basically, your team gets the fraction of the total prize that is equal to the fraction of your team's performance of the total performance by both teams. This means, for example, that if your performance is the same as the performance of the other team that you receive half the total prize. If your performance is half the performance of the other team then you receive 1/3 of the total prize. If your performance is twice as high as the performance of the other team then you receive 2/3 of the total prize.

Note that both the player and the manager have an influence on the cheating decisions for the team. The player will choose the effort for the team.

Cheating

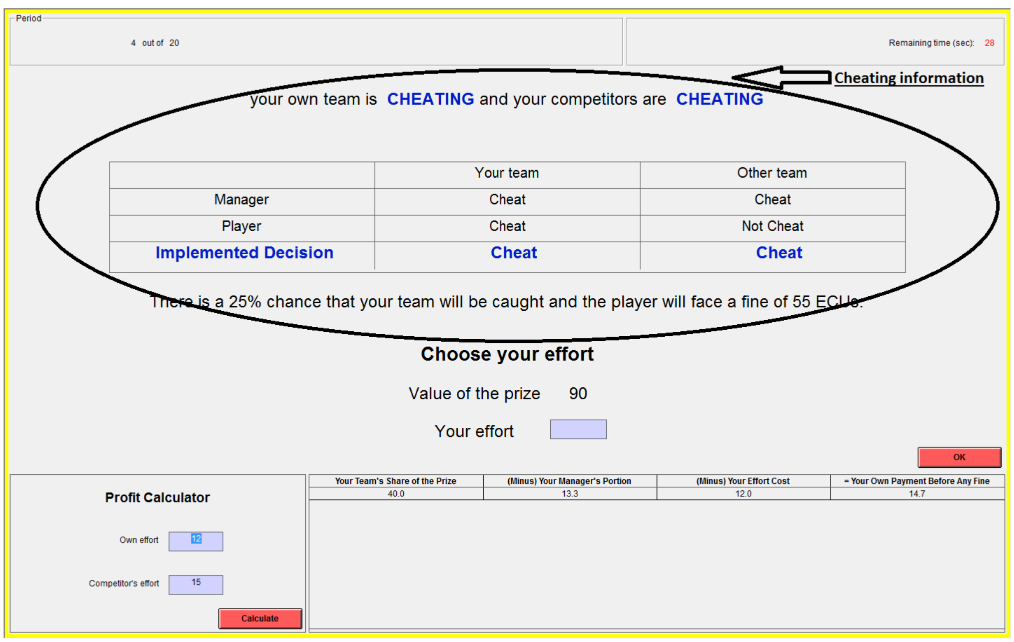
At the beginning of each round, player and manager can indicate if they wish to cheat via a push of a button. Then, the computer flips a coin to determine which team member's choice to implement. So both team members have a 50% chance that their choice is implemented.

If the implemented choice is not cheating, then your team performance is the team effort that will be chosen by the player. If your team is cheating, then your team performance will be double the effort chosen by the player. Hence, by cheating, you can double the team performance. For instance, if the team effort is 30, then cheating yields a team performance of 60. However, there is a potential cost associated with cheating for the player only. Any cheating team might be caught and the player in the team might be fined. The chance of the team getting caught cheating is 25%. If caught, the player from this caught team will face a fine of 55 ECUs. The manager, however, will not be fined.

Player and manager will be asked to newly decide to cheat or not in every of the 20 rounds.

