Lying to be Fair

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Abstract

We experimentally investigate whether lying arises because people think others will lie. Subjects answer questions that measure their analytical ability. They are then informed of the payoff scheme. We employ three payoff schemes (piece-rate, pie-sharing, tournament), and also change whether only one person in a pair or both can lie. Overall, we observe that a small minority of subjects lie. There is no lying in the tournament. We find no effect of varying who can lie; there is no evidence for lying to be fair. We propose a model that captures that lying can be used as a fairness tool, and show that it can predict intermediate levels of lying even in a tournament payoff scheme.

1. Introduction

In many real life situations, whether people behave honestly depends on their beliefs about how others behave. If a person expects dishonest behaviour by many others, then honesty may not be perceived as the social norm anymore and this might help lower the moral cost of cheating. Consider tax evasion. In countries with high tax evasion levels, people state government corruption as one of the most important reasons that justify tax evasion. Tax compliance correlates positively with the strength of the perceived social norm of tax compliance. Also, acceptance attitudes towards tax evasion correlate with the number of tax evaders a person knows (see e.g. Wallschutzky, 1984; Becker et al. 1987; Wenzel, 2004). All of these findings point to the fact that cheating on taxes is easier when compliance norm is broken.

Cheating can also serve as a tool for establishing the 'fair' outcome; that is, the outcome that would have been achieved if everyone were to be honest. Continuing with the tax example, consider the effect of non-compliance by a large group of people: Because the burden created by non-compliers are substantial[1], tax evasion can be seen as a way of off-setting the injustice done by other tax evaders. Therefore, people who would have honestly paid their taxes if everyone were to be honest might prefer cheating on their taxes when expecting others to cheat as well. The recent scandal in professional cycling constitute another good example of how cheating can be used as a fairness tool. When Louis Armstrong was convicted of cheating, his main line of defence was that everyone else was doing it. In an interview, he said that he did not view doping as cheating, but rather, as a "level playing field" (Telegraph Sport, 2013). Thus, in professional cycling, not only the honesty norm was broken, but also, the only way a cyclist would have a chance of winning a competition was by cheating.

In this paper, we study whether lying is used as a tool for restoring the fair outcome. We introduce a real effort task and give some people the opportunity to lie over their outcome. The task consists of answering some analytical questions. Participants are matched in a pair. To find out whether cheating takes place to restore equity, we vary who can lie: In the "one-party" treatments only one person in the pair can lie, and in the "two-party" treatments both parties can lie. If lying serves as a fairness tool, i.e., if reciprocity does indeed play a role, then we should expect less lying

[1] Such a burden can indeed be very large; the estimated effect of tax evasion on income inequality in 2005 in Greece was a 9.7 percent change in the Theil measure of the income distribution implying huge costs on honest tax-payers (Matsaganis and Flevotomou, 2010).

in the one-party treatments than in the two-party treatments. We implement three payoff schemes that vary the effect of lying on the final outcome. These are the piece-rate, tournament, and pie-sharing. In the piece-rate payoff, the only effect of one's lying on the other is via the weakening of the social norm of honesty. In the tournament payoff, however, cheating might take place to restore the fair outcome. Finally, we introduce pie-sharing payoff in which parties get a share of a fixed-sized pie according to the ratio of their declarations. Pie-sharing gives lower incentives for cheating than both the piece-rate and the tournament.

We find that overall, few people lie, and maximal lying is rare. Most lying occurs in the piece-rate and there is no evidence for lying in the tournament. Contrary to what we expected, reciprocity plays no role in lying behaviour. In our analytical task, women perform worse than men, and they do lie more, but only in the piece-rate. There is no evidence that women lie in the tournament or pie-sharing. Men seem unresponsive to the payoff scheme.

As our indirect research questions, we further look into the relationship between lying behaviour and subjects' beliefs on fairness and their (incentivised) estimations on the performance distribution. Our results suggest that lying behaviour is not related to ability, nor beliefs on fairness. We, however, find a relationship between a person's ability and her estimation of the ability distribution: Lower ability people underestimate the ability of others whereas higher ability people overestimate (the so-called Dunning-Kruger effect). Our analysis also shows that fairness considerations are positively correlated with one's ability: the higher the ability of a person, the more that person thinks it is fair to distribute money unequally.

Finally, we introduce a model that incorporates honesty as a social norm while allowing cheating to work as a tool to implement the fair outcome. Our model deals with the moral cost of dishonesty by making deviations from the honest outcome costly *regardless* of the source of deviation. Therefore, in addition to the moral cost of one's own dishonesty, we allow for disutility from the others' dishonesty even if one's payoff is not affected by it. Deviations from the honest outcome have a decreasing marginal cost. Thus, our model captures situations in which a preference for honesty might be overruled by the displeasure of others' cheating and thereby letting cheating to serve as a 'level playing field'. We show that our model can predict intermediate levels of lying commonly observed in experiments on deception.

2. Literature

This paper contributes to the literatures on cheating and gender differences. We know from the growing experimental literature on cheating that people do have a preference for honesty, even at a cost to themselves. For example, Gneezy (2005) studied the effect of the absolute and relative consequences of lies on the participants' propensity to lie. In a two player cheap-talk sender-receiver game, he varied the size of the lie by varying the gains of both the sender and the receiver. He found that people cared about the cost of their lies. Another common finding is that most people lie a little rather than maximally in many different type of experiments (see e.g., Lundquist, Ellingsen, Gribbe and Johannsson, 2009; Erat and Gneezy, 2012; Fischbacher, and Heusi, 2008; Gneezy, Rockenbach, and Serra-Garcia, 2013)

Recent work on the effect of competition on cheating behaviour provides mixed results. Whereas some studies find higher levels of cheating with competition (for status or money), other studies report no change. Schwieren and Weichselbaumer (2010) conducted a computerized maze solving game comparing cheating behaviour in tournament and piece-rate payoff schemes. They found that percentage of subjects involved in cheating is about 40 irrespective of the payoff scheme. This is however driven by gender differences in performance: Women cheated more under tournament and men less, but when performance was taken into account, the gender differences disappeared. They therefore concluded that low ability drives cheating under competition and gender plays no role. Belot and Schröder (2013) found a much lower rate of cheating in their coin-identifying game (about 10 percent), and cheating behavior was significantly higher under tournament for a fixed prize compared to piece-rate and flat-rate payoff schemes. In Pascual-Ezama, Prelec, and Dunfield (2013), subjects were paid for finding 10 instances of two consecutive letters on a sheet with a seemingly random sequence of letters. Apart from replicating the original Ariely, Kamenica and Prelec (2008) study, they also employed a social competition (announcement of the winner to other subjects) and economic competition (additional money for being a winner) treatments. They found more cheating under both of the competition treatments. Their design, however, does not allow for an estimation of percentage of cheaters, nor the analysis of gender.

Empirical and experimental studies on sabotage in tournaments provide evidence for considerable sabotage activities, and the results on gender are mixed. Two notable studies looked at sabotage in tournaments empirically. Garicano and Palacios-Huerta (2006) studied Spanish football league games after a rule change by FIFA, and found that increased incentives for winning led to higher sabotage. Balafoutas, Lindner and Sutter, (2012) studied Judo fights from two consecutive World Championships before and after a rule change that allowed for sabotage. They found a considerable increase in the use of sabotage. In the laboratory, Falk et al., (2008), Harbring et al., (2007), and Harbring and Irlenbusch (2008) studied Tullock contests with sabotage, and found sabotage to be prevalent; in all of these studies, there was no real effort. Carpenter et al. (2010) studied sabotage with a real effort experiment: they asked subjects to prepare letters and envelopes. They employed piece-rate and tournament schemes, and they also found substantial sabotage in the tournament regardless of gender. Charness, Masclet, and Villeval (2013) also report more sabotage when competing for status regardless of gender whereas Dato, and Nieken, (2014) find more sabotage and more cheating in rank-order tournaments, and their results are driven solely by men. Finally, Rigdon and D'Esterre (2012) let their subjects inflate their own performance and also sabotage the other participant's performance. They found that people inflated their own performance to some extent, but they were not willing to sabotage the work of someone else. They did not find an effect of competition for either type of cheating behaviour.

The mixed results of the effect of competition on cheating might stem from different expectations of what others would do in different games. When the possibility of cheating is obvious, and subjects' expectation of cheating is high, we would expect to see high levels of cheating, whereas otherwise, we would expect to see little. In this paper, our main contribution is to study exactly whether there is "reciprocal" cheating. For this purpose, we control who can lie in non-competitive and competitive payoff structures. To our knowledge, this is the first study in the literature to investigate the possibility of cheating as a fairness tool.

3. Experimental design

Procedures

The experiments were conducted at the Center for Research in Experimental Economics and political Decision Making (CREED) of the University of Amsterdam. Subjects were recruited via the online recruitment system of CREED and were mostly undergraduates from a wide variety of majors. Each subject could participate in only one session, and all treatments were across subjects, i.e. in each session only one treatment was run. There were 7 treatments conducted across 24 sessions with 472 students from different disciplines. The experiments lasted about one hour including the time spent on payment. Average pay was 10,7 euros including 3 euros show-up fee.

