Goals, Bonuses and Loss Aversion*

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Abstract

To enhance workers' motivation, organizations often offer monetary bonuses that are linked to meeting production goals. We argue that when workers set these production goals and are sufficiently loss averse, offering a monetary bonus for goal achievement may backfire. The rationale is as follows: while self-chosen goals can act as reference points that motivate loss-averse workers to increase effort and earnings, a monetary bonus for goal achievement may crowd-out the motivation to set an ambitious goal because workers will not want to miss the bonus offered. Hence, monetary bonuses will induce workers set more conservative goals, attenuating the motivational effects of goal setting. We show experimental evidence consistent with this mechanism.

JEL Codes: D86, D90, C91, D81.
Keywords: Loss aversion, Goals, Monetary and Non-monetary incentives.

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1. Introduction

There is ample empirical evidence that individuals exhibit loss aversion (Tversky & Kahneman, 1992; von Gaudecker et al., 2011; Pope & Schweitzer, 2011; L'Haridon & Vieider, 2019), with important implications for behavior in markets (Odean, 1998; Heidhues & Koszegi, 2008), auctions (Rosato & Tymula, 2019), and games (Shalev, 2000; Eil & Lien, 2014). The consensus in the literature is that loss aversion is a cognitive bias, negatively affecting decision-makers' welfare (Wakker 2010; Barberis, 2013).

In this paper, we posit that loss aversion can become a strategic asset that a worker can leverage in a context in which improving performance is desired, such as piece-rate pay systems. When loss-averse workers can set performance goals for themselves, they anticipate that it will become their reference point and that they will exert additional effort to avoid falling short of their goal and experience losses. Consequently, they will set high goals to take advantage of this motivational force and boost their earnings. In this context, we conjecture that introducing a monetary bonus for goal achievement may backfire, as workers may set lower goals to minimize the risk of not receiving the bonus. If this latter effect outweighs the motivational effect of the goal itself, the loss averse worker will be worse-off (earn less) when a monetary bonus is offered than when it's not. In that case, a monetary bonus designed to motivate the worker will backfire.

We conduct a laboratory experiment to test this conjecture. In the experiment, described in Section 2, participants must complete a task that requires effort. The monetary incentives to perform the task depend on the treatment they are randomly assigned to. The design of the experiment can be viewed from the perspective of a firm that is considering changes to a simple piece-rate contract. The first treatment, called LOPR, is a low-powered piece-rate contract. The GOAL treatment adds to LOPR a self-chosen goal without any monetary bonus. Comparing GOAL to LOPR provides a measure of whether there is sufficient improvement in performance from simply adding a self-chosen goal without a monetary bonus attached to its achievement. The treatment GOAL+BONUS is a contract in which LOPR is complemented with a self-chosen goal that yields a monetary bonus if the goal is achieved. Comparing GOAL and GOAL+BONUS is key to our paper and indicates how much more (or less) performance one can get from the bonus. The fourth and last treatment is a higher-powered piece-rate contract called HIPR. Comparing the HIPR and GOAL (or GOAL+BONUS) provides an assessment of performance under self-chosen goals vis-à-vis a substantial piece rate increase.

We hypothesize that GOAL yields higher performance and higher goals than GOAL+BONUS. If this is the case, GOAL dominates GOAL + BONUS from the point of view of the employer, because it involves lower expenditure for higher output. Since our conjecture crucially depends on loss aversion, we also elicit the participants' loss aversion. We implement the parameter-free elicitation method developed by Abdellaoui et al. (2008). This elicitation method has the advantage that it allows the independent measurement of the curvature of participants' utility functions and their degree of loss-aversion, while accounting for the possibility that participants might exhibit probability weighting (Tversky and Kahneman, 1992, Gonzalez and Wu, 1999, Abdellaoui, 2000).

The experimental data, reported in Section 3, confirm our hypotheses. On average, participants assigned to the GOAL treatment set more ambitious goals than those assigned to GOAL+BONUS, and exhibit better performance than participants assigned to any of the other three treatments. Specifically, a contract with a self-chosen goal but without monetary bonus leads to 11% more output, an increase in performance of 0.36 standard deviations, over contract with a self-chosen goal and a monetary bonus. Moreover, as expected, we find that the performance of highly loss averse participants is especially greater when goals are not rewarded with a bonus. Finally, we observe that performance under goals with no bonus is significantly higher than performance under the two piece-rate contracts. We conclude that a goal contract with no monetary bonus is the cheapest way to improve performance among the contracts we study.

Our study contributes to the recent and expanding area of behavioral contract theory (see Köszegi (2014) for a review). Contrasting the results of De Meza and Webb (2007), Dittman et al. (2010), Herweg et al. (2010), and Gonzalez-Jimenez (2024), we show that an incentive scheme with bonuses can backfire and demotivate a loss averse agent. To the best of our knowledge, we are the first to document this adverse effect of contracts with a bonus among loss averse individuals. We also present an environment in which loss aversion can be beneficial to the agent. When the agent receives a contract in which goal setting is encouraged but bonuses are absent, she can fully leverage the motivation from her loss aversion.

More generally, we also contribute to the literature on incentives (Laffont and Martimort 2002). We provide a behavioral justification for the empirical regularity that organizations, against the predictions of standard theory, use fairly simple contracts (Salanie, 2003). In our setting, introducing a bonus for the achievement of a self-chosen goal is a way to make a (linear) piece-rate contract more convex, thereby aligning it more closely with the predictions of standard theory. The results of our experiment show that the principal would be worse off taking this avenue, and instead recommend that goal setting be induced but the bonus omitted. This simpler contract is shown to improve motivation of loss averse workers.

Thirdly, our paper also contributes to the literature on goal setting in economics (Koch and Nafziger, 2011, 2020, Gómez-Miñambres, 2012, Corgnet et al., 2015, 2018). To our knowledge, this is the first paper studying how monetary incentives interact with self-chosen goals and the role of loss aversion in moderating such interaction. This paper also contributes to this literature, as it is, to our knowledge, the first to quantify loss aversion and utility curvature to study their association with goal setting, monetary incentives, and performance. Eliciting these preference parameters also allows us to validate our proposed conjecture.

Finally, we add to the literature that examines how extrinsic incentives crowd-out intrinsic motivation (see Gneezy et al., 2011, and Bowles and Polanía-Reyes, 2012, for reviews). In this literature, crowding-out effects appear when monetary incentives inhibit individuals from signaling to others, or to themselves, a favorable attribute such as pro-sociality (Ariely et al., 2019, Mellstrom and Johannesson, 2016) or norm-conforming behavior (Frey and Oberholzer-Gee, 1997). Our main contribution to this literature is to provide a different microeconomic foundation based on loss aversion for the motivational crowding out effect. Specifically, the intrinsic incentives from setting an ambitious goal, which stem from loss aversion, are offset by monetary incentives that encourage modest goal setting.

2. Experimental Procedures and Hypotheses

2.1 General Procedures

The experiment was conducted at the University of Arizona's Economic Science Laboratory. Participants were all students at the university and were recruited using an electronic system. The dataset consists of 12 sessions with a total of 161 participants. On average, a session lasted approximately 70 minutes. Between 3 and 20 participants took part in each session. The currency used in the experiment was US Dollars. We used Otree (Chen, et al., 2016) to implement and run the experiment. Participants earned on average 20.7 US Dollars. The instructions of the experiment are provided in Appendix C.

The experiment consisted of two parts: A and B. Upon arrival, participants were informed that the sum of earnings from Part A *and* Part B would be their final earnings for the session. Whether participants faced Part A or Part B first was determined at random by the computer. This randomization was implemented to control for order effects.

2.2. Part A: Real Effort Task and Treatments.

In Part A, participants performed a task that required their effort and attention. The task consisted of counting the number of zeros in a table of 100 randomly distributed zeros and ones. This task has been widely used by other researchers (e.g. Abeler et al., 2011 and Koch and Nafzinger, 2020). Participants submitted their answers using the computer interface. Immediately after submission, a new table appeared on the computer screen and participants were invited again to count the number of zeros in the new table.

Participants had six rounds of five minutes each to complete as many correct tables as they could. After each round ended, participants were given feedback about the number of tables they solved correctly and their earnings for that round. If applicable, they were reminded of their goal for that round and were told whether that goal was achieved. To become acquainted with the task, participants also had a five-minute practice round where it was clear that their performance did not count toward their earnings. In total, aside from the practice round, participants had 30 minutes to work on the task, and were given small time intervals between rounds. Since the time between goal setting and performance was almost immediate, we rule out by design any self-control problems.

There were four treatments, LOPR, HIPR, GOAL, and GOAL+BONUS. The treatments differed only with respect to the incentives offered to participants. Each participant was randomly assigned to one of the four treatments. We ensured randomization in our design by having participants in any given experimental session face the same chance of being assigned to any of the treatments. That is, within each session in the laboratory, different individuals were randomized into different treatments. The incentives in effect in each treatment were the following.

- *LOPR*: Participants were paid 0.20 dollars for each correctly solved table.
- *HIPR*: Participants were paid 0.50 dollars for each correctly solved table.
- *GOAL*: Participants were paid 0.20 dollars for each correctly solved table and were asked at the beginning of each round to set an individual goal regarding the number of tables that they aimed to solve in that round. They were asked by the experimenter to provide an accurate target.
- *GOAL+BONUS:* Identical to the *GOAL* treatment, with the exception that participants were offered a monetary bonus for reaching their goals. The bonus in dollars was equivalent to the goal set by the participant, multiplied by a factor of 0.20.

LOPR can be viewed as a baseline condition to which different features that may improve performance are added. HIPR includes an increase in the piece rate, while GOAL adds a goal set by the worker. GOAL+BONUS adds the goal, as well as a monetary payment for reaching it, which is larger the more ambitious the goal.

Including the HIPR treatment has the purpose of evaluating how incentive schemes with self-chosen goals compare in terms of performance to a policy of considerably increasing the piece rate. Notably, the piece rate in HIPR was set so that the worker's compensation would be higher than under GOAL or GOAL+BONUS for any output level. This would allow us to establish, if the output under the two contracts is the same, that a GOAL or GOAL+BONUS contract would be more cost-effective than HIPR.

