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The Dark Side of Monetary Bonuses:
Theory and Experimental Evidence

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The Dark Side of Monetary Bonuses:
Theory and Experimental Evidence[*]

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Abstract

To incentivize workers and boost performance, firms often offer monetary bonuses for the achievement of production goals. Such bonuses appeal to two types of motivations of the worker. On the one hand, the existence of a goal, on its own, triggers an *intrinsic* motivation associated with the desire to not fall short of the goal. On the other hand, the money paid to achieve the goal constitutes an *extrinsic* motivation. This paper studies the possibility that these two effects are substitutes when workers set their own goals. We develop a theoretical model that predicts that if the worker is sufficiently loss averse and faces uncertainty about reaching a production goal, offering a monetary payment contingent on reaching such a goal is counterproductive. This is because under the presence of monetary bonuses, the loss averse worker prefers setting lower goals, which yield lower but more likely bonus payments. Lower goals, in turn, negatively affect subsequent performance. Results from a laboratory experiment corroborate this prediction. This paper highlights the limits of monetary bonuses as an effective incentive when workers are loss averse.

JEL Codes: J41, D90, C91, D81
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1. Introduction

Offering monetary bonuses for the achievement of milestones is a widespread practice used by firms to incentivize workers and company executives. According to Worldatwork (2018), close to 98% of publicly traded American companies use at least one compensation scheme that includes bonuses, and 73% of these companies report that these bonuses are given when an individual or organizational goal is reached. The rationale behind including bonuses in compensation packages is that the additional monetary incentives created by the bonus boost performance, as long as standard assumptions on the worker's preferences and cost of effort hold (Gibbons & Roberts, 2013).

There is also ample empirical evidence from psychology showing that setting a challenging, but attainable, goal can lead to greater effort exertion, stronger attention, and higher endurance in physically and cognitively demanding tasks (Heath et al.,1999; Wu et al., 2008). This is because the goal attains the status of a reference point, making the loss averse worker exert great effort to avoid experiencing the losses in utility that would result from falling short of the goal (Heath et al.,1999). Additionally, economists have shown that fully informed principals can take advantage of this feature by including performance goals in workers' contracts (Corgnet et al., 2018; Corgnet et al., 2015; Gómez-Miñambres, 2012). If this intrinsic motivation to achieve a goal is sufficiently strong, monetary bonuses for goal achievement may not provide an additional incentive, and money spent in this manner would be wasteful expenditure for an employer.

We consider an environment in which workers can set their own goals, rather than having them specified by an employer or another party. Allowing the worker to set own goals is particularly convenient when the principal knows less about workers' potential performance than the worker herself, and also in settings where there is potential heterogeneity regarding workers' ability in the task, but it is inappropriate or illegal for the employer to impose different contracts on different workers. Moreover, evidence shows that workers who set their own target feel they have more control over outcomes, and feel more involved with the firm (Groen et al., 2012).[1]

It is not clear, however, whether the achievement of a self-chosen goal should be monetarily rewarded. On one hand, offering higher monetary bonuses contingent on the achievement of more challenging production goals can incentivize accurate goal setting,

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[1] Setting one's own goal is also common outside the workplace. Fitness apps allow the user to set her own target for minutes exercised or steps walked each day. Many banks offer a calculator in which the account holder sets a savings goal and the amount that has to be saved each month is calculated for them. Apps such as Goals-on-Track and Lifetick permit the user to set their goals in a variety of areas and to track their progress.

which guarantees that workers self-select into a contract that benefits both herself and the principal (Laffont & Tirole, 1993; Myerson, 1981; Green & Laffont, 1977).[2] On the other hand, if the monetary bonus does not yield enough additional benefit to the principal than a goal with no monetary bonus, the employer will be better off not including a monetary component. This is a distinct possibility in view of the literature showing that offering monetary incentives can be counterproductive since they can crowd-out sources of intrinsic motivation (Gneezy et al., 2011; Ariely et al., 2009a; Ariely et al., 2009b, Gneezy & Rustichini, 2000).

This paper aims to understand, using both theoretical and experimental methods, whether, and under which conditions, offering a monetary bonus for the achievement of a self-chosen goal crowds out the motivational benefits of goal setting. To study this question, we develop a theoretical model and test its predictions in a laboratory experiment. The main result of the paper, supported both by theoretical reasoning and the experimental data, is the following: when workers have reference-dependent preferences and do not have complete information about their own ability, offering monetary bonuses for the achievement of self-chosen goals can yield lower performance compared to a situation where bonuses are not offered. This is because a worker facing monetary bonuses will set more conservative goals to increase her chances of obtaining the bonus. These lower goals are less challenging and impair performance relative to goals where no money is involved. Workers with greater loss-aversion, that is, who are more sensitive to the losses associated with not attaining the bonus, set lower goals and exhibit a steeper decrease in performance. In contrast, workers with standard preferences, that is, those who do not weight psychological losses heavily, do not exhibit such effects.

We design a laboratory experiment to test our model's predictions. In the experiment, subjects have to complete a task that requires effort and attention. To incentivize subjects, we use four different contracts assigned at random across subjects. 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 baseline treatment is a low-powered price rate contract, called LOPR. A second treatment is a high-powered piece rate contract, HIPR. Comparing the LOPR and HIPR conditions can indicate how much more (or less) performance one can get from increasing the piece rate, and whether it is worth the extra expenditure imposed by the higher piece rate. The third treatment, GOAL+BONUS, is a contract in which the low-powered piece rate is complemented with a self-chosen goal that yields a monetary bonus in the event that the goal is achieved. Comparing

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[2] Indeed, self-chosen goals contracts have been shown to be more cost-effective than pure piece rate contracts, both in the field (Groen et al., 2015; Brookins et al., 2017) and in the laboratory (Dalton et al., 2016a). Due to its many desirable features, firms are increasingly using this practice (Groen et al., 2012, Bourne et all., 2013).