At the beginning of the experiment, instructions are read out loud. In each session, participants are randomly assigned to one of three player labels: Player A, B or C. Subjects are told that there are two parts in the experiment, and their payment in the experiment is based on the task that they do in the first part. Further, they are informed that the determination of their payment is conducted in the second part. The task involves 14 questions, and all subjects are given 10 minutes to note their answers on the answer sheet[2]. A and B players are randomly matched for the payment of the task, and the C players correct the answer sheets. A and B players are told that the task forms the basis of their payment and that they should note as many correct answers as possible. Since they are not told about the payoff scheme until after they finish answering the questions, we do not expect to have any treatment effects on the real performance of our subjects.

After finishing the task, all player As and Bs are instructed to put their answer sheets blank page facing up, and an experimenter collects the answer sheets. There are no identifiers in the answer sheets, and the only way we keep track of which answer sheet belongs to which table is via the order of collection. The answer sheets are given to the randomly assigned C players. Player C's are instructed to highlight the correct answers with a highlighter. We made sure that the answer sheets are corrected in that same order. The payment of C players are done by randomly picking one of the corrected answer sheets, and controlling whether the correction is fully correct. If the highlighted answers are correct, the C player earns 10 euros, otherwise nothing. C players can take as much time as they wish to make the corrections. After C players correct the answer sheets, the answer sheets are distributed back to A and B players, again blank page facing up. We explained this procedure in detail in the instructions.

After the players A and B receive their corrected answer sheets, the instructions for the second part of the experiment are distributed and then read out loud. In this part, the payment of A and B players is determined. After the payoff scheme is explained, subjects are told who will receive a declaration form (only A players in the one-party treatments or both A and B players in the two-

[2] We employed a real effort task because whether money is earned by putting in effort or by a random device makes a difference in other experiments. Hoffman et. Al (1992, p. 370) state that there is a difference in generosity in whether a player gets assigned the role of divider or earn their right to be so. Ruffle (1998) states that there is also a difference in the behaviour of the proposer in a dictator and ultimatum game when the receiver has performed a task to earn the size of the surplus that is to be divided.

party treatments), and that the declaration forms will be used by the experimenters to calculate their payment. Similar to the first part, all forms are collected blank page facing up such that the experimenter does not see what is declared, and transferred to another experimenter who is not involved in the running of the experiment to calculate the payoffs –and subjects know this-. Finally, the answer sheets of all players are handed back to C players for all answers to be highlighted. This was to minimize the risk of cheating across sessions by using the right answers from subjects of previous sessions. Finally, the declaration forms and the answer sheets are returned to the subjects. Subjects are told that they can keep the declaration forms and the answer sheets.

After the experiment is finished, subjects are asked to fill in a questionnaire stating their gender, studies, the number of experiments they participated in that academic year, the number of times they took a GRE/GMAT type of test, their beliefs on the distribution of correct answers, their guess of the average correct answer, and how they think some money should be divided between a pair under different combinations of correct answers. To elicit the A and B players' beliefs on the distribution of correct answers, they were told that a certain number of people have done the task before[3], and they were asked to guess how many of those subjects have answered 0, 1, 2, … 14 correct answers. They could earn an additional 6 Euros if their guesses matched that of the real distribution, and otherwise every difference cost them 50 Eurocents.

Payment Structures

We implemented three different payoff structures that vary the effect of lying. These payoff structures are depicted across the three rows of Table 1. To study the effect of reciprocity in lying, we varied who can lie. In one case, only one player in the pair could lie, and in the other both players could lie. These are depicted in the columns of Table 1.

As a baseline, piece-rate payoff is implemented: each correct answer gives 1.5 Euros. In the piece-rate, the lies of one party do not harm the other party, and the benefit of each lie is constant. We further varied whether only one person can lie or both parties can lie in the piece-rate. The payoff structures of the two treatments are depicted in the second row of Table 1.

[3] We increased this number in the later experimental sessions in accordance with the increasing number of observations we had for the correct answers. The rationale for such a change was to correct for the small sample size errors. All results reported in this paper are standardized and take ratios into account.

In the pie treatments, players earned a portion of a fixed amount of money according to the ratio of their own declaration to the total declaration within the pair. We chose 15 Euros as the fixed amount based on the results of our pilot which showed approximately five correct answers per person[4]. We then multiplied five answers by the piece-rate payoff of 1.5 Euros for two persons. In the pie treatment, lying increases one's payoffs at a cost to the other, and the benefit from each lie and the cost to the other party is the same. However, the marginal cost of a lie to the other party is decreasing in the number of lies. The pie payoff structure is summarized in the third row of Table 1.

Finally, the third payoff structure is the tournament as commonly implemented in the literature, and is depicted in the fourth row of Table 1. In the tournament, the party with the higher number of correct answers becomes the winner, and earns 3 Euros per correct answer whereas the one with the lower number of correct answers earns nothing. The multiplier of three is chosen to equalize the expected payoff of the persons in the median of the correct answer distribution to that of the piece-rate[5]. Unlike the pie treatment, in the tournament, the benefit of a lie and its cost to the other party is discontinuous. As long as one's declaration is lower than the matched partner's declaration, lying has no benefits nor has any costs. If lying changes the winner, then the cost to the other party is quite high (1.5 Euros times the other's declaration), but it also gives a high benefit of 3 Euros per declaration. Lastly, if the losing party tie-breaks by lying, its cost to the other party is equal to its benefit (1.5 Euros times the declaration).

Overall, we conjecture that there will more lying in the two-party treatments compared to one-party treatments. That is because, if our premise of lying as a fairness tool is correct, and if subjects do anticipate lying by the other party, then they could also lie without much moral cost. In the tournament payoff scheme, it goes one step further: if a person thinks that she should be the rightful winner, but also anticipates a lot of lying from the other party, then she might lie to win. Therefore, we expect most lying to be in the tournament, and the least in the pie payoff scheme.

[4] As it will be explained in the results section, the true average turned out to be 3.61 correct answers instead of 5. This makes the stakes with the pie size 15 Euros somewhat higher than that of piece-rate.

[5] This expectation is conditional on the matched partner being honest, and the persons in the median of the distribution correctly believing that they are in the median of the answer distribution. Whenever there is variation in the outcome of a task across different persons, tournament cannot give the same expected payoff as in piece-rate for all person's involved. Since in this study we are interested in the effect of different payoff schemes on lying, such a difference is of no primary concern for us.

Table 1 : Payment Structure in Different Treatments

	One-party (OP)	**Two-party (TP)**
Piece rate	$P_A = 1.5 * \ Claim_A$ $P_B = \ 1.5 * \ Real_B$	$P_A = 1.5 * \ Claim_A$ $P_B = 1.5 * \ Claim_B$
Pie	$P_A = 15 * \frac{Claim_A}{Claim_A + Real_B}$ $P_B = 15 * \frac{Real_B}{Claim_A + Real_B}$	$P_A = 15 * \frac{Claim_A}{Claim_A + Claim_B}$ $P_A = 15 * \frac{Claim_B}{Claim_A + Claim_B}$
Tournament	$P_{winner} = \ 3 * Claim(Real)_{Winner}$ $P_{loser} \quad = 0$ $P_{tie-break} = \ 1.5 * Claim$	$P_{winner} = \ 3 * Claim_{Winner}$ $P_{loser} \quad = 0$ $P_{tie-break} = \ 1.5 * Claim$

4. Results

The performance of subjects who cannot lie is depicted in Table 2. With no lying, the average number of correct answers is 3.61. The dispersion of the performance is rather high, with a standard deviation of 2.03. We can see from the frequency distribution that about 85 percent of the correct answers are less than or equal to 5. The median of the distribution is 4 correct answers. The mode of the distribution is five; almost one fifth of the subjects had five correct answers. Notice that there is only one person out of 152 subjects who did nine correct, and no one solved more than nine questions correctly.

Table 2. Distribution of correct answers without lying

Correct Answers	0	1	2	3	4	5	6	7	8	9
Percentage of Subjects	5.3	12.5	15.1	14.5	17.1	19.7	7.2	5.3	2.6	0.7

Average=3.61, Standard Deviation= 2.03, N=152

Table 3 depicts the average declarations per treatment. The type of competition is listed in rows, and who can lie in the columns. The comparison of the declarations of each treatment with the no-lie condition is stated below the corresponding treatment values. The last column compares the column treatments. All p-values are when using one-sided Mann-Whitney exact test.

Table 3–Declarations per treatment

No-Lie	3.61 (2.03) N=152		
	One-Party	**Two-Party**	**p***
Piece-rate	4.90 (2.90) N=41	5.11 (3.65) N=38	0.470
	p= 0.010	*p=0.017*	
Pie	4.23 (3.53) N=40	4.81 (2.83) N=42	0.074
	p= 0.407	*p=0.012*	
Tournament	4.26 (2.84) N=42	3.84 (3.02) N=38	0.869
	p=0.110	*p=0.355*	

*Mann-Whitney exact test, one-tailed.