2.3 Part B: Elicitation of Risk Attitudes

In Part B of the experiment, the task was to choose between two binary lotteries in multiple trials. This part of the experiment was designed to elicit participants' loss aversion and utility curvature. The first set of lotteries obtained utility curvature by eliciting the certainty equivalent, x_j, of a lottery of the form $(H_j, 0.5; L_j, 0.5)$, with $j = 1,2,3,4,5$, and $H_j \geq L_j \geq 0$ for all j. The values H_j and L_j used in each lottery are shown in Table 1 below.

Table 1. High and Low Values Used in Lotteries to Measure Utility Curvature

Lottery	$j = 1$	$j = 2$	$j = 3$	$j = 4$	$j = 5$
H_j	4	8	12	20	20
L_j	0	0	0	0	12

The second set of lotteries obtained loss aversion by eliciting the offsetting loss outcome $z_j < 0$ that made each subject indifferent between receiving zero and a mixed lottery $(x_j, 0.5; z_j, 0.5)$ for each $j = \{1,2,3,4,5\}$. A more detailed explanation of this method is provided in Appendix A.

Once participants finished both parts (A and B), they were reminded about their performance in each round of the real-effort task, as well as whether they achieved their goal in that round, if applicable. Participants were also informed about the lottery that was chosen for potential compensation for Part B and its realization. Finally, participants completed a questionnaire about their general willingness to take risks, as well as to take specific risks (health-, job-, and driving-related). The questions were taken from Dohmen et al. (2011). The questionnaire can be found in Appendix C.

2.4. Hypotheses

When formulating our hypotheses, it is assumed, as it is typically found in laboratory experiments, that individuals are loss averse (Tversky and Kahneman 1992, Abdellaoui et al., 2007, 2008, L'Haridon and Vieider, 2019). Regarding goal setting, our hypothesis is that goals are higher when the goal contract does not include a bonus compared to a situation in which a bonus is included. In the former case, individuals take full advantage of their own loss aversion by setting ambitious goals, while in the latter case, individuals set more conservative goals to make sure that they attain the bonus.

Hypothesis 1: *Participants will set higher goals in GOAL than in GOAL+BONUS.*

Regarding performance, which is the number of correct tables in the real-effort task, the main hypothesis is that it will be higher when a goal contract is offered without a bonus as compared to a situation in which a bonus is included. This is because the goals are motivating, and more ambitious goals lead to better performance.

Hypothesis 2: *Participants will exhibit higher performance under GOAL than under GOAL+BONUS.*

If individuals have reference-dependent preferences, then the predicted differences in performance and goal setting between the GOAL and GOAL+BONUS treatments should be greater for participants with higher loss aversion. The greater one's loss aversion, the more conservatively one would like to set a goal when a bonus is included, because failing to attain the bonus carries a relatively large loss. However, the more loss averse one is, the more motivated one is to attain one's goal if there is a risk of falling short of it. Thus, the GOAL treatment should be particularly effective in leading to more ambitious goals and thus high performance for loss averse individuals.

Hypothesis 3: *The difference in performance and goal levels between GOAL and GOAL+BONUS will be larger for participants with relatively high levels of loss aversion.*

Finally, we compare the performance of the goal contract with and without a bonus to that generated by a pure piece rate contract. Although a piece rate contract is only optimal under certain conditions (Holmström and Milgrom, 1987), it has a particularly simple structure and is frequently observed in organizations (Chiappori and Salanie, 2002). It is also often discussed as a benchmark contract structure in contract theory (Laffont and Martimort, 2002).

The contract offered in *LOPR* provides the same pecuniary incentives as GOAL, but it does not nudge subjects to explicitly set a goal. Thus, even if subjects in LOPR have a goal in mind, it is less salient to them, and they are less committed to it as compared to a situation in which they were to report that goal to the experimenter. Therefore, we hypothesize that the motivation from goal setting is experienced to a lesser extent by those subjects and consequently, they exhibit lower performance in the task.

Hypothesis 4: *Participants will exhibit higher performance in GOAL than in LOPR.*

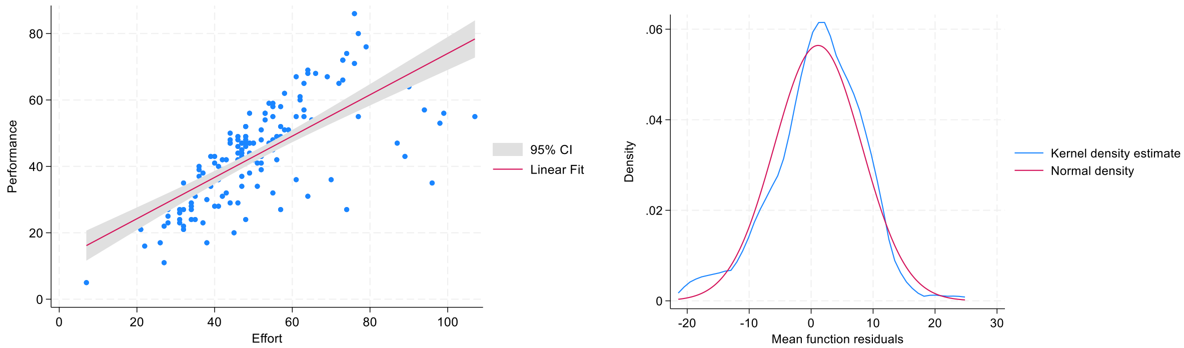
3. Results

3.1 Effort and Performance

We first examine how performance is related to the effort exerted by subjects in the experiment. Recall that we define performance in the experiment as the total number of tables an individual solves correctly. Effort is defined as the total number of tables, whether correct or incorrect, attempted by a subject. It should be emphasized that in all our empirical analyses, unless specified, the experimental data is analyzed at the individual level.

Figure 1a displays a scatterplot of performance against effort. That figure shows that an effort level can result in different performance levels, an indication that performance in the real effort task is stochastic. This is because subjects can incur mistakes of different magnitudes when working on the task. Figure 1b corroborates this finding by presenting the density of residuals resulting from a non-parametric regression of performance against effort. That figure shows that these residuals are substantial and affect performance considerably. For instance, transitioning from the 25th to the 75th quartile of residuals results in a performance improvement of 0.46 standard deviations.

Figure 1. Relationship Between Effort and Performance



a) Scatter plot Performance and Effort

b) Density of Residuals

Figure 1a also shows that despite the aforementioned stochasticity of performance, there is a positive relationship between effort and performance. As a result, a high effort level chosen in the real-effort task does not guarantee high performance, but it increases the *chance* of obtaining a higher performance level.

4.2 Performance Under the Different Contracts

Table 2 reports the descriptive statistics of performance by treatment and Figure 2 shows the Probability Density of performance in GOAL and GOAL+BONUS. As predicted by Hypothesis 2, paying a monetary bonus for achieving a goal backfires, resulting in lower output. On average, participants in GOAL solve more tables (47.58 tables), than participants in GOAL+BONUS (42.897 tables) ($t = 1.485$, $p = 0.07$).[1] The size of this effect is 11.1%, or 0.377 standard deviations.

Furthermore, participants in GOAL solve more tables than participants in LOPR ($t = 1.623$, $p = 0.054$), supporting Hypothesis 4, and even more than in HIPR ($t = 1.6548$, $p=0.051$).[2] These represent differences of 0.401 standard deviations and 0.406 standard deviations, respectively. The fact that output is higher under GOAL than under HIPR suggests that a self-chosen goal contract without a bonus is highly cost-effective.

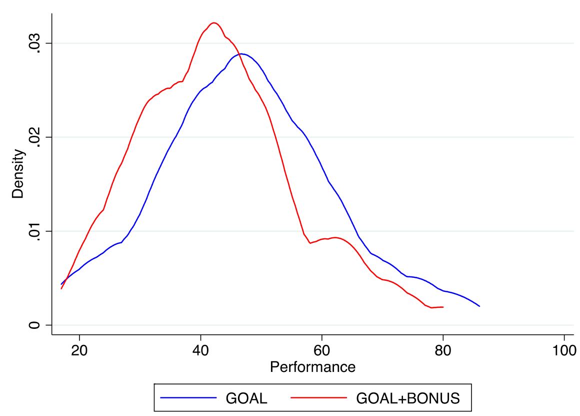
[1] A Wilcoxon-Mann-Whitney test generates the same conclusion ($z= 1.584$, $p=0.056$).

[2] Wilcoxon-Mann-Whitney tests of these differences yield $z= 1.494$ ($p=0.074$) and $z= 1.512$ ($p=0.065$), respectively.

Table 2. Performance by Treatment

Treatment	N	Mean	Median	S.D.	25th	75th	Max	Min	Mean Cost (Dollars)
GOAL +BONUS	39	42.897	43	13.480	34	48	80	17	9.74
GOAL	41	47.585	47	14.747	39	56	86	17	9.517
HIPR	41	42.073	43	15.408	31	48.5	72	5	21.036
LOPR	39	42.179	41	15.022	27	55	72	16	8.436
Total	**160**	**44.3**	**43.5**	**14.734**	**34**	**54**	**86**	**5**	**12.259**

Figure 2. Probability Density Function of Performance in the Treatments with Goal Setting



However, we do not find significant differences in performance between GOAL+BONUS and LOPR ($t = 0.222$, $p= 0.824$), GOAL+BONUS and HIPR ($t = 0.255$, $p= 0.799$) or LOPR and HIPR ($t = 0.312$, $p= 0.975$).[3] Raising the piece rate or adding a bonus for goal achievement did not improve average performance over LOPR in our experiment.