Effort

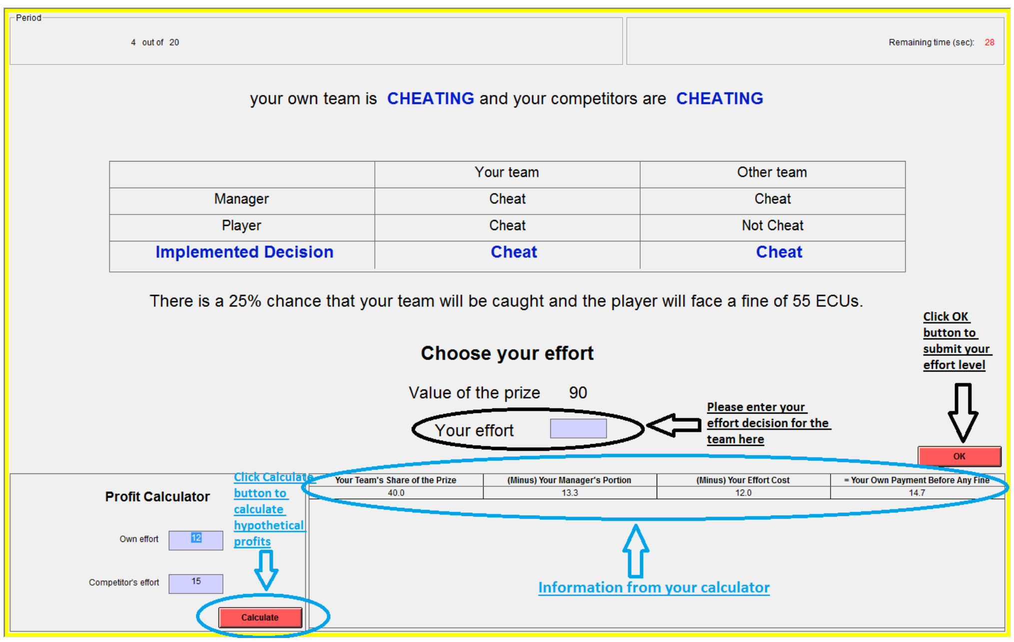
Once the cheating decisions are implemented, managers and players will be informed about the cheating decisions within their and their rival team. See the screenshot below.



In this stage, the players in both teams have to decide on their team's effort. The higher the effort chosen, for a given performance of the competitor, the larger is the share of the prize that your team gets. Recall that a team's performance is equal to the effort (if not cheating) or twice the effort (if cheating). While increasing the effort increases the share of the prize, there is a cost associated with the effort. For each unit of effort the player puts in, he or she has to pay one ECU. Note that effort cost has to be paid for by the player in full. They are not shared between the player and the manager.

To help players to make better effort decisions, there is a profit calculator on their screen. A player can put in hypothetical own efforts and efforts of the opposing team, and the calculator will show the prize money the team would earn, how much the player has to give to the manager, the effort cost the player will incur and the resulting payoff for the player (not including potential fines).

A player can calculate payoffs for different pairs of hypothetical efforts as many times as he or she wants. Once the player is ready to decide on her effective effort, he or she should enter a number in the field “Your effort” and then click the OK button. Please see the screenshot below.



While a team’s player is calculating hypothetical payoffs and is taking the effort decision, the manager, who cannot make any choices here, will be able to observe all actions of the players on his or her screen.

Payment

After each round of the competition, every participant will be informed about the payoff received in this round. All players will see the cheating decisions, the effort decisions, the resulting shares of the prize and the fine imposed on the player if relevant.

Recall that your team share of the prize is calculated as:

$$\frac{Your\ team\ performance}{Your\ team\ performance + Your\ competitor's\ performance} \times 90ECUs$$

This team share is then divided between the player and the manager at a ratio of 2:1. A fixed fine of 55 ECUs is paid by the player only, if a team is caught cheating.

Therefore, a player's payment for each competition round is:

$$Player's\ payment = Team\ share\ in\ ECUs \times \frac{2}{3} - Effort\ cost - possible fine$$

A manager's payment for each competition round is:

$$Manager's\ payment = Team\ share\ in\ ECUs \times \frac{1}{3}$$

B.3.2 Individual liability high fine treatment

General Information

The experiment you are about to participate in consists of 20 rounds of team competitions. At the beginning of the first round, you will be placed in a team of two (you and another unidentified team member). Then, you and your team member will compete with another team that also consists of two players. You will compete with the same other team for 20 rounds.

You will receive a show-up fee of 5 Dollars for this experiment. In addition to the show-up fee you can earn money by making smart choices in the contest game. Your earnings will be measured in Experimental Currency Units (ECUs). At the conclusion of the last round, the ECUs you have earned will be converted into real money at an exchange rate of 10:1 (10 ECUs for 1 Dollar).