A first observation is that overall, there is very little lying. Most lying happens in the piece-rate, and even then, the average amount of lies are approximately 1.40 correct answers. Given that there were 14 questions, the amount of lies are about 14 percent of the total possibility. Furthermore, the declarations in the tournament treatment as well as the pie treatment with only one party lying are not significantly different than no-lie condition. Lying in the pie treatment only happens when both parties can lie, and the average declaration is 1.20 units higher than the No-lie condition. When we look at the effect of reciprocity, we conclude that in none of the payment schemes, reciprocity plays a role. Moreover, in the tournament treatment, the effect is in the opposite direction than expected.

Moreover, we do not find any support for our conjecture that there will be more lying in the two-party treatments of tournament and piece-rate. There is weak support for more lying with two-party in the pie payoff scheme. The comparison of the declarations across the payoff schemes reject our second conjecture: Tournament has the lowest level of lies (statistically indistinguishable from the No-lie condition) whereas piece-rate has the highest. Furthermore, the difference between pie and tournament is not significant. We will provide further support for these results in the next section.

Finally, we can try to estimate the percentage of lying across different treatments. Although our design does not let us know the exact amount of lies, we can infer from the No-lie distribution that any declaration that is 9 or higher is almost surely a lie. This gives a lower bound on the percentage of liars. In Table 4, we report the number of persons who declared a number between 9 and 14 in each treatment and the cumulative percentage of those people. One can see that the highest percentage of lying is in the Pie Two-Party treatment with 14.3 percent, and the lowest is in the one-party tournament treatment with only 1 person out of 42. If we leave out these persons who declared 9 or higher, and repeat the statistical test on the comparison of each treatment with the No-Lie treatment, we see that none of the treatments turn out to be statistically significantly different than the No-Lie treatment[6]. Such a result implies that lying with lower declarations are at most in very few cases, therefore we can conclude that percentage of liars are close the cumulative percentages reported in Table 4.

Table 4. Frequency of declaring 9 or higher

	9	10	11	12	13	14	Cumulative Percent
No-Lie N=152	1	0	0	0	0	0	0.7
Piece-rate One-Party N=41	1	1	1	2	0	0	12.2
Piece-rate Two-Party N=38	0	1	0	1	0	3	13.2
Pie One-Party N=40	0	0	0	0	0	3	7.5
Pie Two-Party N=42	2	1	2	1	0	0	14.3
Tournament One-Party N=42	0	0	0	0	0	1	2.4
Tournament Two-Party N=38	0	1	0	1	0	1	7.9

Gender Results

We first look at whether there is a performance difference between the genders. The averages per gender in the no-lie condition are reported in Table 5. Since there was a mistake with labelling the questionnaires in one of our sessions, we have in total 122 observations for gender. We can see that women perform significantly worse than men and the difference is about 0.9 questions.

[6] The relevant p-values from the comparison with the No-lie treatment with one-sided Mann-Whitney exact test while excluding declarations 9 or higher are as follows: Piece-Rate One-Party, 0.102; Piece-Rate Two-Party, 0.164; Pie One-Party, 0.332; Pie Two-Party, 0.167; Tournament One-Party, 0.141; Tournament Two-Party, 0.128.

Table 5. Averages per gender in the No-Lie condition

Average	Females	Males
3.61	3.12	4.01
(2.03)	N=60	N=62
N=152		
	Two-tailed Mann-Whitney exact test p=0.005	

To investigate whether women and men behave differently under different payment schemes, we run a linear regression to explain the difference between a person's outcome from the average in the No-Lie condition of his or her gender controlling for gender, payment scheme and the interaction effects. This way, we can solely focus on the deviations from the average in the No-lie treatment. Thus, the regression is as follows:

$$Declaration_i - AvgNoLie_{gender(i)} = \alpha + \beta Gender + \gamma Piece + \delta Pie + \eta Reciprocity + \theta Interaction\ Terms + \varepsilon$$

If people of different genders lie significantly differently, then we expect to see the gender variable to have a significant effect. Moreover, if different genders behave differently under different schemes, we expect to see the interaction effect of the treatment with gender to be significant. Table 6 reports the results of the regression that includes (Model I) and excludes reciprocity (Model II). The first column in the table depicts the variable name, the estimated coefficient and the significance results of each model are below the models. Notice that this specification results in all comparisons being made with the tournament.

The regression including reciprocity terms (Model I) shows no significant effect of any of the variables, not even the intercept that establishes that there is lying. Dropping the reciprocity terms gives us Model II. We can then see that without the reciprocity terms, lying becomes marginally significant (intercept p-value=0.072), and there is no effect of the type of competition nor gender. The only weak effect comes from the fact that women lie more in the piece-rate than men (p=0.082).

Finally, to clarify how lying depends on gender, we include the averages with respect to men and women using the pooled data for each payoff scheme in Table 7. We also report the relevant two-sided Mann-Whitney exact test results. We can see that while men are unresponsive to the payoff scheme and lie about the same rate in all treatments, women only lie in the piece-rate.

Table 6. Regression Results

	Model I			Model II		
	Coefficient	Std. Error	Sig	Coefficient	Std. Error	Sig
Intercept	0.935	0.762	.221	0.935	0.517	.072
Female	-1.052	1.001	.295	-0.608	0.685	.376
Piece-Rate	-0.333	1.459	.819	-0.258	0.748	.731
Pie	0.077	0.968	.937	0.091	0.688	.895
Reciprocity	0.000	1.047	1.000	-		
Female x Piece-Rate	2.333	2.024	.250	1.909	1.093	.082
Female x Pie	1.298	1.393	.352	0.384	0.960	.690
Female x Reciprocity	0.870	1.386	.531	-		
Piece-Rate x Reciprocity	0.093	1.736	.957	-		
Pie x Reciprocity	0.034	1.403	.981	-		
Female x Piece-Rate x Reciprocity	-0.830	2.451	.735	-		
Female x Pie x Reciprocity	-1.707	1.954	.383	-		
	R^2=0.029			R^2=0.022		

Table 7. Gender averages per payoff scheme

	Female	Male	p*
Piece-rate	5.10 (3.36) N=21	4.74 (2.90) N=31	0.805
Pie	3.92 (2.92) N=37	5.09 (3.34) N=44	0.089
Tournament	3.44 (2.37) N=45	5.00 (3.30) N=34	0.040

* Two-sided Mann-Whitney exact test

5. Beliefs:

We elicited two types of beliefs after the experiment: beliefs about fairness and beliefs about the distribution of correct answers. To elicit the subjects' fairness ideas, we asked how a fixed amount of money (15 Euros) should be distributed within a pair assuming different combinations of correct answers. In total they were asked to state 12 choices with the following correct answers within a pair: (14,0), (12,2), (10,4), (8,6), (7,7), (14,7), (6,5), (6,4), (6,3), (6,2), (6,1), (6,0). Since there is almost no variation in the subjects' choices for (7,7)[7], it is dropped from our subsequent analysis. To elicit the subjects' beliefs about the distribution of correct answers, we asked them to guess

[7] The reason that we included (7,7) was to capture concave preferences that value an extreme distribution over an equal one. We did not find any evidence for such preferences.

the average number of correct answers. Additionally, we asked them to estimate how many subjects answered 0 question correctly, 1 question correctly,…, 14 questions correctly. We incentivized the answers by paying 6 Euros for a fully correct estimation with 50 eurocents reduction per deviation. If there were 12 or more differences, the earnings were zero. We standardized their answers to ratios. By looking at the subjects' answers, we can also calculate the average of the distribution they guessed. We also report the difference between the estimated distribution average and their guessed average. The mean and the standard deviation of all the variables are included in the Table 8.

We exclude the fair division (7,7) and the difference between the averages from further analysis, and are therefore left with 28 variables. These variables are highly correlated with one another in a specific pattern. As can be expected, the results on the 'fair division' of the pie and the guesses of the distribution of correct answers are not correlated. The fair division answers highly correlate with each other, and the distribution of correct answers highly correlate with each other and with the guessed average. This leaves room for factor analysis so that we can reduce the number of variables in a way that explains the most variance. The rotated matrix of the factor analysis is reported in the Appendix. The results of the factor analysis shows that there are indeed two blocks of variables which are highly correlated with one another. The resulting number of factors are six; four variables mostly consist of the estimation of the distribution of correct answers and the averages, and the other two variables are about the division of money.

We also run non-parametric Mann-Whitney exact tests to compare the distribution of the variables as well as the resulting factors between each treatment and the No-lie condition. We do not find any significant difference in the distributions of factors, nor variables, and thus, we conclude that there is no significant difference in the questionnaire answers across different treatments[8].