Our (ex-post) interpretation for the lack of differences in performance across the piece-rate treatments is based on the results of Camerer et al. (1997), Fehr and Goette (2007), and Crawford and Meng (2015), who find that individuals supply more labor the further away they are from their daily target income. In the context of our experiment, this behavior emerges when it is assumed that all participants exhibit reference dependence, which as will be shown in Section 4.3 is exhibited by most subjects, and participants in HIPR and LOPR have the same reference income that they expect to earn in the experiment. Under that assumption, subjects in HIPR may not need to exert as much effort as those in LOPR to reach that reference point. When this demotivation from reference dependence is sufficiently strong, it can fully counteract the standard motivational

[3] These conclusions are also confirmed by Wilcoxon-Mann-Whitney tests. The z-statistics of these comparisons and their respective p-values are $z= 0.110$ ($p= 0.912$), $z= 0.048$ ($p= 0.961$), and $z= 0.034$ ($p= 0.973$), respectively.

effect of higher piece rates, resulting in comparable performance between the LOPR and HIPR treatments.

We also perform regressions of individual performance on treatment dummies that confirm these results. We use Poisson count regressions to account for the count nature of the performance data. Table 3 shows that the coefficient associated with GOAL is positive and significant at the 5% level for all specifications, indicating that participants in GOAL exhibit higher average performance than participants in GOAL+BONUS, the benchmark category in the regression. Similarly, the coefficient of GOAL is significantly larger than the coefficient of LOPR (χ^2 = 13.28, p= 0.001) and HIPR (χ^2 = 16.79, p= 0.001).[4] [5] [6] These results are robust to controlling for loss aversion (Column 2).

In Column 3 of Table 3 we show regression estimates when the sample is restricted to participants with linear utility. For these subjects, the effect of loss aversion is not confounded by utility curvature, and we should expect to observe a more pronounced treatment effect. Indeed, all the results reported above are robust to this sample restriction.

Table B.6 in Appendix B shows that our results on performance are robust to excluding outliers from the sample. Specifically, the higher performance under GOAL with respect to other treatments holds when the 10 highest performing participants (6.25% of data) are not included in the sample. We also perform randomization inference to overcome potential problems arising from having small sample sizes, e.g. that our results could be an artifact of a few high performers assigned to GOAL. We apply that procedure to the null of no treatment effect in the regression in Table 1, Col 1 and find that our result that GOAL yields higher performance emerges *for all possible assignments to the treatment* and not only for the one we performed (p=0.05, 500 resampling replications). Finally, Table B.7 in Appendix B shows that this result also emerges when the data are analyzed as a panel, which exploits the variation in performance over the experimental rounds.

We summarize the above analysis on performance as follows:

Result 1: *Performance is significantly higher in GOAL than in any of the other treatments, including GOAL+BONUS.*

[4] The coefficients for the LOPR and HIPR treatments are not significantly different for the specification in columns (1) and (2) (χ^2 = 0.16, p= 0.688).
[5] We use the estimates of column (2) in Table 5 for statistical inference.
[6] All results are robust to adding an ability variable in the regression, measured by the number of correct tables that participants completed in the 5-minute practice round.

Table 3. Performance as Function of Treatment and Preference Parameters

	(1)	(2)	(3)
	Performance (all participants)	**Performance (all participants)**	**Performance (linear utility only)**
GOAL	0.104***	0.102***	0.177***
	(0.033)	(0.033)	(0.045)
HIPR	-0.019	-0.034	0.098**
	(0.034)	(0.034)	(0.038)
LOPR	-0.017	-0.020	-0.134***
	(0.035)	(0.035)	(0.048)
Loss Averse		0.135***	0.169***
		(0.028)	(0.038)
Constant	3.759***	3.664***	3.585***
	(0.024)	(0.032)	(0.043)
Log-Likelihood	-846.727	-834.826	-442.010
N	160	160	91

Note: This table presents the estimates of Poisson count regressions of the statistical model $\text{Performance}_i = \beta_0 + \beta_1\text{GOAL} + \beta_2\text{HIPR} + \beta_3\text{LOPR} + \beta_4\text{Loss Averse} + \mathcal{E}_i$ with $\mathcal{E}_i \sim \text{Poisson}\ (\omega)$. "Performance" is the total number of tables a participant solves correctly over the six rounds of the real-effort task. Participants were assigned either to the GOAL, HIPR, LOPR, or GOAL+BONUS treatment. The GOAL+BONUS treatment is the benchmark category of the regression. ``Loss Averse'' is a dummy variable that indicates whether a participant is loss averse or not. A participant is classified as loss averse when at least four of her variables λ_j, where $\lambda_j \equiv x_j/z_j$, are greater than one. A participant is classified as having a linear utility function when for at least four Δ_{ij}s the null hypothesis that they are equal to zero was not rejected. Model (3) presents estimates of a regression including only those participants classified as having linear utility. Standard errors are in parenthesis. * indicates a p-value <0.1, ** indicates a p-value <0.05, ***indicates a p-value <0.01

4.3 Goal Setting

Regarding goals, we conjecture that participants will set higher average goals in GOAL than in GOAL+BONUS (Hypothesis 1) if most participants have reference-dependence preferences. Table 4 presents the descriptive statistics of goals by treatment and Figure 3 presents the Probability Density Functions of goals in the two treatments. As conjectured in Hypothesis 1, participants in GOAL set significantly higher goals on average (48.82 tables) than participants in GOAL+BONUS (37.48 tables) (t=2.842, p=0.005).[7] This represents a difference of 30.2%, or 0.573 standard deviations.

In Table B.1, presented in Appendix B, we show that the difference in the goals set between GOAL and GOAL+BONUS increases in later rounds, indicating that participants adjust their goals after being provided with feedback, and this adjustment induces a larger difference in goal setting

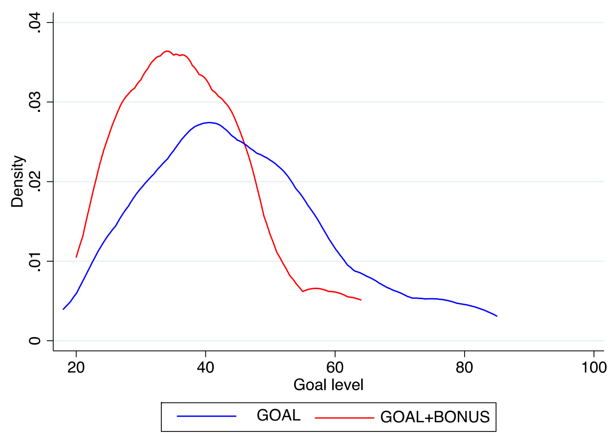
[7] A Wilcoxon-Mann-Whitney test yields the same conclusion (z=2.842, p=0.004).

between the two treatments. This finding rules out the possibility that the observed difference in goals is an artifact of inexperience with the task.

Table 4. Mean and Median Goals Set, by Treatment

Treatment	N	Mean	Median	S.D.	25th perc.	75th perc.	Max.	Min.
GOAL +BONUS	39	37.487	38	10.308	29	43	64	20
GOAL	41	48.829	45	25.706	34	54	180	18
Total	**80**	**44.300**	**40**	**22.758**	**31**	**48.5**	**180**	**18**

Figure 3. Probability Density Function of Goals Set, by Treatment



In Table 5, we report estimates from regressions relating the goals set by participants and the treatment assignment. In some specifications, we control for loss aversion with a dummy variable (Columns (2) and (3)). These estimates confirm the result that participants set higher goals when goal achievement is not rewarded with a bonus.

Table B.6 in Appendix B shows that this result is robust to excluding outliers from the sample. In that analysis, the treatment effect is significant despite the fact that the 10 highest performance values were not included in the data. We also apply randomization inference to overcome this potential problem of outliers and other potential issues that could emerge due to small samples. We find that that the treatment effect is significant under all possible assignments to the GOAL treatment and not only the one we performed (p=0.02, 500 resampling replications). Additionally, Table B.7 in Appendix B shows that when the data are analyzed as a panel, i.e., with round as the time variable, the result that goal setting is higher under GOAL also emerges.

Table 5. Goals as Function of Treatment and Loss Aversion

	(1)	(2)	(3)
	Goal Level (all participants)	**Goal Level (all participants)**	**Goal Level (linear utility only)**
GOAL	0.264^{***}	0.262^{***}	0.378^{***}
	(0.034)	(0.034)	(0.045)
Loss Averse		0.133^{***}	0.241^{***}
		(0.038)	(0.054)
Constant	3.624^{***}	3.530^{***}	3.426^{***}
	(0.026)	(0.038)	(0.053)
Log-Likelihood	-475.870	-469.699	-280.819
N	80	80	44

Note: This table presents the estimates of Poisson count regressions of the statistical model $\text{Goal Level} = \beta_0 + \beta_1\text{GOAL} + \Gamma'\text{Controls} + \mathcal{E}_i$ with $\mathcal{E}_i \sim \text{Poisson}\ (\omega)$. "Goal Level" equals the sum of a participant's goals over all six rounds of the real-effort task. Participants were randomly assigned either to the "GOAL" or the "GOAL+BONUS" treatment. The latter is the benchmark condition of the regression. ``Loss Averse'' is a dummy variable that captures whether a participant is loss averse or not. A participant is classified as loss averse when at least four variables λ_j, where $\lambda_j \equiv x_j/z_j$, are larger than one. Model (3) presents estimates of a regression including only participants classified as having linear utility. Standard errors presented in parenthesis. * indicates a p-value <0.1, ** indicates a p-value <0.05, ***indicates a p-value <0.0

We summarize the above analysis on goal setting as follows:

Result 2: *Goals are higher under GOAL than under the GOAL+BONUS.*

To conclude this section, we underscore the fact that subjects in GOAL+BONUS are on average 13.6% more likely to achieve their goal (t=3.412, p<0.001). This result supports our conjecture that the bonus disincentivizes the setting of challenging goals as subjects seek to secure a bonus. This difference in goal achievement across treatments is driven by a significantly higher achievement in GOAL+BONUS for rounds 2, 4, and 5 of the real-effort task.[8]

4.4 Risk Attitudes

We now investigate the subjects' risk attitudes. To that end, we use the data from part B of the experiment, where we elicited the certainty equivalents of five lotteries that offer positive payments, $\{x_1, x_2, x_3, x_4, x_5\}$, and the negative outcomes, $\{z_1, z_2, z_3, z_4, z_5\}$, that made subjects indifferent between receiving nothing and a mixed lottery $(x_j, 0.5; z_j, 0.5)$ for each $j = \{1,2,3,4,5\}$. Using these values, we classify participants according to the curvature of their utility function in the domain of gains, as well as their sensitivity toward losses.