Competition

At the beginning of the first round you will be randomly assigned a role in your team. Each team will consist of one manager and one player. You will keep the assigned role throughout the 20 rounds of the experiment. In each round, your team will compete with your opponent team for a share of a prize of 90 ECUs. How much of the share your team gets will depend on your team's performance relative to that of the competitor. Your team performance will be determined by the choice of costly effort by the player and by the team's decision to cheat or not to cheat. The part of the prize your team wins will be shared between the player, who receives 2/3 of wining share and the manager, who receives the remaining 1/3.

Your team share of the prize is calculated as:

$$\frac{Your\ team\ performance}{Your\ team\ performance + Your\ competitor's\ performance} \times 90ECUs$$

Basically, your team gets the fraction of the total prize that is equal to the fraction of your team's performance of the total performance by both teams. This means, for example, that if your performance is the same as the performance of the other team that you receive half the total prize. If your performance is half the performance of the other team then you receive 1/3 of the total prize. If your performance is twice as high as the performance of the other team then you receive 2/3 of the total prize.

Note that both the player and the manager have an influence on the cheating decisions for the team. The player will choose the effort for the team.

Cheating

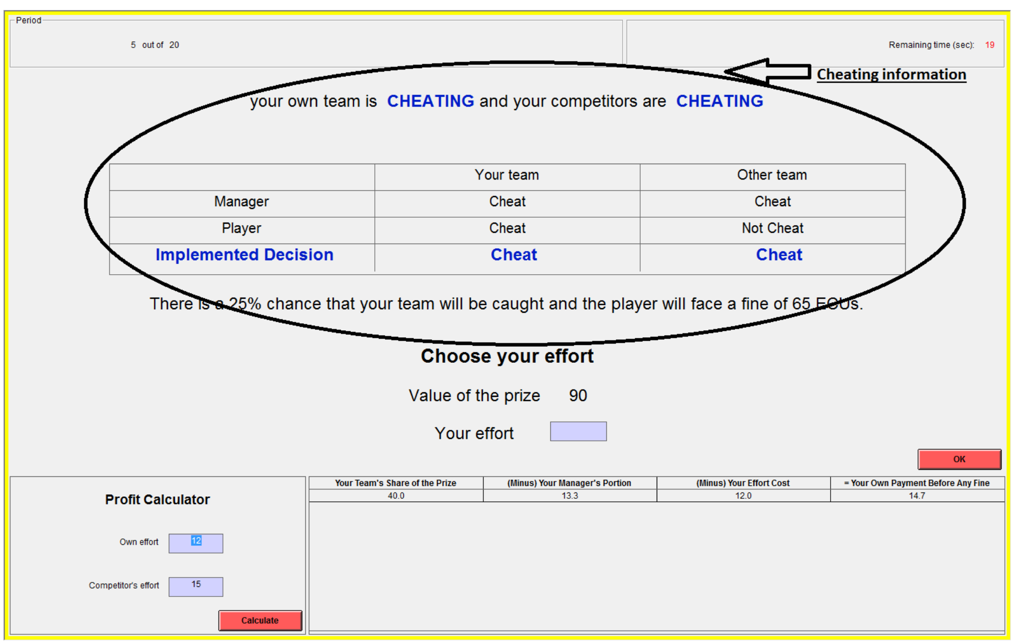
At the beginning of each round, player and manager can indicate if they wish to cheat via a push of a button. Then, the computer flips a coin to determine which team member's choice to implement. So both team members have a 50% chance that their choice is implemented.

If the implemented choice is not cheating, then your team performance is the team effort that will be chosen by the player. If your team is cheating, then your team performance will be double the effort chosen by the player. Hence, by cheating, you can double the team performance. For instance, if the team effort is 30, then cheating yields a team performance of 60. However, there is a potential cost associated with cheating for the player only. Any cheating team might be caught and the player in the team might be fined. The chance of the team getting caught cheating is 25%. If caught, the player from this caught team will face a fine of 65 ECUs. The manager, however, will not be fined.