The first, third, fifth and sixth factors are derived from the estimations of the distribution. Following the literature, we focus only on variables with correlation levels larger than 0.30 in absolute value. The contribution of the averages (both the guessed, and derived from the

[8] Given that there are 28 variables per treatment, there are 168 comparisons in total, therefore the threshold for significance have to be adjusted by 1/168 (Bonferroni adjustment). This is necessary to rule out finding significance due to a large number of tests. With the usual p-level of 0.05, 11 of these comparisons show up as significant, but none of them survive the adjusted threshold.

distribution) to the first factor are very highly positive. The ratio of persons who had 0, 1, 2,3 or 4 correct answers have a negative relationship whereas the ratio of persons with 6, 7, …, 11 correct answers are positive. Notice that the subjects think that the average correct answers are about five (whereas the real average is 3.61). This also explains why the ratio of persons below five has a negative effect on this factor whereas the ratio of persons larger than five has a positive effect.

Table 8. Averages of fairness answers and estimated distribution

Fairness Answers	N	Mean (Std Dev)
Division 14,0	338	13.78 (2.05)
Division 12,2	337	12.01 (1.74)
Division 10,4	337	10.38 (1.46)
Division 8,6	337	8.68 (1.25)
Division 7,7	337	7.50 (0.45)
Division 14,7	335	10.06 (1.46)
Division 6,5	336	8.44 (3.89)
Division 6,4	336	8.89 (1.29)
Division 6,3	336	9.71 (1.38)
Division 6,2	336	10.63 (1.63)
Division 6,1	335	11.78 (1.87)
Division 6,0	336	13.15 (2.53)
Estimated Distribution		
	N	Mean (Std Dev)
Average Correct Answers	347	5.02 (1.69)
Percentage of 0 correct	346	0.04 (0.07)
Percentage of 1 correct	346	0.06 (0.08)
Percentage of 2 correct	346	0.10 (0.08)
Percentage of 3 correct	345	0.13 (0.09)
Percentage of 4 correct	345	0.15 (0.08)
Percentage of 5 correct	346	0.14 (0.09)
Percentage of 6 correct	346	0.12 (0.08)
Percentage of 7 correct	345	0.09 (0.07)
Percentage of 8 correct	346	0.06 (0.05)
Percentage of 9 correct	345	0.04 (0.04)
Percentage of 10 correct	346	0.03 (0.03)
Percentage of 11 correct	346	0.02 (0.02)
Percentage of 12 correct	346	0.01 (0.02)
Percentage of 13 correct	345	0.01 (0.02)
Percentage of 14 correct	346	0.01 (0.02)
Average from Estimation	341	4.96 (1.53)

Difference between Avg's	341	-0.07 (1.21)

The third factor is a combination of average and the derived averages as well as the ratios of persons who declare 9 or higher. The fifth factor is a combination of the guesses of 0 and 1 correct answers (negative correlation) and 4 and 5 correct answers (positive correlation). Notice that the cut-off from negative to positive correlation is different in the fifth factor than in the first factor providing evidence for two different types of people: The first type guesses about five correct answers, and this is the majority. The second type guesses about three correct answers. Finally, the last factor is a combination of the guesses to 2 and 5 correct answers.

The second and fourth factors are related to the answers to the fair division questions. The division of (14,0), (12,2), (10,4), (6,4), (6,3), (6,2), (6,1), and (6,0) correlate highly positively with the second factor. Answers to the division of (10,4), (8,6), (14,7), (6,5), (6,4), (6,3), and (6,2) are positively correlated with the fourth factor. These two factors together imply two types of answers that are somewhat distinct from one another. Keep in mind that the contribution of the second factor is much more than the contribution of the fourth factor.

Using these factors, we can study the relationship between declarations and estimated ability distribution as well as the relationship between ability and fairness considerations. We know from the Dunning–Kruger effect (Dunning and Kruger, 1999; Schlösser, Dunning, Johnsonand Kruger, 2013) that people tend to think others are like them when judging the ability distribution. Thus, low ability people underestimate the ability of others whereas high ability people overestimate the ability of others. If such an effect exists in our experiment, then we would expect to see a positive effect of the factors 1, 3, and 5.

The second relationship that we can investigate is the one between perceptions of fairness and ability. There is some research that study whether fairness considerations take effort into account (see for example Almås, Cappelen, Sørensen, and Tungodden, 2010; Cappelen, Hole, Sørensen, and Tungodden, 2007) however to our knowledge there is no study that investigates whether ability and fairness considerations are correlated. We expect higher ability people to think that higher ability people should get a large share of the pie whereas low ability people to opt for a fairer share of the pie. If our premise is correct, we would expect to have a positive effect of the factors 2 and 4.

Table 9 depicts the regression results using the variables derived from factor analysis. The dependent variable is, as in the previous regressions, the difference between one's performance and the mean of his or her gender in the No-Lie condition. The control variables are the six factors, gender, treatment, and gender and treatment interaction effect. Note that the magnitude of the factored variables are not easy to interpret, therefore we will only focus on the sign of the estimated coefficients.

We can see from Table 9 that the inclusion of the six factors help explain a substantial amount of variance in the independent variable (the difference between a person's declaration and the average correct answers for that gender), and the R^2 increases from 0.022 to 0.187. Among the six factors, the first, second and the fifth have a significantly positive effect on the difference of the declarations from the baseline.

Table 9. Regressions results using factors

Variable	**Coefficient**	**Std. Error**	**Significance**
Intercept	0.923	0.525	0.081
Factor 1	1.073	0.197	0.000
Factor 2	0.431	0.205	0.037
Factor 3	0.261	0.192	0.177
Factor 4	-0.004	0.178	0.981
Factor 5	0.452	0.212	0.035
Factor 6	-0.164	0.190	0.387
Female	-0.574	0.676	0.397
Piece-Rate	-0.753	0.738	0.309
Pie	0.195	0.684	0.776
Female*Piece-Rate	2.017	1.048	0.056
Female*Pie	0.711	0.930	0.446

R^2=0.187

The estimated ratio of the persons in the population with 0, 1, 2, 3, 4 correct answers correlates negatively with Factor 1, whereas the ratio of the persons with 6, 7, ..11 correct answers correlate positively. Thus, the positive coefficient of the first factor in the regression tells us that people who declare higher than the *real average* of 3.6 guess a distribution to the right of the *average estimated* distribution (centered at 5 correct answers), and persons who guess a distribution to the left of the *average estimated* distribution declare lower than the *real average*. To put it differently, any person who thinks most others did four or fewer correct answers declares less than 3.6, and any person who thinks that most others did six or more declares more than 3.6. This points to possibly two distinct biases: a general overestimation of the population ability, and a bias in the judgment of performance of others in the direction of one's own performance. However, the regression in Table 9 alone cannot tell us whether the latter bias is related to lying or only stems from the misjudgement of other's ability. We will further analyze this in the next subsection.

Factor 5 also has a significantly positive effect. Remember that this factor is related to the guesses of 0 and 1 correct answers (negative correlation) and 4 and 5 correct answers (positive correlation pointing to a different type of participant than the one captured by Factor 1. This second type guesses about three correct answers, and they are closer to the real distribution of the population. However, the bias with respect to the judgment of others' performance being close to one's own performance (Dunning-Kruger effect) remains.

Answers to the fair distribution questions also matter. The effect of the second factor is significantly positive. This factor is mainly driven by the answers to how to distribute 15 Euros when a pair of players have (14,0), (12,2), (10,4), (6,4), (6,3), (6,2), (6,1), (6,0) correct answers. Since the effect of the factor is positive, there is evidence that people with higher declarations think people with higher declarations should earn more. We will further investigate whether there is any systematic difference in the fairness factor with or without lying.

Finally, we can confirm from this regression that there is no systematic significant effect of gender in the amount of lies nor the type of competition except in the piece-rate.

Relationship between beliefs, fairness and lying:

If lying is not dependent on ability, then we would expect everyone to lie about the same rate, and the Dunning-Kruger effect would be observed irrespective of whether the observations come from the No-Lie treatment or lying treatments. It is however, possible that low and high ability people lie at different rates. The regression in Table 9 cannot say whether that is the case. Similarly, if there is a correlation between what one considers fair and the rate of lying, we would not be able to capture that effect with the previous regression. To test whether lying is dependent on ability or is correlated with fairness attitudes, we first run separate linear regressions with all the factors with the No-Lie and lie treatments. The No-Lie treatment gives us the population estimates. Any difference in the estimated coefficients between the No-Lie treatment and the lie treatments standardized with the estimated standard errors is approximately distributed with a t-distribution[9]. We can thus test whether lying –or the possibility thereof- changes the perceptions of what is fair[10].