[8] t-tests supporting these differences are those from Round 2 (t = 2.640, p= 0.01), Round 4 (t=2.215, p=0.03), and Round 5 (t=2.240, p=0.027)

Most participants in our sample have linear utility functions in the domain of gains. Specifically, 91 participants are classified as having a linear utility function (proportions test against the value 0.5, p=0.014), while 65 have concave, and only five have convex utility. Details of this classification are included in Appendix A.[9] If a power utility function $u(x) = x^{\theta}$ is assumed, the pooled estimate overall participants is $\hat{\theta} = 0.945$, close to risk neutrality. In Appendix A, we show that similar conclusions are reached when other families of utility functions are assumed.

Table 6 presents descriptive statistics of the loss aversion coefficients, λ_j, obtained by computing $\lambda_j = x_j / z_j$, for each $j = 1, \dots, 5$. Following Abdellaoui et al. (2008), we compute one loss aversion coefficient for each mixed lottery that we include in Part B. We find that participants are on average loss averse for each mixed lottery because the null hypothesis $\lambda_j = 1$ is rejected at each j. Moreover, we cannot reject the null hypothesis that the five loss aversion coefficients are equal to each other (F(4,805)=0.63, sphericity-corrected p-value=0.644), corroborating the result that sign-dependence, rather than the magnitude of the loss, determines loss aversion (Köbberling and Wakker, 2005).

Table 6. Loss Aversion Levels for Each of the Five Lotteries
$\lambda_j = z_j / x_j$

	$\boldsymbol{\lambda_1}$	$\boldsymbol{\lambda_2}$	$\boldsymbol{\lambda_3}$	$\boldsymbol{\lambda_4}$	$\boldsymbol{\lambda_5}$	$\boldsymbol{\lambda_{average}}$	$\boldsymbol{\lambda_{median}}$
Mean	3.459	3.676	3.712	3.548	3.945	3.668	3.417
Median	1.777	1.777	1.777	1.777	2.285	2.136	1.777
S.D.	4.798	4.716	4.699	4.166	4.566	3.752	4.152
25th perc.	0.516	1.066	1.066	1.230	1.066	1.208	1.230
75th perc,	3.2	3.2	3.2	5.333	5.333	4.48	3.2

Following Abdellaoui et al. (2008), we classify a subject as loss averse when at least four of variables λ_j, are greater than one. We find that the great majority of participants are loss averse. Specifically, 117 participants are classified as loss averse and 23 as gain-seeking (more sensitive to gains than losses of the same magnitude). Table A.4 in Appendix A presents further details of this classification. Importantly, participants are balanced across treatments with respect to both the mean level of loss aversion and the proportion of loss averse participants.[10]

[9] In short, to classify participants according to their curvature we constructed variables $\Delta_{ij} \equiv x_{ij} - EV_j$, where x_{ij} is the certainty equivalent of participant i for lottery j, EV_j stands for the expected value of the lottery, and $j = \{1, \dots, 5\}$ is an indicator of the lottery used. A participant was classified as having a linear utility function if for at least four Δ_{ij}s the null hypothesis that they are equal to zero was not rejected.

[10] The proportion of loss averse participants is 0.717 in LOPR, 0.6923 in GOAL, 0.6923 in GOAL+BONUS and 0.804 in HIPR. We use a two-sample test of proportions and find that these proportions are not significantly different from each other (LOPR vs. GOAL (p=0.786), HIPR vs. GOAL (p= 0.230), GOAL+BONUS vs. GOAL (p= 0.985)). Mean loss aversion is on average 3.44 for GOAL, 3.94 for GOAL+BONUS, 3.55 for HIPR and 3.75 for LOPR. The distribution of loss aversion is not significantly different between pairs of treatments, according to Mann-Whitney tests (LOPR vs. GOAL (p= 0.461), HIPR vs. GOAL (p=0.639), GOAL+BONUS vs. GOAL (p= 0.533)).

Aggregating the loss aversion coefficients across lotteries and participants, we observe that participants exhibit a median loss aversion coefficient of 2.136. This implies that, for the median participant, losses loomed approximately 2.14 times larger than equally sized gains. Previous studies that used the same definition of loss aversion found a median loss aversion coefficient of similar magnitude. For instance, Tversky and Kahneman's (1992) estimate was 2.25, Abdellaoui et al. (2007) reported an estimate of 2.54, and Abdellaoui et al. (2008), using the same method to elicit loss aversion as we have employed here, obtained a median loss aversion parameter equal to 2.61. Notably, as in previous studies, we observe considerable heterogeneity in loss aversion reflected in the size of the interquartile range (the difference between the 25th and 75th percentile).

4.5 Loss Aversion and its Relationship with Performance and Goal Setting

To test Hypothesis 3, we first create a dummy variable labeled "Loss Averse" that equals one if the participant is classified as exhibiting loss aversion, and zero otherwise. We then extend the Poisson count regression models presented above by adding the interaction between the "Loss Averse" dummy and the GOAL dummy. For simplicity, we perform this empirical analysis only with participants assigned to either GOAL or GOAL+BONUS.

Table 7, Column 1 presents the results of the regression. The coefficient of the interaction term "GOAL* Loss Averse" is positive and significantly larger than that of ``Loss Averse'', which implies that loss averse participants perform better when assigned to GOAL than when assigned to GOAL+BONUS (Wald test, $\chi^2(1)$ =7.76, p<0.01). In addition, the lack of significance of the coefficient GOAL shows that participants who are not loss averse perform equally well under GOAL than under GOAL+BONUS. Figure 4(a) illustrates this result using the marginal effects of these estimates.

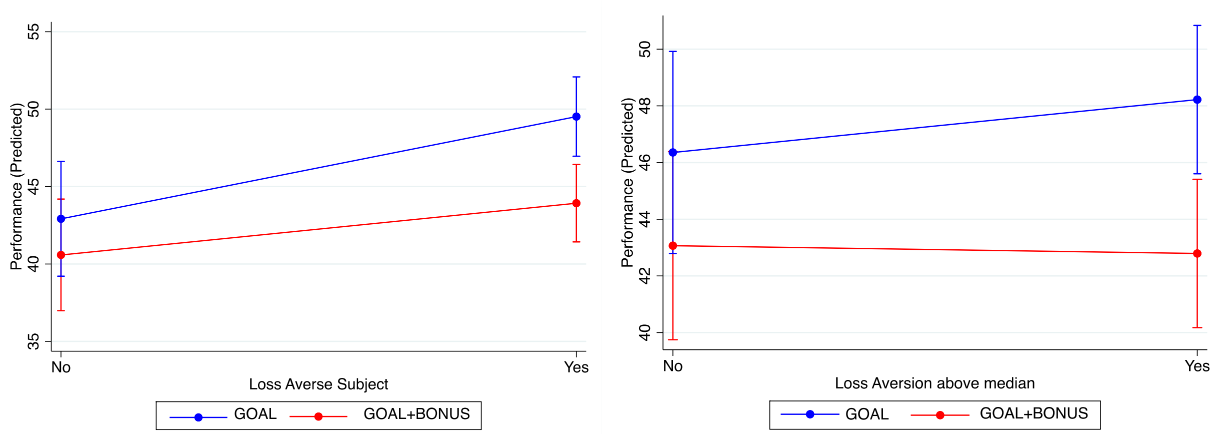
To dig further into the interaction between the levels of loss aversion and the monetary bonus, we now classify participants as being either above (High Loss Averse) or below (Low Loss Averse) the median loss aversion level (1.77). As above, we use the Poisson count regression model with the interaction term. The results are presented in Column 2 of Table 7, and the marginal effects are presented in Figure 4(b). Again, we observe that participants classified as High Loss Averse perform significantly better under GOAL than under GOAL+BONUS, while there is no significant difference in performance across treatments for participants classified as Low Loss Averse.

Table 7. Heterogeneity of Treatment Effects by Participant Loss Aversion Level

	(1)	**(2)**
	Performance	**Performance**
GOAL	0.055	0.073
	(0.063)	(0.055)
Loss Averse	0.079	
	(0.053)	
GOAL* Loss Averse	0.198***	
	(0.052)	
High Loss Averse		-0.006
		(0.050)
GOAL* High Loss Averse		0.113***
		(0.048)
Constant	3.703***	3.762***
	(0.045)	(0.039)
Log-Likelihood	-391.929	-396.641
N	80	80

Note: This table presents the estimates of a Poisson count regression of the specification $\text{Performance}_i = \beta_0 + \beta_1 \text{GOAL} * \text{Loss Averse} + \beta_2 \text{GOAL} + \beta_3 \text{LOPR} + \beta_4 \text{LOPR} + \beta_5 \text{Loss Averse} + \mathcal{E}_i$ with $\mathcal{E}_i \sim \text{Poisson}\ (\omega)$ with $\mathcal{E}_i \sim \text{Poisson}\ (\omega)$. "Performance" is the total number of correctly solved tables by a participant over all rounds. GOAL+BONUS is the benchmark category. ``Loss Averse'' is a dummy variable that captures whether a participant is loss averse or not. A participant is loss averse when at least four of her variables $\lambda_j$, where $\lambda_j \equiv x_j/z_j$, are greater than one. In the second column ``Loss Averse'' is replaced by ``High Loss averse'' which equals 1 if her average λ is greater than that of the median participant in the sample and 0 otherwise. See Appendix A for a detailed explanation of these measurements. Standard errors are in parenthesis. * indicates a p-value <0.1, ** indicates a p-value <0.05, ***indicates a p-value <0.01.