Player and manager will be asked to newly decide to cheat or not in every of the 20 rounds.

Effort

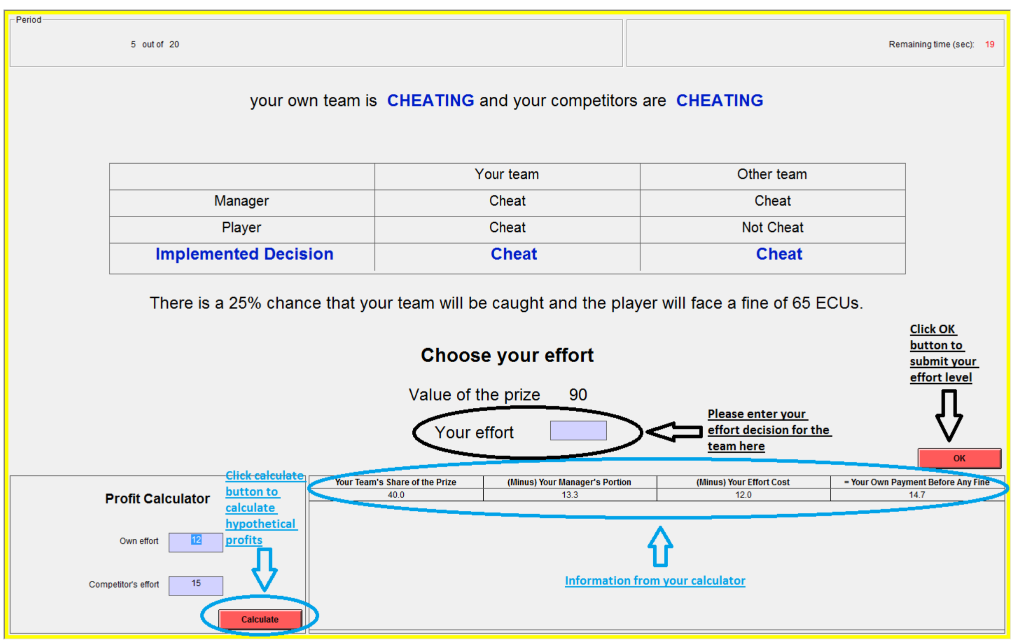
Once the cheating decisions are implemented, managers and players will be informed about the cheating decisions within their and their rival team. See the screenshot below.



In this stage, the players in both teams have to decide on their team's effort. The higher the effort chosen, for a given performance of the competitor, the larger is the share of the prize that your team gets. Recall that a team's performance is equal to the effort (if not cheating) or twice the effort (if cheating). While increasing the effort increases the share of the prize, there is a cost associated with the effort. For each unit of effort the player puts in, he or she has to pay one ECU. Note that effort cost has to be paid by the player in full. They are not shared between the player and the manager.

To help players to make better effort decisions, there is a profit calculator on their screen. A player can put in hypothetical own efforts and efforts of the opposing team, and the calculator will show the prize money the team would earn, how much the player has to give to the manager, the effort cost the player will incur and the resulting payoff for the player (not including potential fines).

A player can calculate payoffs for different pairs of hypothetical efforts as many times as he or she wants. Once the player is ready to decide on her effective effort, he or she should enter a number in the field “Your effort” and then click the OK button. Please see the screenshot below.



While a team’s player is calculating hypothetical payoffs and is taking the effort decision, the manager, who cannot make any choices here, will be able to observe all actions of the players on his or her screen.

Payment

After each round of the competition, every participant will be informed about the payoff received in this round. All players will see the cheating decisions, the effort decisions, the resulting shares of the prize and the fine imposed on the player if relevant.

Recall that your team share of the prize is calculated as:

$$\frac{Your\ team\ performance}{Your\ team\ performance + Your\ competitor's\ performance} \times 90ECUs$$

This team share is then divided between the player and the manager at a ratio of 2:1. A fixed fine of 65 ECUs is paid by the player only, if a team is caught cheating.