Table 10. Separate Linear Regressions

	No-Lie			Lie		
	Coefficient	Std. Error	p	B	Std. Error	p
Constant	3.235	0.202	0.000	4.054	0.281	0.000
Factor 1	0.985	0.143	0.000	1.057	0.196	0.000
Factor 2	0.322	0.139	0.022	0.459	0.205	0.026
Factor 3	-0.189	0.158	0.235	0.206	0.190	0.280
Factor 4	0.054	0.192	0.780	-0.035	0.177	0.841
Factor 5	0.541	0.131	0.000	0.426	0.211	0.044
Factor 6	-0.365	0.160	0.024	-0.156	0.190	0.414
Male	0.882	0.287	0.003	0.800	0.403	0.049
	N=115, R^2=0.465			N=200, R^2=0.188		

From Table 10, we can see that most of the estimated coefficients in both the No-Lie and lie treatments are similar. Among the six factors, only the third factor is significantly different in the

[9] Formally, if the estimated coefficient is $\hat{\beta}$ and the standard error is $\hat{\sigma}$ from the Lie treatments, and the estimated coefficient is β from the No-Lie treatment, then $\widehat{(\beta - \beta)}/\hat{\sigma}$ is distributed with a t-distribution with (Number of observations-Number of variables-1) degrees of freedom.

[10] Notice that we coded only the scores of the higher performer; the other person's payoff was 15-this score by construction. Therefore, we would expect to see at least half the share of the payoff for the higher performer in all our answers.

two conditions with a two-sided t-test p=0.039. Since this third factor is driven by the estimated ratios of persons who declare 9 or higher, there is evidence that people who estimate a relatively high percentage of high declarations declare high values themselves only in the lying treatments. This suggests that liars think that others did quite well. However, it is important to note that none of the factors that significantly contributed to explaining the variance in declarations have a significantly different coefficient in the No-Lie and lie treatments. Therefore, we can conclude that low and high ability people do not lie at different rates and there is no correlation between what is considered fair and the rate of lying.

6. A Model of Lying

We would like to have a model that introduces disutility from lying because lying changes payoff outcomes, but not because honesty is a rigid moral norm from which deviation is costly[11]. Such a model should thus take into account how much the final outcome changes compared to the honest outcome when one lies. Thus, lying is costly whenever it changes the final outcome, and its cost is increasing in the amount of change it induces. If lying changes the final outcome a lot compared to the honest outcome, then it introduces a large cost, whereas if lying does not change the final outcome, it does not have a cost. This way, we can focus on the effect of lies rather than the magnitude. Suppose by lying only a small amount, a person can change the whole distribution of payoffs within a group of people, we expect that such a lie is unlikely with even low lie-aversion levels because of its large effect in the group. A model that only takes into account the magnitude of lies would however would predict otherwise.

We would further like our model to incorporate the possibility of lying to serve as a 'level playing field'. We therefore suggest that the disutility of lying is decreasing in the other person's lie. Consider otherwise: If one's lying decision is independent of the other person's lying level, then the optimal level of lying would only be driven by the comparison of its payoff benefits to its moral cost. This would then mean that an honest person is honest, and a liar is lying regardless of how many other people are lying as long as they are not affected by others' lies. We, however, know from the large literature in psychology on conformity -starting with the Asch conformity

[11] It is possible that for some people lying is costly regardless of its consequences, however, we suspect that this is a minority of the people. This premise is not without support: Recently emerging literature on moral behavior suggest that only a few people are Kantians who strictly adhere to a moral norm. See for example the work by Falk and Szech (2013).

experiments- that people adhere by the norms of a group and tend to behave like others. Therefore, there is no reason to expect one's honesty norm not to conform to the group. Additionally, as pointed out in the introduction, a variety of studies as well as routine declarations by professional sportsmen show that cheating correlates with the amount of (expected) cheating by others.

To sum up, we would like to have a model that compares the monetary benefit of lying to its cost where the cost is measured by the amount of deviation from the honest outcome. We propose the following utility function in a two persons game to capture both of these aspects:

$$U_i(l_i / x_i, y_j, l_j) = \pi_i(x_i + l_i, y_j + l_j) - \mu \left\| \pi_i(x_i + l_i, y_j + l_j) - \pi_i(x_i, y_j) \right\|,$$

in which (x_i, y_j) denotes the honest outcome of person *i* and *j*, respectively; $x_i + l_i$ is the declaration of person *i*, and $y_j + l_j$ is the declaration of person *j*. $\pi_i(x_i + l_i, y_j + l_j)$ denotes the payoff when $(x_i + l_i, y_j + l_j)$ is declared. μ is the disutility parameter and measures the cost of a unit deviation from the honest outcome. We assume that μ is constant[12]. $\left\| \pi_i(x_i + l_i, y_j + l_j) - \pi_i(x_i, y_j) \right\|$ is the Euclidian distance of the declared payoff from the honest payoff. This distance, together with μ, determines the disutility of lying by taking into account the lies of *both* parties involved in a pair. Notice that, since the distance is applied to the difference in payoffs, not to lies, changing the payoff function also changes the shape of the disutility term. Regardless, this utility function captures lying as a fairness tool: if a person suspects that the other lies a lot, the disutility of a unit of lie is smaller than the disutility of a lie if the other person does not lie. Moreover, if lying helps the person get closer to the fair outcome, lying would only be beneficial because it would reduce the cost of deviation from the fair outcome. Thus, such a model can explain 'everybody else was doing it' argument in tournaments.

Below we report the optimal strategies by applying this utility function to the different payoff schemes reported in this paper. To make exposition simpler, we use the word intermediate levels when referring to situations with at least one person has an optimal strategy that is not maximal lying within a sub-range of the specified lie-aversion parameter. This defer all calculations of Nash equilibrium with any possible combination of μ levels within the pair to Appendix A. Since, the utility function is constructed in such a way that lowers the cost of a lie when expecting the other

[12] A more realistic model would let μ also depend on the level of lies, but the essence of our arguments can be captured with the simpler model assuming μ is constant.

one to lie, all two-party treatments should give at least as much lying as one-party treatments. Below, we focus only on two-party predictions.

In the piece-rate payoff scheme, if the other party cannot lie, lying becomes a binary decision: if the disutility from a unit of lie is higher than its utility ($\mu > 1$), then there is no lying, otherwise ($\mu < 1$), there is maximal lying. If the other party can lie, however, the disutility of deviation from the honest outcome might lead a lie-averse[13] player towards lying. The optimal level of lying depends on how much the other party lies as well as the level of lie-aversion. Even with moderate levels of lie-aversion ($1 < \mu < \sqrt{2}$), any level of lies can be supported in equilibrium.

In the pie payoff scheme, if we assume players have the same lie aversion level μ, lying does not depend on whether the other party can lie or not; the only determinant of the amount of lies is the magnitude of the lie-aversion parameter μ: If the disutility from a unit of lie is higher than its utility ($\mu > 1/\sqrt{2}$), then there is no lying, otherwise ($\mu < 1/\sqrt{2}$), there is maximal lying.

Table 11: Optimal strategies

Piece rate	If μ<1, max lie If μ>1, intermediate levels
Pie	If μ<1/$\sqrt{2}$, max lie If μ>1/$\sqrt{2}$, intermediate levels
Tournament	If μ<1/$\sqrt{2}$, max lie If μ>1/$\sqrt{2}$: $\begin{cases} x_i > y_j & \text{max lie or } i \text{ wins} \\ x_i = y_j & \text{any } tie-break \end{cases}$

In the tournament payoff scheme, when only one party can lie, unlike other payoff schemes, there can be intermediate levels of lying, maximal lying, or no lying. If μ>1, there is no lying, and if $\mu < 1/\sqrt{2}$ there is maximum lying when the performance of the parties are unequal. For the lie-aversion parameters in between, lying to tie-break can be preferred over lying to win when the

[13] In this paper, we will call persons with $\mu > 1$ lie-averse, since the disutility of lying for such persons is higher than its monetary benefit without a second player.

honest outcome is losing. Finally, when there is a tie-break, no lying can also be an equilibrium with low levels of lie-aversion. When both persons can lie, and if $\mu < 1/\sqrt{2}$, max lie by both parties is the only equilibrium. If $\mu > 1/\sqrt{2}$ intermediate levels of lying are also supported in equilibrium. That is because, if a player would win or tie-break with the honest outcome, then lying to win or tie-break is *always* preferred over no lying regardless of the μ. Therefore, there are equilibria in which a person lies to win, and the other person declares one unit less. This, however, does not mean that any combination of lies are supported in equilibrium. Depending on the lie-aversion level, after a certain lie-level, only lying maximally can be an equilibrium. Finally, whether a player lies to win when he was to lose with the honest outcome depends on his lie-aversion parameter as well as the honest outcome: if the lie-aversion is moderate (just above 1), lying to win can be supported. Therefore, with moderate levels of μ, we would also expect maximum lying in equilibrium.

Taken together, the above results suggest that, with even moderate lie-aversion levels, we would get intermediate levels of lying if people believe others are honest or lie minimally. Thus, as in our experiment, there is overall very little lying, then we should expect the payoff scheme not to have an effect. On the other hand, in tasks with a high percentage of subjects lying –with the correct beliefs about the lies of others, we would expect higher levels of lying in tournament compared to piece-rate. [14]

7. Discussion and Conclusion

In this paper, we experimentally investigated whether lying is used as a tool for restoring equity. We introduced a real effort (analytical) task that gave some people the opportunity to lie. To find out whether cheating takes place to restore equity, we introduced the "one-party" treatments in which only one person in the pair can lie and compared the results to the "two party" treatments.