Figure 4. Treatment differences in performance by loss aversion levels.



a) With $\lambda = 1$ as threshold   b) With median λ as threshold (median split)

To complement this analysis, we also use a continuous measure of loss aversion. In that model, we allow for different slopes for loss averse relative to non-loss averse subjects. Our previous results are again confirmed: for loss averse subjects the slope in GOAL is significant and positive whereas that in GOAL+BONUS is significant and negative (p=0.004). Hence, subjects with higher loss aversion exhibit a larger performance difference between GOAL and GOAL+BONUS. These results are presented in Table B.2 in Appendix B.

Because the number of subjects who are not loss averse is small in our sample, the statistical tests presented above might be biased in favor of rejecting the null that the treatment effect is stronger among loss averse individuals. To overcome this problem, we use randomization inference. A test that has been shown to provide robust statistical inference when the treatment assignment is interacted with participant covariates (Young, 2019). We find that loss averse subjects exhibit more of a treatment effect in terms of performance under all potential assignments of the treatment (p=0.028, 500 resampling replications).

Result 3: *Performance differences between GOAL and GOAL+BONUS are more pronounced for participants with high loss aversion.*

To further test Hypothesis 3, we take goal level as a dependent variable and run models with interaction terms like those we used to establish Result 3. Table 8 presents the estimates. Participants in GOAL set higher goals than those in GOAL+BONUS, and this difference is larger when they are classified to be loss averse (Wald test, $\chi^2(1)$ =15.37, p=0.001) (Column 1 and Figure 5(a)). In another specification (Col 2-Table 8), we investigate whether the difference in goal levels between GOAL and GOAL+BONUS is greater for participants with above-median levels of loss aversion than for participants with below-median levels of loss aversion. The results in Column 2 and Figure 5 (b) confirm this hypothesis.

Table 8 also shows that loss averse individuals assigned to GOAL+BONUS do not set higher goals relative to individuals assigned to the same treatment but who do not exhibit loss aversion. Hence, the significant coefficient associated to ``Loss Averse'' in Table 5 is due to the higher goal setting of individuals with reference-dependent preferences who are assigned to GOAL. It appears that they set higher goals because they anticipate that by doing so, they will subsequently exert higher effort and achieve higher performance and earnings, as shown by Table 7.

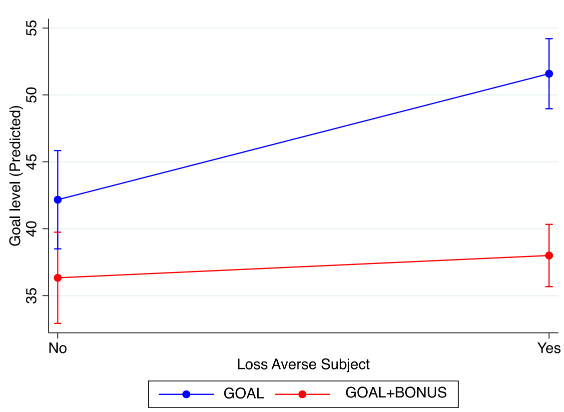
Finally, we use a continuous measure of loss aversion and estimate a model of goal setting that considers different slopes for loss averse and non-loss averse subjects. Estimates given in Appendix B, Table B.2, confirm that participants with higher loss aversion display a larger goal setting difference between GOAL and GOAL+BONUS. That is because the slope of loss averse subjects under GOAL is significant and positive and that of loss averse subjects in GOAL+BONUS is significant and negative.

Table 8. Heterogeneity of Treatment Effects by Participant Loss Aversion Level

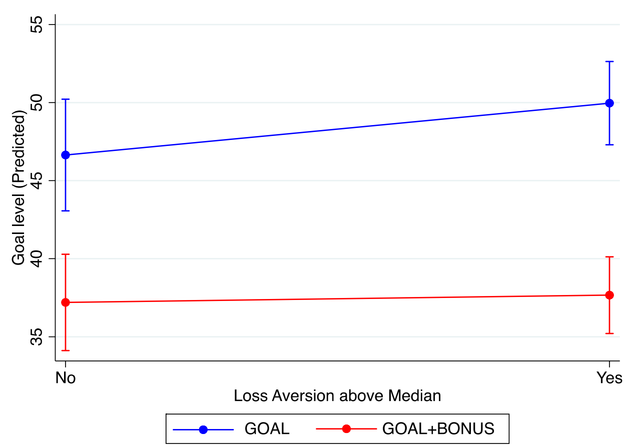
	(1)	(2)
	Goal Level	**Goal Level**
GOAL	0.148**	0.159*
	(0.065)	(0.083)
GOAL * Loss Averse	0.350***	
	(0.054)	
Loss Averse	0.045	
	(0.057)	
GOAL * High Loss Averse		0.309***
		(0.072)
High Loss Averse		0.026
		(0.075)
Constant	3.593***	3.601**
	(0.048)	(0.067)
Log-Likelihood	-467.624	-469.951
N	80	80

Note: This table presents the estimates of the Poisson regression of the specification $\text{Goal level}_i = \beta_0 + \beta_1 \text{GOAL} * \text{Loss Averse} + \beta_2 \text{GOAL} + \beta_3 \text{LOPR} + \beta_4 \text{LOPR} + \beta_5 \text{Loss Averse} + I$ with $\varepsilon_i \sim \text{Poisson}(\omega)$. "Goal level" is the sum of the goals set by the participant over all rounds. GOAL+BONUS is the benchmark category for the regression. ``Loss Averse'' is a dummy variable that captures whether a participant is loss averse or not. A participant is loss averse when at least four of her variables $\lambda_j$, where $\lambda_j \equiv x_j/z_j$, are greater than one. ``High Loss averse' equals 1 if a participant is loss averse and her average λ is greater than that of the median participant in the sample and 0 otherwise. See Appendix A for a detailed explanation of these measurements. Standard errors are in parenthesis. * indicates a p-value <0.1, ** indicates a p-value <0.05, ***indicates a p-value <0.01.

Figure 5. Treatment effects in goal setting by loss aversion levels.



a) With $\lambda = 1$ as threshold



b) With median λ as threshold

We also perform randomization inference to ensure that the finding of higher goal setting among loss averse subjects is not an artifact of the imbalance in observations between loss averse and non-loss averse groups. We find that this result emerges under all plausible assignments to the treatment (p=0.04, 500 resampling replications).

Result 4: *The difference in goal levels between GOAL and GOAL+BONUS is greater for participants with greater loss aversion.*

In Table B.6 in Appendix B, we show that Result 3 and Result 4 are robust to outliers. Moreover, Table B.7 in Appendix B shows the robustness of these results when the data are analyzed as a panel.

4. Conclusion

This paper shows that offering monetary bonuses for the achievement of self-chosen goals can backfire, and result in worse performance than would be achieved without the bonus. In a setting in which workers exhibit a sufficient degree of loss aversion, a monetary bonus for meeting a self-chosen goal can crowd out the motivational effect of the goal itself. That is because lower goals will be set to increase the likelihood of reaching the monetary bonus, which will in turn lead to lower performance. Thus, a self-chosen goal contract with no bonus attached can lead to better performance than one where achieving the goal yields a bonus. The results from our experiment confirm this prediction.

While a self-chosen goal might be desirable in settings of asymmetric information—in which the principal does not exactly know the agent's ability—, it has the problem that the agent might not internalize other relevant aspects that also determine pay in organizations. For example, these might be the organizations' own goals, or the managers' expectation about performance. A practice that could help overcome these difficulties is allowing principal and agent to negotiate the goal, i.e. participative goal setting (Anderson et al., 2010). We view our study as analyzing the limiting case in which the agent has complete bargaining power to set the goal, and the principal evaluates the best course of action in terms of setting the bonus structure. Future research should investigate the conditions under which our result holds when the agent does not have full discretion when setting the goal.

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Appendix A. Details of the Risk Attitude Classifications

In this appendix, we describe the Abdellaoui et al. (2008) method and report some additional analysis of the data from part B of the experiment.

A.1. Description of Abdellaoui et al.'s (2008) method.

Our implementation of Abdellaoui et al.'s (2008) method consisted of 10 decision sets. Each decision set was designed to elicit indifference between two initial lotteries through bisection. The algorithm was programmed so that the participant's choice between two initial lotteries determined the next choice problem that the participant faced. Specifically, in the next choice trial, either the lottery chosen in the preceding trial was replaced by a less attractive alternative, or the one not chosen was replaced by a more attractive alternative, while the other choice remained the same. The participant was again invited to choose between the two available options. This process was repeated four times.

Decision sets 1 to 5 elicited participants' utility curvature. In each decision set, the algorithm elicited the certainty equivalent x_j of a lottery of the form $Lottery_j = (H_j, 0.5; L_j, 0.5)$, with $j = 1,2,3,4,5$, and $H_j \geq L_j \geq 0$. The values of H_j and L_j used in each decision set are shown in Table 1.

Panel A of Table A.1 below details an example of the bisection algorithm used to find x_1, the certainty equivalent of L_1. Note that initially, option R is a degenerate lottery that pays the expected value of option L, which, in turn, is equal to L_1. The example shows that after having made a first choice, the participant faces a new problem whereby R, the option that was chosen before, becomes less attractive. In the remaining repetitions, the individual's preferred option is L, even though lottery R becomes more attractive. The certainty equivalent is eventually determined as x_2 =1.625, the midpoint between 1.75 and 1.5.

Decision sets 6 to 10 elicited participants' loss aversion. The program was designed to find the outcome $z_j < 0$ that made an individual indifferent between a sure outcome of zero and a mixed lottery of the form $(k_j, 0.5; z_j, 0.5)$, with $k_j > 0$ for $j = 1,2,3,4,5$. A loss averse participant would require low values of z_j to be indifferent, whereas a gain-seeking participant would require large values of z_j to be indifferent. The starting values of the program were set at the certainty equivalent of a decision set j, i.e. $k_j = x_i$, and its mirror image, that is $z_j = -x_j$.

Panel B of Table A.1 presents an example of the bisection algorithm used to find these negative outcomes. Note that in this example, the certainty equivalent elicited in Panel A, x_1 =1.625, is used as an outcome of the mixed lottery. Also note that the mirror image of x_1, -1.625, is used initially as the other outcome of the mixed lottery. The elicited value in this example, z_1 =-1.40, was the value that made the participant indifferent between the lottery $(1.625_j, 0.5; -1.40, 0.5)$ and zero.