Therefore, a player's payment for each competition round is:

$$Player^{'}s\ payment = Team\ share\ in\ ECUs \times \frac{2}{3} - Effort\ cost - possible fine$$

A manager's payment for each competition round is:

$$Manager^{'}s\ payment = Team\ share\ in\ ECUs \times \frac{1}{3}$$

B.3.3 Joint liability low fine treatment

General Information

The experiment you are about to participate in consists of 20 rounds of team competitions. At the beginning of the first round, you will be placed in a team of two (you and another unidentified team member). Then, you and your team member will compete with another team that also consists of two players. You will compete with the same other team for 20 rounds.

You will receive a show-up fee of 5 Dollars for this experiment. In addition to the show-up fee you can earn money by making smart choices in the contest game. Your earnings will be measured in Experimental Currency Units (ECUs). At the conclusion of the last round, the ECUs you have earned will be converted into real money at an exchange rate of 10:1 (10 ECUs for 1 Dollar).

Competition

At the beginning of the first round you will be randomly assigned a role in your team. Each team will consist of one manager and one player. You will keep the assigned role throughout the 20 rounds of the experiment. In each round, your team will compete with your opponent team for a share of a prize of 90 ECUs. How much of the share your team gets will depend on your team's performance relative to that of the competitor. Your team performance will be determined by the choice of costly effort by the player and by the team's decision to cheat or not to cheat. The part of the prize your team wins will be shared between the player, who receives 2/3 of wining share and the manager, who receives the remaining 1/3.

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Note that both the player and the manager have an influence on the cheating decisions for the team. The player will choose the effort for the team.

Cheating

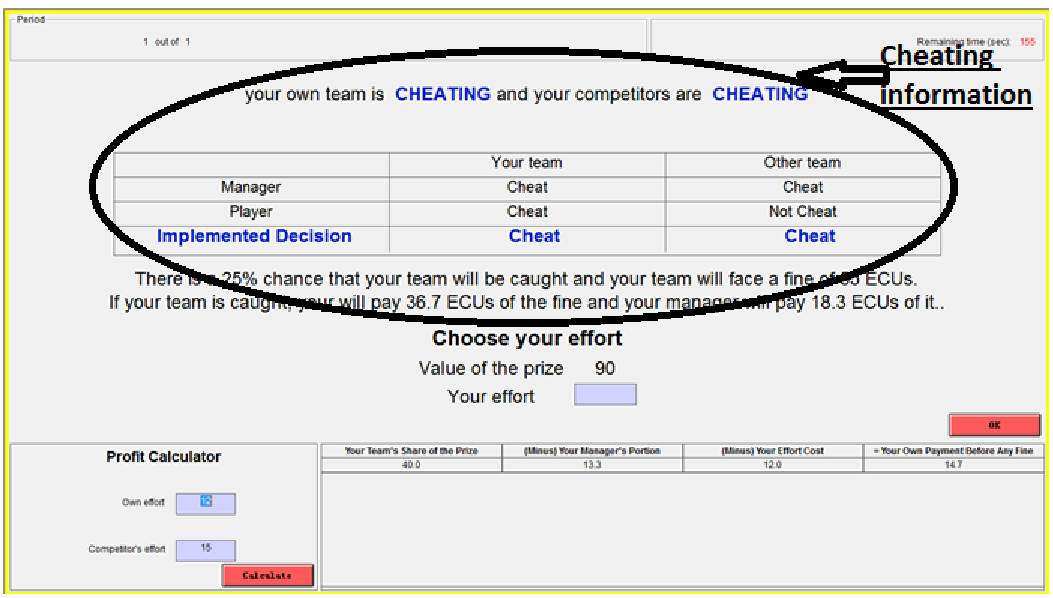
At the beginning of each round player and manager can indicate if they wish to cheat via a push of a button. Then the computer flips a coin which team member's choice to implement. So both team members have a 50% chance that their choice is implemented.