We found that overall, only few people lie, and most lying is at an intermediate level. Our results showed that reciprocity plays no role in lying behaviour. Furthermore, somewhat at odds with the results of previous studies, we found that most lying occurs in the piece-rate and that there is no

[14] An appropriate test for this claim could be done by eliciting the beliefs about others' lying and analyzing whether this correlates with one's own lying behavior. Our experiment does not let us study this: Since we wanted to make sure that our experimental subjects remained ignorant about our research questions, we never used the word lying, nor suggested the possibility of lying anywhere in the experiment including in the questionnaires.

evidence for lying in the tournament. Finally, in our analytical task, women perform worse than men, but they do lie more only in the piece-rate. There is no evidence for women lying in the pie and tournament payoffs. Men, however, seem unresponsive to the payment scheme. Further analysis on the subjects' beliefs on fairness and their estimations of the performance distribution showed a systematic bias in the ability judgments. The results are in line with the Dunning–Kruger effect. Finally, we found evidence for the fairness judgments to be positively correlated with ability.

The discrepancy between the lying rates in our setup and the ones reported in the literature suggest that the choice of task can have an important effect on lying. That is because expectations of what others possibly depend on the task. To capture our arguments of honesty as a social norm while allowing lying to be used as a tool for implementing the honest outcome, we introduced a model that introduces a cost of deviating from the honest outcome. Thus, we allow for situations in which a preference for honesty might be overruled by the displeasure of others' cheating. We then show that, such a model indeed gives intermediate levels of lying as an equilibrium outcome in both the tournament and piece-rate payoff schemes. A proper test of how beliefs of others' lies affect one's own lying behaviour is left for future research.

Finally, studying the effect of different type of tasks on lying behaviour remains an open question. It is not inconceivable that a coin flipping or die-throwing task makes it much easier to lie not only because the tasks do not capture any ability but also because subjects perceive it unfair to be paid by a random device. Finally, how obvious it is that one can cheat and whether this is explicitly stated in the experiment can have a large influence in the outcomes, and should be taken into consideration in future research.

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Appendix: Equilibrium calculations

In all the calculations below, for the sake of brevity, we will drop the subscript for inequality aversion parameter.

(i) Equilibrium Predictions in the Piece-rate

In the piece-rate payoff scheme the utility is as follows:

$$U_i(l_i \;/\; x_i, y_j, l_j) = 1.5(x_i + l_i) - 1.5\mu\sqrt{\left(l_i\right)^2 + \left(l_j\right)^2}$$

Given a level of l_j, if the marginal benefit of a lie is positive, there will be lying. So, we have to check

$\frac{dU_i}{dl_i} = 1.5 - 1.5\mu\frac{2l_i}{2\sqrt{\left(l_i\right)^2 + \left(l_j\right)^2}} \overset{?}{\geq} 0$. This implies $\left(l_i\right)^2(1-\mu^2) \geq -\left(l_j\right)^2$. Notice that the inequality would be satisfied with any positive level of lying if μ<1. Thus, if μ<1, irrespective of the value of l_j, it pays off to lie maximally. When 1<μ<$\sqrt{2}$, for any level of l_j, $l_i \geq l_j$ satisfies this inequality. Therefore, the optimal strategy involves lying at least as much as the other. Note that for levels of μ close to 1, the optimal level of lies can be maximal. For larger values of μ, the optimal l_i would be a fraction *j*'s lie, i.e., $l_i < l_j$ always holds. When $l_j=0$, the decision to lie depends on comparing the cost to the benefit, i.e., if μ<1, there will be maximum lying, and if μ>1, there will be no lying.

These predictions are summarized in Table A1 below. Notice that, only when the lie aversion parameter is higher than 1, we would predict intermediate levels of lying. The optimal strategy then depends on the exact level of μ for both of the players. When one player has a moderate level of lie-aversion (1<μ<$\sqrt{2}$)and the other one has high (μ>$\sqrt{2}$), we can support any declaration as an equilibrium outcome with different values of μ within the given ranges.

Table A1. The equilibrium prediction of declarations in the piece-rate

		***j*'s lie-aversion level**		
		μ<1	**1<μ<$\sqrt{2}$**	**μ>$\sqrt{2}$**
***i*'s lie-aversion level**	**μ<1**	14,14	14,14	14, $\{l_j : l_i > l_j\}$
	1<μ<$\sqrt{2}$	-	$l_i=l_j$	$l_i>l_j$
	μ>$\sqrt{2}$	-	-	0,0

(ii) Equilibrium Predictions in the Pie

In the pie treatment, the utility function is as follows:

$$U_i(l_i \,/\, x_i, y_j, l_j)$$
$$= 15\frac{x_i + l_i}{x_i + l_i + y_j + l_j} - \mu 15\sqrt{\left(\frac{x_i + l_i}{x_i + l_i + y_j + l_j} - \frac{x_i}{x_i + y_j}\right)^2 + \left(\frac{y_j + l_j}{x_i + l_i + y_j + l_j} - \frac{y_j}{x_i + y_j}\right)^2}$$
$$= 15\frac{(x_i + l_i)\left(x_i + y_j\right) - \sqrt{2}\mu\left|y_j l_i - x_i l_j\right|}{\left(x_i + l_i + y_j + l_j\right)\left(x_i + y_j\right)}$$

To see when this utility function is maximized, consider the two conditions that can arise:

a) If $y_j l_i - x_i l_j > 0$:

$$FOC: \frac{\left(x_i + y_j\right) - \sqrt{2}\mu y_j}{\left(x_i + l_i + y_j + l_j\right)} - \frac{(x_i + l_i)\left(x_i + y_j\right) - \sqrt{2}\mu(y_j l_i - x_i l_j)}{\left(x_i + l_i + y_j + l_j\right)^2} = 0$$
$$\rightarrow (x_i + y_j)(y_j + l_j)(1 - \sqrt{2}\mu) \overset{?}{=} 0$$

Notice that the variable l_i drops from the first order condition indicating that this is a monotonous function. If μ<1/√2, the function is increasing, and the optimal strategy is to lie maximal. Notice that, the optimal level of lying is independent of the real performance of both parties, as well as the amount of lie of the other party. If μ>1/√2, the function is decreasing, then the optimal lie is the minimum possible such that $y_j l_i - x_i l_j = 0$.

b) When $y_j l_i - x_i l_j < 0$:

$$FOC: \frac{\left(x_i + y_j\right) - \sqrt{2}\mu y_j}{\left(x_i + l_i + y_j + l_j\right)} - \frac{(x_i + l_i)\left(x_i + y_j\right) + \sqrt{2}\mu(y_j l_i - x_i l_j)}{\left(x_i + l_i + y_j + l_j\right)^2} = 0$$
$$l_i{*} = \frac{\left(1 - \sqrt{2}\mu\right) y_j \left(x_i + y_j + l_j\right) + \left(1 + \sqrt{2}\mu\right) x_i l_j}{2\sqrt{2}\mu y_j}$$

The second order condition is as follows:

$$SOC: -\frac{\left(x_i + y_j\right) - \sqrt{2}\mu y_j}{\left(x_i + l_i + y_j + l_j\right)^2} + 2\frac{(x_i + l_i)\left(x_i + y_j\right) + \sqrt{2}\mu(y_j l_i - x_i l_j)}{\left(x_i + l_i + y_j + l_j\right)^3} - \frac{\left(x_i + y_j\right) + \sqrt{2}\mu y_j}{\left(x_i + l_i + y_j + l_j\right)^2} \overset{?}{<} 0$$
$$\rightarrow -\left(x_i + y_j\right)\left(x_i + l_i + y_j + l_j\right) + (x_i + l_i)\left(x_i + y_j\right) + \sqrt{2}\mu(y_j l_i - x_i l_j) \overset{?}{<} 0$$

Notice that the second order condition is satisfied if condition (b) is satisfied. Therefore, let us look at the conditions that satisfy the FOC: If $1-\sqrt{2}\mu > 0$, then condition (b) $l_i^* < \frac{x_i l_j}{y_j}$ and the FOC cannot be both satisfied. And since we have a function with a unique maximum in the specified domain, the function must be increasing with l_i until $y_j l_i - x_i l_j = 0$ is satisfied. This would lead us back to condition (a), and hence, to maximal lying. If $1-\sqrt{2}\mu < 0$, $l_i^* < \frac{x_i l_j}{y_j}$ is satisfied, and l_i* can be positive or negative depending on the value of μ. If μ is close to 1/√2, then l_i*>0, and if μ is large, l_i*<0. To summarize, if μ> 1/√2

$$l_i^* = Max\left\{0, \frac{\left(1-\sqrt{2}\mu\right) y_j \left(x_i + y_j + l_j\right) + \left(1+\sqrt{2}\mu\right) x_i l_j}{2\sqrt{2}\mu y_j}\right\}.$$

Let us now check whether both l_i* and l_j* can be larger than zero.