Table A.1. Example of the Elicitation Procedure for Certainty Equivalents and Loss Aversion

	Panel A			**Panel B**		
Repetition	Lottery L	Lottery R	Choice	Lottery L	Lottery R	Choice
Initial lottery	(4,0.5;0,0.5)	2	**R**	(1.62,0.5; -1.62,0.5)	0	**R**
1	(4,0.5;0,0.5)	1	**L**	(1.62,0.5; -0.81,0.5)	0	**L**
2	(4,0.5;0,0.5)	1.5	**L**	(1.62,0.5; -1.20,0.5)	0	**L**
3	(4,0.5;0,0.5)	1.75	**L**	(1.62,0.5; -1.40,0.5)	0	**R**
Final Elicitation		$\boldsymbol{x_1}$ **=1.875**		$\boldsymbol{z_1}$ **=-1.30**		

Note: This table presents an example of Abdellaoui et al.'s (2008) algorithm used to find certainty equivalents $\{x_1, x_2, x_3, x_4, x_5\}$ and the sequence of offsetting negative numbers $\{z_1 z_2, z_3, z_4, z_5\}$. The left panel presents how x_1 is elicited with the algorithm. The right panel shows how z_1 is elicited.

A.2. Risk attitudes in the domain of gains

We begin by studying the elicited sequence $\{x_1, x_2, x_3, x_4, x_5\}$ which informs us about the risk attitudes of participants in the domain of gains. We classify each participant according to their risk attitude. To that end we compute the difference $\Delta_{ij} \equiv x_{ij} - EV_j$, where the index j indicates the lottery number, and EV_j stands for the expected value of that lottery, that is, $EV_j = 0.5H_j + 0.5L_j$. The sign of Δ_{ij} is a non-parametric measure of the risk attitude of participant i with respect to lottery j. If the participant exhibits $\Delta_{ij} > 0$, the lowest price at which she is willing to sell the lottery is larger than its expected value, denoting a risk-seeking attitude. If $\Delta_{ij} < 0$, the participant has a risk averse attitude toward that lottery. Whenever $\Delta_{ij} = 0$, the participant is risk neutral.

We perform a classification of participants based on the statistical significance of their elicited Δ_{ij}. We compute confidence intervals around zero to determine whether a Δ_{ij} is statistically relevant given the overall variation in the data. Specifically, we calculate the standard deviation of $\sum_i \Delta_{ij}$ for each lottery j, and multiply it by the factors 0.64 and -0.64. A significantly positive Δ_{ij} indicates that participant i is risk seeking with respect to lottery j, while a significantly negative Δ_{ij} indicates risk aversion. Under the assumption that the data follow a normal distribution, approximately 50% of the data must lie within this confidence interval. Furthermore, to account for response error, we classify a participant to have a risk averse attitude when at least four of her Δ_{ij}s are negative. A participant is risk seeking when at least four of her Δ_{ij}s are positive, and a participant has linear utility when at least four Δ_{ij}s are not different from zero. This is also the approach followed by Abdellaoui (2000) and Abdellaoui et al. (2008).

Table A.2 shows that, by this criterion, the majority of participants, 57%, is classified as having linear utility. A proportion test rejects the hypothesis that the fraction is 0.5, p=0.049, indicating that a significant majority has linear utility, 40% of participants are classified as having concave utility, and only five individuals (3%) as having convex utility.

The second analysis we conduct on these data assumes that the utility function of participants follows a particular functional form. We fit the certainty equivalents to these functionals to examine the participants' risk attitudes. Specifically, we assume that the utility of participants is of the power utility form, $x_{ij} = EV_j{}^{\alpha}$, which belongs to the CRRA family, or of the exponential utility form, $x_{ij} = 1 - \exp\left(-\rho EV_j\right)$, which belongs to the CARA family. We estimate the parameters of these functionals, using the non-linear least squares method, for the pooled data of all participants.

Table A.2 Classification of individuals' risk attitudes towards lotteries with gains

Lottery/Classification	Concave Utility	Convex Utility	Linear Utility
Lottery 1	60	24	77
Lottery 2	80	15	66
Lottery 3	98	16	47
Lottery 4	77	9	75
Lottery 5	100	11	50
Total num. participants	**65**	**5**	**91**

Note: This table presents the classification of individuals according to their risk attitudes in the domain of gains. Each row presents the number of participants classified as having concave, convex or linear utility, which is equivalent to saying that they are risk averse, risk seeking, or risk neutral, respectively. A participant i is classified as having concave utility for lottery j whenever the difference $\Delta_{ij} \equiv x_{ij} - EV_j < 0$. A participant i is classified as having convex utility for lottery j whenever the difference $\Delta_{ij} > 0$. A participant i is classified as having linear utility for lottery j whenever the difference Δ_{ij} is not significantly different from zero. The last row presents the number of participants classified as having concave, convex, and linear utility over all lotteries. A participant is classified to have concave utility if she displays risk averse attitudes toward at least four lotteries. A participant is classified to have convex utility if she displays risk seeking attitudes toward at least four lotteries. Having risk neutral attitudes for at least four lotteries classify a participant as having linear utility.

Table A.3 presents the estimates of the parameters. We find that the estimate $\hat{\alpha}$ is significantly less than one, though only modestly so. This implies a utility function for a representative agent that has slightly risk averse attitudes (F(1,160)=127.651, p<0.001). Similarly, we find that the estimate $\hat{\rho}$ is significantly greater than zero, though still fairly small in magnitude. This also reveals a small degree of risk aversion on the part of the representative individual (F(1,160)= 3.4e+05, p<0.001). Thus, we find that participants in aggregate display moderate risk aversion when functional forms with CARA and CRRA are estimated. This is in line with the statistical analysis of the data at the individual level, which found that the majority of participants were risk-neutral, but that there was also a share of participants more appropriately classified as risk averse.

Table A.3 Estimates of parameters of the utility function of the representative participant

Parametric form	**Coefficient**	**St. Error**	$\boldsymbol{R^2}$
$x_{ij} = EV_j^{\alpha}$	$\alpha =$.9480115	.0048	0.946
$x_{ij} = \dfrac{1 - \exp\left(-\rho EV_j\right)}{\rho}$	$\rho =$. 01854	.0016	0.942

A.3 Loss aversion

Next, we analyze the sequence of negative outcomes $\{z_1, z_2, z_3, z_4, z_5\}$ that made the participants indifferent between receiving zero for sure and a lottery consisting of $(z_j, 0.5; x_j, 0.5)$, where x_j was an elicited certainty equivalent of one of the lotteries containing only positive outcomes. The analysis of these data reveals the degree of a participant's loss aversion. The measure of loss aversion is the coefficient $\lambda_j \equiv x_j/z_j$. When the λ_i coefficient takes the value of one, the participant is indifferent between accepting and declining a lottery that consists of a gain and a loss of equal magnitude, each occurring with probability 0.5, and thus the participant exhibits no loss aversion or gain seeking. If the coefficient λ_i takes on a value larger than one, it indicates the presence of loss aversion.

We first analyze the loss aversion coefficients at the individual level. A participant is classified as loss averse when at least four (out of five) of her loss aversion coefficients satisfy $\lambda_i > 1$. A participant is classified as gain-seeking when at least four (out of five) of her loss aversion coefficients have $\lambda_i < 1$. Finally, a participant is classified as having mixed attitudes toward losses if she cannot be classified as either loss averse or gain seeking. Table B.4 shows that the large majority of participants is loss averse. Specifically, 72% of participants are classified as loss averse and 14% as gain-seeking.

Table A.4 Individuals classified as loss averse for each x_j

Classification	**Loss Averse**	**Gain-Seeking**	**Mixed**
Lottery 6	106	55	-
Lottery 7	125	36	-
Lottery 8	128	33	-
Lottery 9	128	33	-
Lottery 10	124	37	-
Total	**117**	**23**	**21**
Average	**134**	**27**	**0**

We also perform a second analysis of these data featuring the average of the loss aversion coefficient that an individual exhibits over all five lotteries. The last row in Table A.4 shows that according to this analysis, 134 participants, or 85% of participants, are loss averse, and the remaining 27 participants are gain-seeking. Thus, both analyses conclude that the great majority of the participants is loss averse.

Appendix B. Additional Tables and Analyses

Table B.1 Descriptive statistics of goals set by round in the GOAL+BONUS and GOAL treatments

	round 1	round 2	round 3	round 4	round 5	round 6
GOAL+BONUS						
Mean	6.076	5.948	6.179	6.205	6.461	6.615
Median	6	5	6	6	6.5	6
S.D.	2.056	1.986	2.186	2.142	1.889	2.034
GOAL						
Mean	8.658	8.024	7.902	8	7.829	8.414
Median	7	7	7	8	7	8
S.D.	5.803	4.470	4.409	4.494	4.510	4.460

Table B.2 Effect of treatment and continuous loss aversion level

	(1)	(2)
	Performance	**Goal Level**
GOAL* Loss Aversion	0.018***	0.025***
	(0.007)	(0.006)
GOAL* No Loss aversion	-0.243	-0.350***
	(0.182)	(0.191)
Loss Aversion	-0.012***	-0.013**
	(0.005)	(0.005)
No Loss Aversion	0.207	0.349**
	(0.1548)	(0.163)
Constant	3.825***	3.780***
	(0.021)	(0.022)
Log-Likelihood	-396.611	-496.029
N	80	80