If the implement choice is not cheating, then your team performance is the team effort that will be chosen by the player. If your team is cheating, then your team performance will be double the effort chosen by the player. Hence, by cheating, you can double the team performance. For instance, if the team effort is 30, then cheating yields a team performance of 60. However, there is a potential cost associated with cheating. Any cheating team might be caught and fined. The chance of getting caught cheating is 25%. If caught, your team will face a fine of 55 ECUs. If fined, then the player will pay 2/3 of the fine (36.7 ECUs), while the manager pays the remaining 1/3 (18.3 ECUs). So player and manager are sharing the fine payment in the same way they are sharing the prize.

Player and manager will be asked to newly decide to cheat or not in every of the 20 rounds.

Effort

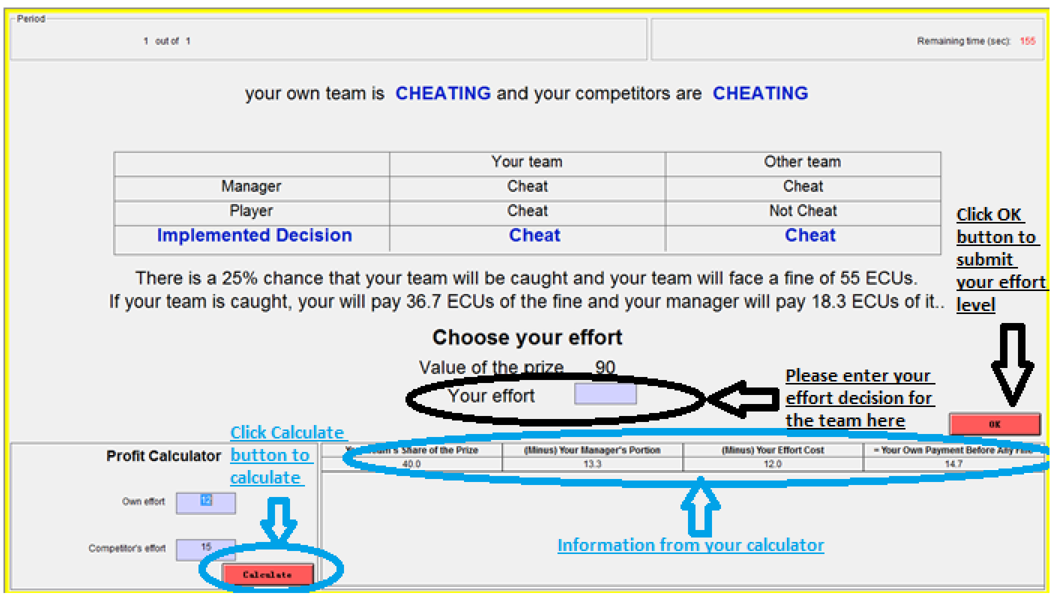
Once the cheating decisions are implemented, managers and players will be informed about the cheating decisions within their and their rival team. See the screenshot below:



In this stage, the players in each team have to decide on their team's effort. The higher the effort chosen, for a given performance of the competitor, the larger is the share of the prize that your team gets. Recall that a team's performance is equal to the effort (if not cheating) or twice the effort (if cheating). While increasing the effort increases the share of the prize, there is a cost associated with the effort. For each unit of effort the player puts in, he or she has to pay one ECU. Note that effort cost has to be paid for by the player in full. They are not shared between the player and the manager.

To help players to make better effort decisions, there is a profit calculator on their screen. A player can put in hypothetical own efforts and efforts of the opposing team, and the calculator will show the prize money the team would earn, how much the player has to give to the manager, the effort cost the player will incur and the resulting payoff for the player (not including potential fines).

A player can calculate payoffs for different pairs of hypothetical efforts as many times as he or she wants. Once the player is ready to decide on her effective effort, he or she should enter a number in the field "Your effort" and then click the OK button. Please see the screenshot below.



While a team's player is calculating hypothetical payoffs and is taking the effort decision, the manager, who cannot make any choices here, will be able to observe all actions of the player on his or her screen.

Payment

After each round of the competition, every participant will be informed about the payoff received in this round. All players will see the cheating decisions, the effort decisions, the resulting shares of the prize and the fines if relevant.