Assume that $\mu_i \neq \mu_j$. If both l_i* and l_j* are larger than zero, then two equations have to be satisfied simultaneously, which leads to:

$$l_i^* \left\{(2\mu_i\mu_j - 1)(x_i + y_j)^2 - \sqrt{2}\left(\mu_i - \mu_j\right)(x_i^2 - y_j^2)\right\} =$$
$$(x_i + y_j)x_i \left\{(1-\sqrt{2}\mu_i)(1+\sqrt{2}\mu_j)y_j + (1-\sqrt{2}\mu_j)(1+\sqrt{2}\mu_i)x_i\right\}$$

Note that, the multiplier of l_i*is always positive. The right hand side of the equation is always negative since both μ's are larger than 1/√2. Therefore, it cannot be the case that both lies are positive.

The only other option to check is whether it is possible to have a zero lie level for one player, and a positive lie level for the other. Assume l_j=0. In such a case $l_i^* = Max\left\{0, \frac{\left(1-\sqrt{2}\mu\right) y_j \left(x_i + y_j\right)}{2\sqrt{2}\mu y_j}\right\} = 0$ because the second argument in the maximization is always negative since μ is assumed to be larger than 1/√2. Thus, the only equilibrium is both players not lying.

To summarize, in equilibrium the following will hold:

Table A2. Equilibrium predictions in the pie

	j's lie-aversion	
i's	**μ<1/√2**	**μ> 1/√2**

μ< 1/√2	14,14	14, $Max\left\{0,\dfrac{\left(1-\sqrt{2}\mu_i\right)x_i\left(y_j+14\right)+\left(1+\sqrt{2}\mu_i\right)y_j(14-x_i)}{2\sqrt{2}\mu_i x_i}\right\}$
μ> 1/√2	-	No lie

Finally, when $l_j=0$, notice that there will be maximal lying when $\mu<1/\sqrt{2}$ and no lying when $\mu>1/\sqrt{2}$.

(iii) Equilibrium Predictions in the Tournament

In the tournament treatment, the optimal lie depends on one's belief on the performance and the amount of lie of the other party. We will analyze three situations when both parties are honest: if *i* wins, if *i* loses, and if *i* draws.

a) *i* wins when (x_i,y_j)

If *i* loses with (x_i+l_i, y_j+l_j), but wins when (x_i,y_j) then the utility function is $U_i(l_i\,/\,x_i,y_j,l_j)=0-\mu\sqrt{9(x_i)^2+9(y_j+l_j)^2}$. Now consider another lie level such that it makes player *i* win the tournament. Let us call that l_i'. Now the utility is: $U_i(l_i'/\,x_i,y_j,l_j)=3(x_i+l_i')-\mu\sqrt{(3l_i')^2}$. Comparing the two lie levels, we can see that $U_i(l_i'/\,x_i,y_j,l_j)>U_i(l_i\,/\,x_i,y_j,l_j)$ implies $(x_i+l_i')-\mu(l_i')>-\mu\sqrt{(x_i)^2+(y_j+l_j)^2}$. A sufficient condition for the last inequality to hold is that $l_i'\leq Max\{x_i, y_j+l_j\}$. Since by construction $x_i<y_j+l_j$, $l_i'\leq y_j+l_j$ is sufficient for the inequality to hold. Furthermore, we can always find such an l_i' since $x_i>y_j$. Notice that this is regardless of the level of μ: As long as $\mu<1$, the utility is increasing in l_i, and therefore there should be maximum lying. If $\mu>1$, then the utility is decreasing with l_i, thus the optimal lies are such that it is enough to win.

The last thing to check is whether lying to tie-break (l_i*) is preferred over lying to win. With l_i*, the utility is $U_i(l_i*/x_i,y_j,l_j)=1.5(x_i+l_i*)-\mu\sqrt{(1.5x_i-1.5l_i*)^2+(1.5y_j+1.5l_j)^2}$. Notice that, $l_i*<l_i'$. If lying to win is preferred over lying to tie-break, the following should hold: $3(x_i+l_i')-\mu\sqrt{(3l_i')^2}>1.5(x_i+l_i*)-\mu\sqrt{(1.5x_i-1.5l_i*)^2+(1.5y_j+1.5l_j)^2}$. Let us focus on the case of when $l_i'=l_i*+1$. For the inequality to hold, it is enough to satisfy $l_i*+1<\sqrt{2(x_i^2+l_i*^2)}$.

Rearranging gives $1 + 2l_i^* < 2x_i^2 + l_i^{*2}$. If x_i>0, this inequality holds for any $l_i^* \geq 2$. If $l_i^* = 1$, the utility from lying is equal to the utility from tie-breaking only if x_i=1, and larger otherwise. Thus, lying to win is preferred over lying to tie-break for any level of μ if x_i>1.

b) <u>*i* loses when (x_i,y_j)</u>

if *i* wins with (x_i+l_i, y_j+l_j), then the utility of *i* is as follows:

$$U_i(l_i \,/\, x_i, y_j, l_j) = 3(x_i + l_i) - \mu\sqrt{9(x_i + l_i)^2 + 9y_j^2}$$

The optimal amount of lying is determined from the maximization as follows:

$$\begin{aligned} &Max\ \ U_i = 3(x_i + l_i) - \mu\sqrt{9(x_i + l_i)^2 + 9y_j^2} \\ &FOC: 1 - \mu\frac{(x_i + l_i)}{\sqrt{(x_i + l_i)^2 + y_j^2}} = 0 \\ &\rightarrow (1 - \mu^2)(x_i + l_i)^2 = -y_j^2 \end{aligned}$$

The second order condition is always satisfied, to see:

$$\begin{aligned} &SOC: -\frac{1}{\sqrt{(x_i + l_i)^2 + y_j^2}} + \frac{2(x_i + l_i)^2}{2\left((x_i + l_i)^2 + y_j^2\right)^{3/2}} \overset{?}{<} 0 \\ &\rightarrow (x_i + l_i)^2 \overset{?}{<} \left((x_i + l_i)^2 + y_j^2\right) \end{aligned}$$

Notice that, whenever μ<1 and x_i+l_i>0, the FOC is always larger than zero regardless of what the other party does. Then, there will be maximum lying. However, it is also possible that maximal lying does not give a higher utility than losing. Notice that if μ >1, the optimal level of lies are never enough to win the tournament. To see it we have to check $x_i + l_i^* = \sqrt{\frac{y_j^2}{\mu^2 - 1}} \overset{?}{>} y_j + l_j$. Notice that the latter inequality can never be satisfied when μ >1. Therefore, we are at a corner solution, and we have to compare the utilities of lying enough to win to not winning. If l_i'<l_i such that *i* loses, then $U_i(l_i') = 0 - 3\mu(l_j)$. Since, x_i+l_i=y_j+l_j+1, for lying enough to win to be preferred over losing, the following should hold:

$(x_i + l_i) - \mu\sqrt{(x_i + l_i)^2 + y_j^2} > -\mu(x_i + l_i - y_j - 1)$. Rearranging gives:

$\left(y_j + l_j + 1 + \mu l_j\right)^2 > \mu^2\left((y_j + l_j + 1)^2 + y_j^2\right)$. For any level of $\mu > 1$, whether this inequality is satisfied depends on the level of y_j, and l_j. When μ is close to 1, the inequality is satisfied for most combinations of y_j and l_j, whereas if *μ* gets large, it cannot be satisfied for large ranges of y_j, and l_j. with maximal lying, the comparison is slightly different. Now, $x_i + l_i^* = 14$. If lying maximally is preferred over losing, the following should hold: $14 - \mu\sqrt{14^2 + y_j^2} > -\mu(l_j)$. Clearly, this inequality might not hold for certain levels of μ<1, and high levels of y_j. It always holds when μ<1/√2.

A second thing to check is whether lying to tie-break is preferred over losing. The comparison is as follows: $U_i(l_i'/\, x_i, y_j, l_j) = 1.5(x_i + l_i') - \mu\sqrt{1.5^2(x_i + l_i')^2 + 1.5^2 y_j^2} > -3\mu l_j$. This can be simplified to $y_j(1 - \mu\sqrt{2}) > -2\mu l_j$. If the left-hand-side is positive, the inequality trivially holds. That happens when $\mu^2 < 0.5$. When $\mu^2 > 0.5$, for every level of l_j, there is a range of y_j in which there will be lying to tie-break. Finally, under the rather strong assumption of $l_j \geq y_j$, any $\mu \geq 1/(2+\sqrt{2})$ (≈ 0.30) satisfies this inequality. That means, if the lies of the other party are large relative to performance, then there is always lying to tie-break even if a person should have lost the tournament with an honest outcome.