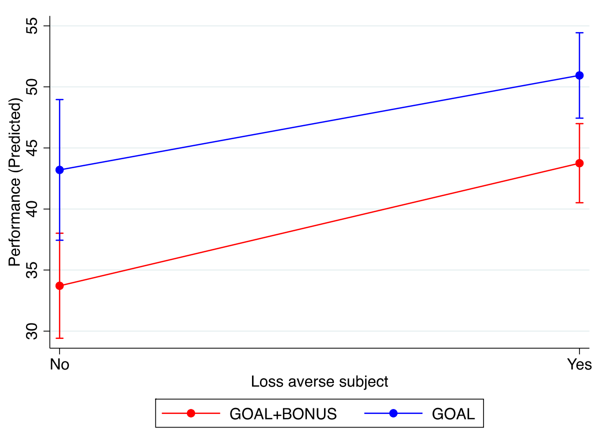
Note: This table presents the estimates of a Poisson count regression of the specification $\text{Performance}_i = \beta_0 + \beta_1 \text{GOAL} * \text{Loss Aversion} + \beta_2 \text{GOAL} * \text{No Loss Aversion} + \beta_3 \text{Loss Aversion} + \beta_4 \text{ No Loss Aversion} + \mathcal{E}_i$ with $\mathcal{E}_i \sim \text{Poisson}\ (\omega)$, as well as the Poisson regression of the statistical model $\text{Goal level}_i = \beta_0 + \beta_1 \text{GOAL} * \text{Loss Aversion} + \beta_2 \text{GOAL} * \text{No Loss Aversion} + \beta_3 \text{Loss Aversion} + \beta_4 \text{ No Loss Aversion} + \mathcal{E}_i$ with $\mathcal{E}_i \sim \text{Poisson}\ (\omega)$. "Performance" is the number of tables a participant correctly solves over all rounds and "Goal setting" the sum of the goals set by the participant over all rounds. Participants were assigned either to the GOAL or GOAL+BONUS treatment, where the latter is the benchmark category for the regression. ``Loss Aversion'' is a variable constructed as $\max(\lambda_i - 1, 0)$ and ``No Loss Aversion'' is a variable constructed as defined as $\min(\lambda_i - 1, 0)$ Standard errors are in parenthesis. * indicates a p-value <0.1, ** indicates a p-value <0.05, ***indicates a p-value <0.01.

Table B.3 Effect of treatment and loss aversion on performance and goals for participants with linear utility only

	(1) **Performance**	(2) **Performance**	(3) **Goal Level**	(4) **Goal Level**
GOAL* Loss Averse	0.412^{***}		0.559^{***}	
	(0.073)		(0.073)	
GOAL* High Loss Averse		0.213^{***}		0.476^{***}
		(0.061)		(0.062)
Loss Averse	0.260^{***}		0.134^{*}	
	(0.075)		(0.077)	
High Loss Averse		0.067		0.094
		(0.065)		(0.069)
GOAL	0.247^{*}	0.241^{***}	0.218^{***}	0.373^{***}
	(0.094)	(0.071)	(0.095)	(0.073)
Constant	3.517^{***}	3.670^{***}	3.505^{***}	3.550^{***}
	(0.065)	(0.048)	(0.065)	(0.051)
Log-Likelihood	-203.44	-437.376	-278.999	-288.899
N	44	44	44	44

Note: This table presents the estimates of the Poisson regression of the specification $\text{Performance}_i = \beta_0 + \beta_1\text{GOAL} * \text{Loss Averse} + \beta_2\text{GOAL} + \beta_3\text{LOPR} + \beta_4\text{LOPR} + \beta_5\text{Loss Averse} + \varepsilon_i$ with $\varepsilon_i \sim \text{Poisson}\ (\omega)$, as well as the Poisson regression of the statistical model $\text{Goal level}_i = \beta_0 + \beta_1\text{GOAL} * \text{Loss Averse} + \beta_2\text{GOAL} + \beta_3\text{LOPR} + \beta_4\text{LOPR} + \beta_5\text{Loss Averse} + \varepsilon_i$ with $\varepsilon_i \sim \text{Poisson}\ (\omega)$. "Performance" is the total number of tables a participant solves correctly over all rounds and "Goal setting" is the sum of the goals set by the participant over all rounds. Participants were assigned either to the GOAL or GOAL+BONUS treatment. GOAL+BONUS is the benchmark category for the regression. ``Loss Averse'' is a dummy variable that captures whether a participant is loss averse or not. A participant is loss averse when at least four variables $\lambda_j$, where $\lambda_j \equiv x_j/z_j$, are greater than one, ``High Loss averse' equals 1 if a participant is loss averse and her average λ is lower than the median participant in the sample and 0 otherwise. All models include only participants classified as having linear utility. Standard errors presented in parenthesis. * indicates a p-value <0.1, ** indicates a p-value <0.05, ***indicates a p-value <0.01.

Figure B.1 Effect of treatment and loss aversion on performance and goals for participants with linear utility only



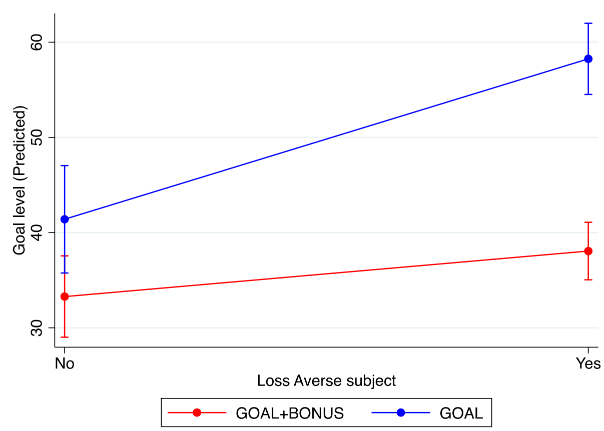


Table B.4 Effect of treatment and loss aversion terciles on performance and goals

	(1)	(2)
	Performance	**Goal Level**
GOAL* Loss Aversion Highest tercile	0.123^{**}	0.366^{***}
	(0.070)	(0.074)
GOAL* Loss Aversion Middle tercile	0.170^{**}	0.242^{***}
	(0.075)	(0.061)
GOAL* Loss Aversion Lowest tercile	0.058	0.159^{*}
	(0.078)	(0.082)
Loss Aversion Highest tercile	0.010	0.032
	(0.074)	(0.032)
Loss Aversion Middle tercile	0.028	0.020
	(0.072)	(0.077)
Constant	3.741^{***}	3.601^{***}
	(0.062)	(0.067)
Log-Likelihood	-395.325	-468.352
N	80	80

Note: This table presents the estimates of the Poisson regression of the specification $\text{Performance}_i = \beta_0 + \beta_1 \text{GOAL} * \text{Loss Averse} + \beta_2 \text{GOAL} + \beta_5 \text{Loss Averse} + \varepsilon_i$ with $\varepsilon_i \sim \text{Poisson}(\omega)$, as well as the Poisson regression of the statistical model $\text{Goal level}_i = \beta_0 + \beta_1 \text{GOAL} * \text{Loss Averse} + \beta_2 \text{GOAL} + \beta_5 \text{Loss Averse} + \varepsilon_i$ with $\varepsilon_i \sim \text{Poisson}(\omega)$. "Performance" is the number of tables a participant correctly solves over all rounds and "Goal setting" the sum of the goals set by the participant over all rounds. Participants were assigned either to the GOAL or GOAL+BONUS treatment, where the latter is the benchmark category for the regression. ``Loss Averse'' is a dummy variable that indicates whether a participant is loss averse or not. A participant is loss averse when at least four of her λ_j, where $\lambda_j \equiv x_j/z_j$, are greater than one. ` Standard errors are in parenthesis. * indicates a p-value <0.1, ** indicates a p-value <0.05, ***indicates a p-value <0.01.

Figure B.2 Effect of treatment and loss aversion terciles on performance and goals

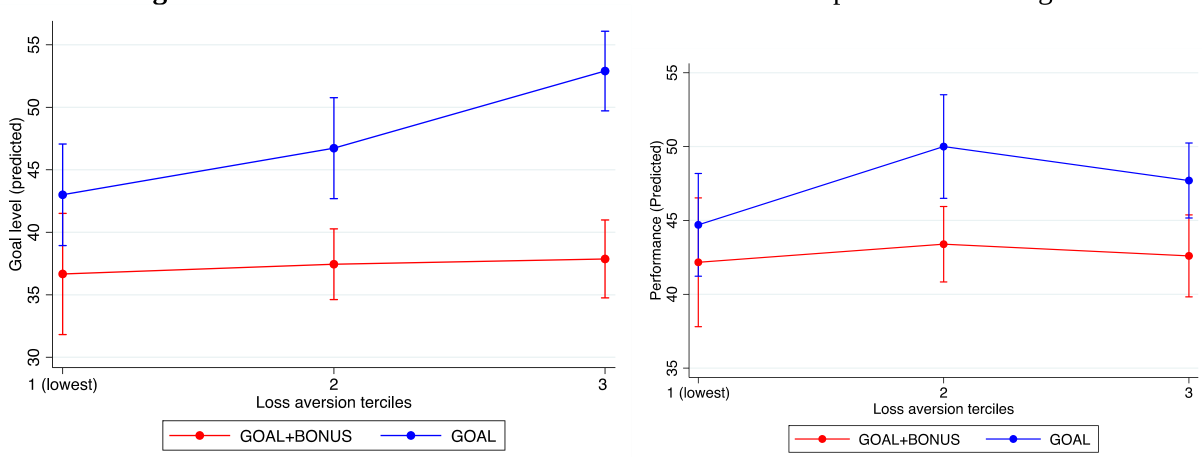


Table B.5 Analyses without the top 5 highest performers.