Recall that your team share of the prize is calculated as:

$$\frac{Your\ team\ performance}{Your\ team\ performance + Your\ competitor's\ performance} \times 90ECUs$$

This team share is then divided between the player and the manager at a ratio of 2:1. A fixed fine of 55 ECUs is shared in the same way, if a team is caught cheating.

Therefore, a player's payment for each competition round is:

$$Player's\ payment = Team\ share\ in\ ECUs \times \frac{2}{3} - Effort\ cost - possible\ fine \times \frac{2}{3}$$

A manager's payment for each competition round is:

$$Manager's\ payment = Team\ share\ in\ ECUs \times \frac{1}{3} - possible\ fine \times \frac{1}{3}$$

B.3.4 Joint liability high fine treatment

General Information

The experiment you are about to participate in consists of 20 rounds of team competitions. At the beginning of the first round, you will be placed in a team of two (you and another unidentified team member). Then, you and your team member will compete with another team that also consists of two players. You will compete with the same other team for 20 rounds.

You will receive a show-up fee of 5 Dollars for this experiment. In addition to the show-up fee you can earn money by making smart choices in the contest game. Your earnings will be measured in Experimental Currency Units (ECUs). At the conclusion of the last round, the ECUs you have earned will be converted into real money at an exchange rate of 10:1 (10 ECUs for 1 Dollar).

Competition

At the beginning of the first round you will be randomly assigned a role in your team. Each team will consist of one manager and one player. You will keep the assigned role throughout the 20 rounds of the experiment. In each round, your team will compete with your opponent team for a share of a prize of 90 ECUs. How much of the share your team gets will depend on your team's performance relative to that of the competitor. Your team performance will be determined by the choice of costly effort by the player and by the team's decision to cheat or not to cheat. The part of the prize your team wins will be shared between the player, who receives 2/3 of wining share and the manager, who receives the remaining 1/3.

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Cheating

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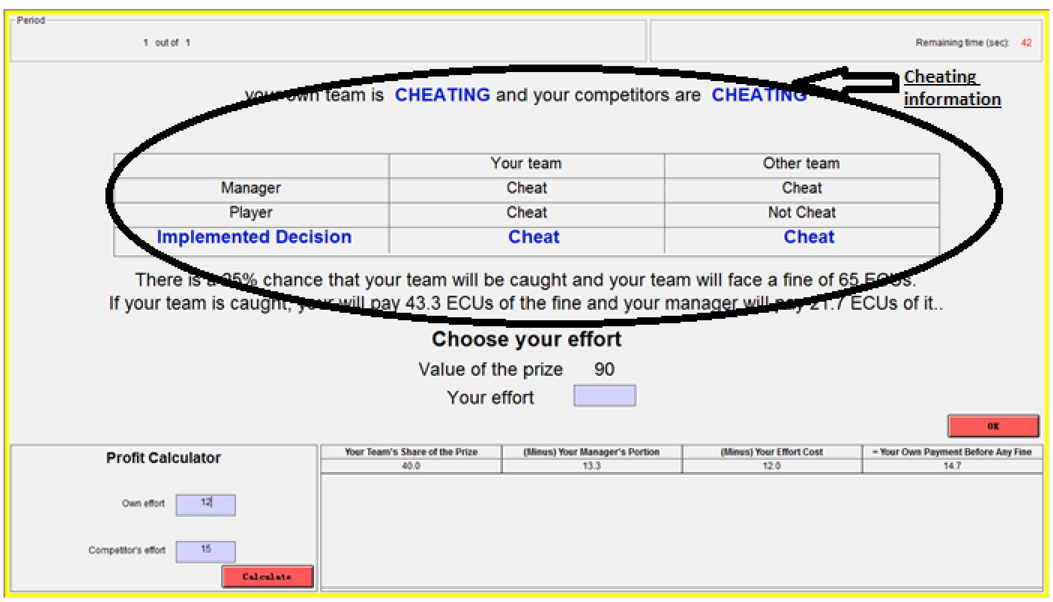
If the implement choice is not cheating, then your team performance is the team effort that will be chosen by the player. If your team is cheating, then your team performance will be double the effort chosen by the player. Hence, by cheating, you can double the team performance. For instance, if the team effort is 30, then cheating yields a team performance of 60. However, there is a potential cost associated with cheating. Any cheating team might be caught and fined. The chance of getting caught cheating is 25%. If caught, your team will face a fine of 65 ECUs. If fined, then the player will pay 2/3 of the fine (43.3 ECUs), while the manager pays the remaining 1/3 (21.7 ECUs). So player and manager are sharing the fine payment in the same way they are sharing the prize.