A third thing to check is whether lying to win is preferred over tie-breaking. Lying to win gives a utility of $3(x_i + l_i) - 3\mu\sqrt{(x_i + l_i)^2 + y_j^2}$, whereas tie-breaking $1.5(x_i + l_i') - \mu\sqrt{1.5^2(x_i + l_i')^2 + 1.5^2 y_j^2}$. Notice that, the former utility is double the latter with a larger l_i. Since this utility function is increasing in l_i when μ<1, the former is always larger than the latter. Therefore, whenever there is lying to tie-break, there is lying to win. Remember however that, lying to win might not be preferred over losing. When μ>1, the picture is less clear. Lying to tie-break gives a higher utility than lying to win with large values of μ or low values of y_j. Again, remember however that, lying to tie-break might not be preferred over losing.

Finally, consider the case in which l_j=0. When l_j=0, the comparison between lying enough to win or losing is simplified to $(1 - \mu^2)(x_i + l_i)^2 > \mu^2 y_j^2$. Consider again the minimum l_i required to win. Then $x_i + l_i = y_j + 1$. This gives $(1 - \mu^2)(y_j + 1)^2 > \mu^2 y_j^2$. If μ>1, it is trivial to see that this inequality cannot be satisfied. Therefore, there is no lying to win. We have established at the beginning of part (b) that whenever μ<1 and x_i+l_i>0, there will be maximum lying in a wide range of parameters –but lying to tie-break might also be preferred when y_j is high.

c) ***i* tie-breaks when (x_i,y_j)**

There is equality in the performances, x_i=y_j. Consider the case of losing with (x_i+l_i, y_j+l_j). Should *i* lie to make the declarations equal? Consider that lie level to be l_i'. Then l_i'=l_j.

$U_i(l_i'/\, x_i, y_j, l_j) = 1.5(x_i + l_i') - \mu\sqrt{(1.5 l_i')^2 + (1.5 l_j)^2}$. The utility from losing with l_i<l_i' is

$U_i(l_i \,/\, x_i, y_j, l_j) = -\mu\sqrt{(1.5x_i)^2 + (1.5y_j + 3l_j)^2}$ .The latter is always smaller than the former. Thus, *i* should lie at least as much as *j* regardless of μ.

Should *i* lie to win? If $l_i > l_j = l_i'$, then *i* wins. The utility is

$U_i(l_i \,/\, x_i, y_j, l_j) = 3(x_i + l_i) - \mu\sqrt{(1.5x_i + 3l_i)^2 + (1.5y_j)^2}$. The optimal amount of lying to win gives the following first and second order conditions:

$$FOC : 1 - \mu\frac{(x_i + 2l_i)}{\sqrt{(x_i + 2l_i)^2 + {y_j}^2}} = 0$$
$$\rightarrow (1 - \mu^2)(x_i + 2l_i)^2 = -{y_j}^2$$

The second order condition is always satisfied:

$$SOC : -\frac{2}{\sqrt{(x_i + 2l_i)^2 + {y_j}^2}} + \frac{4(x_i + 2l_i)^2}{2\left((x_i + 2l_i)^2 + {y_j}^2\right)^{3/2}} \overset{?}{<} 0$$
$$\rightarrow (x_i + 2l_i)^2 < \left((x_i + 2l_i)^2 + {y_j}^2\right)$$

Notice that, whenever μ<1, the FOC is always larger than zero regardless of what the other party does. Then, there will be maximum lying. If μ >1, the optimal level of lies are never enough to win the tournament. To see it we have to check $x_i + 2l_i = \sqrt{\frac{{y_j}^2}{\mu^2 - 1}} \overset{?}{>} y_j + l_j$. Notice that the latter inequality can never be satisfied when μ >1. Thus, we can have a corner solution in which lying the minimally to win is preferred over l tie-breaking.

Let us compare lying to win to lying to tie-break. Lying to win would happen when

$3(x_i + l_i) - \mu\sqrt{(1.5x_i + 3l_i)^2 + (1.5y_j)^2} > 1.5(x_i + l_i') - \mu\sqrt{(1.5l_i')^2 + (1.5l_j)^2}$. Remember that, when μ>1, there can be at most lying to win. Imputing $l_i = l_i'+1$, $l_i' = l_j$, and $x_i = y_j$, and rearranging gives:

$x_i + (1 + \sqrt{2}\mu)l_i' + 2 > \mu\sqrt{(x_i + 2(l_i' + 1))^2 + (x_i)^2}$. This inequality always holds if

$\mu < \frac{x_i + l_i' + 2}{\sqrt{(x_i + 2(l_i' + 1))^2 + (x_i)^2} - \sqrt{2}l_i'}$. Note that the denominator of the RHS is always positive. We cannot say much about the range of *μ* that satisfies this inequality. It can be satisfied when *μ* >1. Therefore, lying to win can be preferred over lying to tie-break when the honest outcome is tie-breaking. When μ<1, there is maximal lying. Imputing $x_i + l_i = 14$, $l_i' = l_j$, and $x_i = y_j$, and rearranging gives:

$28 - \mu\sqrt{(28 - x_i)^2 + {x_i}^2} > x_i + l_i' - \mu\sqrt{2}l_i'$. This inequality holds if

$\mu < \frac{28-(x_i+l_i')}{\sqrt{(28-x_i)^2+(x_i)^2-\sqrt{2}l_i'}}$. Note that the denominator of the RHS is always positive. When μ<1/√2, it is always satisfied. It can also be satisfied with larger μ levels. Therefore, lying to win is always preferred over lying to tie-break if μ<1/√2, and might be preferred for larger μ levels.

One final check is when *j* cannot lie. Then $x_i=y_j$, and $l_i'=0$. So would *i* lie to win? The comparison of lying and winning to not lying is as follows: $3(x_i+l_i)-\mu\sqrt{(1.5x_i+3l_i)^2+(1.5y_j)^2} > 1.5(x_i)$ which becomes $x_i+2l_i > \mu\sqrt{(x_i+2l_i)^2+(y_j)^2}$. If μ>1, this inequality does not hold. Thus, there cannot be lying to win. The values of μ satisfying the inequality is $\mu < \frac{x_i+2l_i}{\sqrt{(x_i+2l_i)^2+(x_i)^2}}$. Notice that the RHS is increasing in l_i. Therefore, given a level of μ, either there is no lying, or there is maximum lying.

<u>General Results for Tournament:</u>

Combining all the results gives the following equilibria:

Table A3. Equilibrium predictions in the tournament

***i*'s lie-aversion level**		***j*'s lie-aversion** μ<1/√2	***j*'s lie-aversion** 1/√2 <μ<1	***j*'s lie-aversion** μ>1
$x_i<y_j$	**μ<1/√2**	14,14	14,14	14,14
	1/√2< μ<1	-	14,14; interm lying (j wins)	14,14; interm lying (j wins)
	μ>1	-	-	14,14; interm lying (j wins)
$x_i=y_j$	**μ<1/√2**	14,14	14,14	14,14
	1/√2< μ<1	-	14,14 or tie-break	14,14 or tie-break
	μ>1	-	-	14,14 or tie-break

Appendix-Factor Analysis

Rotated Component Matrix

	Component					
	1	2	3	4	5	6
Division140	.062	.849	-.090	.022	.106	.100
Division122	.035	.826	-.103	.229	.172	.107
Division104	.004	.648	-.050	.482	.209	.142
Division86	-.053	.297	.011	.772	.154	.147
Division147	.034	.249	-.010	.572	.168	.221
Division65	.072	-.016	-.059	.493	-.102	-.243
Division64	.028	.397	.051	.791	-.096	-.075
Division63	.066	.586	.039	.647	-.133	-.117
Division62	.049	.720	-.002	.427	-.085	-.137
Division61	.025	.835	.034	.234	-.063	-.056
Division60	-.047	.883	-.004	.078	-.075	-.090
Average	.680	.009	.300	-.017	.215	-.072
Updated0	-.334	-.082	-.036	-.005	-.732	.060
Updated1	-.500	.002	-.141	-.048	-.632	.223
Updated2	-.715	-.052	-.206	-.035	-.216	.400
Updated3	-.773	.031	-.237	-.027	.237	.248
Updated4	-.527	-.010	-.238	.002	.576	-.251
Updated5	.136	.050	-.215	.002	.326	-.767
Updated6	.717	-.077	-.174	.079	.164	-.256
Updated7	.870	.036	-.055	.056	.075	.013
Updated8	.812	.085	.159	.030	.033	.233
Updated9	.708	.057	.363	-.038	.025	.246
Updated10	.473	.091	.667	-.048	.007	.227
Updated11	.331	.108	.765	.030	-.012	.188
Updated12	.133	.011	.907	.063	-.015	.039
Updated13	.118	-.105	.861	-.053	-.019	-.007
Updated14	.018	-.187	.712	-.027	.020	-.059
UpdatedAvg	.791	.034	.523	.027	.293	-.058

Total Variance Explained

Component	Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %
1	5.676	20.272	20.272
2	4.568	16.313	36.585
3	3.908	13.957	50.542
4	2.768	9.884	60.427
5	1.834	6.550	66.977
6	1.427	5.098	72.075