	(1) **Performance**	(2) **Goal Level**	(3) **Performance**	(4) **Goal Level**
GOAL	0.073^{***}	0.258^{***}	0.055	0.073^{**}
	(0.034)	(0.035)	(0.063)	(0.055)
Loss Averse	0.060	0.104	0.047	0.018
	(0.037)	(0.038)	(0.054)	(0.057)
GOAL* Loss Averse			0.128^{***}	0.322^{***}
			(0.053)	(0.055)
Constant	3.694^{***}	3.532^{***}	3.703^{***}	3.592^{***}
	(0.036)	(0.038)	(0.045)	(0.047)
Log-Likelihood	-341.753	-433.105	-341.696	-431.12
N	76	76	76	76

Note: This table presents the estimates of the Poisson regression of the specification $\text{Performance}_i = \beta_0 + \beta_1 \text{GOAL} * \text{Loss Averse} + \beta_2 \text{GOAL} + \beta_3 \text{Loss Averse} + \varepsilon_i$ with $\varepsilon_i \sim \text{Poisson}(\omega)$, as well as the Poisson regression of the statistical model $\text{Goal level}_i = \beta_0 + \beta_1 \text{GOAL} * \text{Loss Averse} + \beta_2 \text{GOAL} + \beta_3 \text{Loss Averse} + \varepsilon_i$ with $\varepsilon_i \sim \text{Poisson}(\omega)$. "Performance" is the total number of tables a participant solves correctly over all rounds and "Goal setting" is the sum of the goals set by the participant over all rounds. Participants were assigned either to the GOAL or GOAL+BONUS treatment and were not included as the top 5 highest performers. GOAL+BONUS is the benchmark category for the regression. ``Loss Averse'' is a dummy variable that captures whether a participant is loss averse or not. A participant is loss averse when at least four variables λ_j, where $\lambda_j \equiv x_j/z_j$, are greater than one. Standard errors presented in parenthesis. * indicates a p-value <0.1, ** indicates a p-value <0.05, ***indicates a p-value <0.01.

Table B.6 Analyses without the top 10 highest performers.

	(1) **Performance**	(2) **Goal Level**	(3) **Performance**	(4) **Goal Level**
GOAL	0.085^{***}	0.290^{***}	0.189	0.266^{**}
	(0.036)	(0.037)	(0.061)	(0.071)
Loss Averse	0.102	0.155	0.198	0.135
	(0.040)	(0.040)	(0.069)	(0.064)
GOAL* Loss Averse			0.231^{***}	0.435^{***}
			(0.061)	(0.062)
Constant	3.626^{***}	3.460^{***}	3.561^{***}	3.475^{***}
	(0.039)	(0.041)	(0.053)	(0.055)
Log-Likelihood	-341.753	-406.637	-301.532	-406.559
N	72	72	72	72

Note: This table presents the estimates of the Poisson regression of the specification $\text{Performance}_i = \beta_0 + \beta_1 \text{GOAL} * \text{Loss Averse} + \beta_2 \text{GOAL} + \beta_3 \text{Loss Averse} + \varepsilon_i$ with $\varepsilon_i \sim \text{Poisson}(\omega)$, as well as the Poisson regression of the statistical model $\text{Goal level}_i = \beta_0 + \beta_1 \text{GOAL} * \text{Loss Averse} + \beta_2 \text{GOAL} + \beta_3 \text{Loss Averse} + \varepsilon_i$ with $\varepsilon_i \sim \text{Poisson}(\omega)$. "Performance" is the total number of tables a participant solves correctly over all rounds and "Goal setting" is the sum of the goals set by the participant over all rounds. Participants were assigned either to the GOAL or GOAL+BONUS treatment. GOAL+BONUS is the benchmark category for the regression. ``Loss Averse'' is a dummy variable that captures whether a participant is loss averse or not. A participant is loss averse when at least four variables λ_j, where $\lambda_j \equiv x_j/z_j$, are greater than one. Standard errors presented in parenthesis. * indicates a p-value <0.1, ** indicates a p-value <0.05, ***indicates a p-value <0.01.

Table B.7 Analyses using a panel data structure

	(1)	(2)	(3)	(4)
	Performance	**Goal Level**	**Performance**	**Goal Level**
GOAL	0.085**	0.301***	0.055	0.148
	(0.036)	(0.081)	(0.126)	(0.140)
Loss Averse	-.0200	0.052	0.079	0.044
	(0.090)	(0.088)	(0.107)	(0.119)
GOAL* Loss Averse			0 198*	0.350***
			(0.106)	(0.118)
Constant	1.981***	3.587***	1.911***	3.592***
	(0.087)	(0.084)	(0.089)	(0.099)
Log-Likelihood	-1159.299	-1533.516	-1104.616	-1505.19
N	480	480	480	480

Note: This table presents the estimates of the Random Effects Poisson regression of the model $\text{Performance}_{it} = \beta_0 + \beta_1 \text{GOAL} * \text{Loss Averse} + \beta_2 \text{GOAL} + \beta_3 \text{Loss Averse} + \mathcal{E}_{it}$ with $\mathcal{E}_{it} \sim \text{Poisson}\ (\omega)$, as well as the Random Effects Poisson regression of the statistical model $\text{Goal level}_{it} = \beta_0 + \beta_1 \text{GOAL} * \text{Loss Averse} + \beta_2 \text{GOAL} + \beta_3 \text{Loss Averse} + \mathcal{E}_{i}$ with $\mathcal{E}_{i}\text{t} \sim \text{Poisson}\ (\omega)$. "Performance" is the total number of tables a participant solves correctly in a round and "Goal setting" is the goals set by the participant in a round. Participants were assigned either to the GOAL or GOAL+BONUS treatment. GOAL+BONUS is the benchmark category for the regression. ``Loss Averse'' is a dummy variable that captures whether a participant is loss averse or not. A participant is loss averse when at least four variables λ_j, where $\lambda_j \equiv x_j/z_j$, are greater than one. Standard errors presented in parenthesis. * indicates a p-value <0.1, ** indicates a p-value <0.05, ***indicates a p-value <0.01.

Appendix C. Experimental Instructions

C.1 Welcome

This is an experiment in the economics of decision-making. The instructions are simple and if you follow them and make good decisions, you might earn a considerable amount of money, which will be paid to you at the end of the experiment. The amount of payment you receive depends on your decisions, your effort, and partly on luck. The currency used throughout the experiment is Dollars.

Once the experiment has started, no one is allowed to talk to anybody other than the experimenter. Anyone who violates this rule will lose his or her right to participate in this experiment. If you have further questions when reading these instructions please do not hesitate to raise your hand and formulate the question to the experimenter.

The experiment consists of two parts. A **counting task** part and a **decision-making** part. Both tasks will count towards your final earnings.

C.2 Part A: Counting task

-Initial Screen

This part of the experiment consists of a sequence of **6 rounds** of **5 minutes** each. In each round you need to complete as many tasks as possible. A task is completed when you count the correct number of zeros in a table that contains 100 zeros and ones.

As soon as you know the correct number of zeros contained in a table, you have to input your answer using the keyboard. Once you have entered the number, click "Next". Immediately afterwards a new table will be displayed and, again, you have to count the number of zeros in this new table. This procedure is repeated until the time is up. A timer is displayed in the upper part of your screen. After each round is over you receive feedback about your performance in that round.

Counting Tips: Of course you can count the zeros in any way you want. Speaking from experience, however, it is helpful to always count two zeros at once and multiply the resulting number by two at the end. In addition, you miscount less frequently if you track the number you are currently counting with the mouse cursor.

you will see an example when you press "Next".

(example is displayed after subject clicks “Next”)

-Payments Screen

(LOPR treatment)

For each correct task that you complete you receive 0.20 Dollars, but if your answer was wrong you receive nothing.

The formula we use to calculate your earnings is Earnings = # correct tasks * 0.20 Dollars.

(HIPR treatment)

For each correct task that you complete you receive 0.50 Dollars, but if your answer was wrong you receive nothing.

The formula we use to calculate your earnings is Earnings = # correct tasks * 0.50 Dollars.

(GOAL treatment)

For each correct task that you complete you receive 0.20 Dollars, but if your answer was wrong you receive nothing.

Goal: At the beginning of each round you will be asked to set a goal in terms of the number of tables you aim at solving correctly in that specific round. Provide this target at this best ability, we would like to see how accurate is your prediction.

The formula we use to calculate your earnings is Earnings = # correct tasks * 0.20 Dollars

(GOAL+BONUS treatment)

For each correct task that you complete you receive 0.20 Dollars, but if your answer was wrong you receive nothing.

Goal: At the beginning of each round you will be asked to set a goal in terms of the number of tables you aim at solving correctly in that specific round. If you achieve your goal or you surpass it, you will be paid an additional bonus. The bonus is larger the large the goal is set. If your goal is high and you achieve it or surpass you will be given a high monetary reward. But, if your goal is low and you accomplish it or surpass it you will be given a low monetary reward. Also be aware that if you set a very high goal and you cannot accomplish it you will get no bonus.

The formula we use to calculate your earnings is Earnings = # correct tasks * 0.20 Dollars + goal* 0.20 Dollars (if the goal is achieved)**.**

Are you ready to start now? As soon as you press "Next" the task will start.

-Screen for eliciting goals at the beginning of each round (Only for GOAL and GOAL+BONUS).

Now, set your goal for the next round of five minutes: How many tables you aim at counting correctly?

-Screen of feedback after each round

(All treatments)

Number of correct tasks in this round: (number of correct tasks here).

Earnings from the number of correct tasks completed in this round: (earnings according to treatment here).

(for GOAL+BONUS)

Bonus for the achievement of your goal: (bonus, if applicable, here).

(All treatments)

Your total earnings for this round are: **(total earnings for previous round, here)**

C.3 Part B: decision-making part

-Initial Screen

In the following, you will face a series of decisions. Your task in each decision is to choose among two possible alternatives. Your earnings on this part of the experiment depend on your choices.

You will be faced with 10 decision sets. Each decision set contains several choices. In each of decision you need to choose between the option R, that delivers a sure amount of money, and the option L that results in one of two different monetary amounts.

Note that in each decision set you need to choose between L and R multiple times. But, you need to be careful since the offered amounts of money could change from one decision to the next.

you will see an example when you press "Next"

-Payments Screen

At the end of this part of the experiment **one** randomly chosen decision will be played and paid. Hence, a random number chosen by the program will be drawn to determine which decision counts towards your earnings.

This means that each choice that you make might be chosen and paid.
If it is clear what you have to do in this part of the experiment, press "Next" to start.

C.4 Exit Questionnaire.

This is the last part of the experiment. Please answer the following questions at your best ability.

Enter the computer (Letter plus digit) you are at.
Enter your age.
What is the program you are studying?
Enter your gender.
Male Female
What is your nationality?