Player and manager will be asked to newly decide to cheat or not in every of the 20 rounds.

Effort

Once the cheating decisions are implemented, managers and players will be informed about the cheating decisions within their and their rival team. See the screenshot below:



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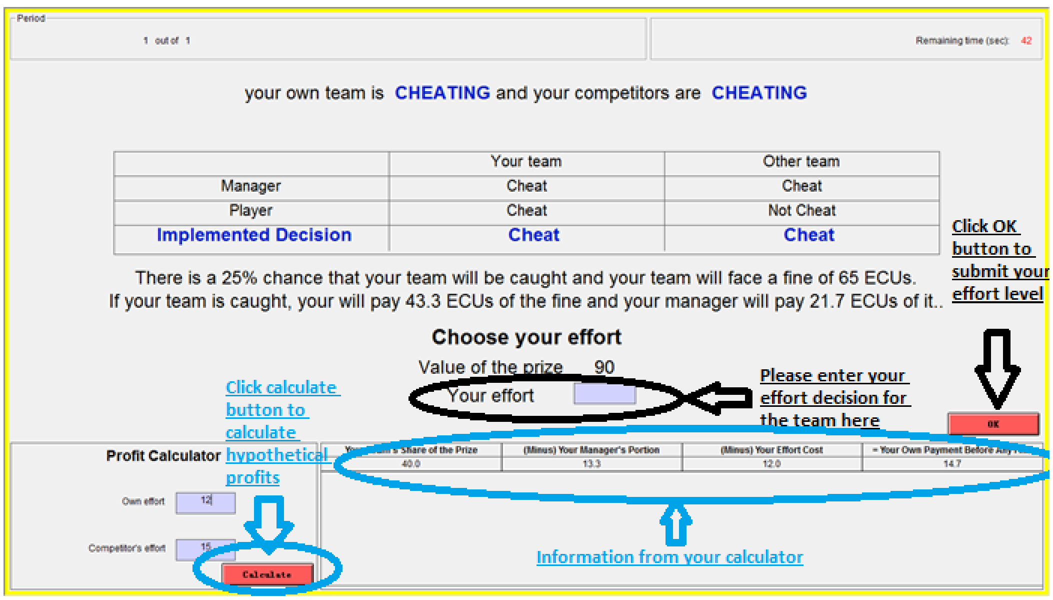
A player can calculate payoffs for different pairs of hypothetical efforts as many times as he or she wants. Once the player is ready to decide on her effective effort, he or she should enter a number in the field "Your effort" and then click the OK button. Please see the screenshot below.



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Payment

After each round of the competition, every participant will be informed about the payoff received in this round. All players will see the cheating decisions, the effort decisions, the resulting shares of the prize and the fines if relevant.

Recall that your team share of the prize is calculated as:

$$\frac{Your\ team\ performance}{Your\ team\ performance + Your\ competitor's\ performance} \times 90 ECUs$$

This team share is then divided between the player and the manager at a ratio of 2:1. A fixed fine of 65 ECUs is shared in the same way, if a team is caught cheating.

Therefore, a player's payment for each competition round is:

$$Player's\ payment = Team\ share\ in\ ECUs \times \frac{2}{3} - Effort\ cost - possible\ fine \times \frac{2}{3}$$

A manager's payment for each competition round is:

$$Manager's\ payment = Team\ share\ in\ ECUs \times \frac{1}{3} - possible\ fine \times \frac{1}{3}$$

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