GOAL+BONUS to LOPR provides a measure of whether there is sufficient improvement in performance from adding a self-chosen GOAL to more than offset the bonuses that are paid. The final contract, GOAL, adds a self-chosen goal without any monetary bonus to the low piece rate. This contract represents no extra expenditure on the part of the employer, and has the possibility of inducing better performance at the least cost. Our model predicts that if individuals are sufficiently loss averse, GOAL would yield better performance than GOAL+BONUS. If this turns out to be the case, GOAL would dominate GOAL + BONUS because it would involve lower employer expenditure for higher output.

Since our theoretical predictions greatly depend on the extent of individuals' loss aversion, and because goal setting can also depend on subjects' curvature of the utility function, we elicit subjects' risk and loss attitudes. We implement the parameter-free elicitation method developed by Abdellaoui et al. (2008). This elicitation method has the advantage that it allows elicitation of the curvature of subjects' utility functions, as well as of their degree of loss-aversion, while accounting for the possibility that subjects might exhibit probability weighting (Abdellaoui, 2000; Gonzalez & Wu, 1999; Tversky & Kahneman, 1992).

The experimental data confirm the main prediction of the model: subjects assigned to the GOAL treatment set more ambitious goals than those assigned to GOAL+BONUS and exhibit higher performance than subjects assigned to any of the other three contracts. Specifically, a non-paid goal contract leads to 11% more output, an increase in performance of 0.36 standard deviations, over a paid goal contract. Moreover, as predicted by the model, we find that performance of loss averse subjects in particular is greater when goals are not rewarded monetarily. In addition, we find that loss aversion is a relevant determinant of goal setting, while concavity of the utility function is not. Finally, we observe that performance under non-paid goals is 8% higher than performance under the piece rate contract that offers the same linear monetary incentives without goals. We conclude that a GOAL contract with no monetary incentives is the cheapest way to improve performance among the contracts we study.

This paper relates to several strands of literature. First, it adds to the literature on incentives and contracting (Gibbons & Roberts, 2013; Laffont & Martimort, 2002; Laffont & Tirole, 1993). We show that offering monetary bonuses can be counterproductive when they are linked to a production goal that is set by the workers. This goes against standard theories of incentives and constitutes a proof of principle that in certain environments, offering monetary incentives could inhibit psychological motives that would otherwise stimulate effort.

Second, our paper contributes to the emerging literature on goal setting in economics (Wu et al., 2008; Gómez-Miñambres, 2012; Corgnet et al., 2015; Dalton et al. 2016a, Kaur et al. 2015, Brookins et al., 2017, Hsiaw, 2018; Koch & Nafziger, 2011, 2019). We propose a model of self-chosen goals in which workers have reference-dependent preferences with the goal as the reference point, as is common in the literature. We depart from the existing literature in two fundamental ways. First, we do not assume dynamic inconsistency as in Hsiaw (2013), Kaur et al. (2015), Hsiaw (2018) and Koch & Nafziger (2011; 2019). Second, we relax the assumption of certainty about reaching the goal as assumed by Wu et al. (2008), Corgnet et al. (2015), and Dalton et al. (2016a, 2016b). In a setting with certainty, the property of diminishing sensitivity is necessary to make effort increase with goals.[3] We show that when the worker faces uncertainty about reaching a goal, loss aversion alone motivates higher effort. This motivational aspect of loss aversion was highlighted in early work by Heath et al. (1999, p. 85): *"people who are below their goal by x units will perceive their current performance as a loss relative to their goal; thus they will work harder to increase their performance by a given increment than people who are above their goal by x units"*. Thus, our model captures the idea of loss aversion as a motivating device.

In addition, including uncertainty about reaching a self-chosen goal yields the novel and perhaps counterintuitive prediction that adding monetary bonuses for the achievement of a goal may lead to lower performance. This occurs because in our setting, the level of goal that is chosen determines how likely it is that the agent receives the bonus, with less ambitious goals more likely to be achieved. Hence, there is a trade-off based on the likelihood of reaching the goal, the monetary payment if reached and the psychological loss if not reached.

This paper also contributes to the goal-setting literature as it is, to our knowledge, the first to quantify loss aversion and utility curvature parameters elicited in an incentive compatible way to study its association with goal-setting, monetary incentives, and individual performance. Eliciting these preference parameters allows us to empirically validate the mechanisms of the model.

Finally, this paper contributes to the literature that examines how extrinsic incentives crowd-out intrinsic incentives (see Gneezy et al., 2011 and Bowles & Polanía-Reyes, 2012 for reviews and Benabou & Tirole, 2003, for a theoretical framework). In this literature, crowding-out effects appear when monetary incentives inhibit individuals from signaling to others, or even themselves, a favorable attribute such as intelligence (Ariely, et al., 2009b), pro-sociality (Ariely et al., 2009a; Mellstrom & Johannesson, 2016) or norm-

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[3] Kahneman and Tversky (1979) refer to the property that the value function is convex over losses and concave over gains as *diminishing sensitivity*.

conforming behavior (Frey & Oberholzer-Gee, 1997; Gneezy & Rustichini, 2000). We demonstrate the existence of a crowding-out effect through a completely different channel: intrinsic incentives that stem from individual preferences, such as loss aversion, can be offset by the presence of monetary incentives.

Similarly, some work in behavioral and experimental economics has shown that stronger monetary incentives could induce lower labor supply if workers have reference-dependent preferences (Crawford & Meng, 2011; Farber, 2008; Fehr & Goette, 2007; Camerer et al., 2002;). While our findings are similar, our suggested mechanism is fundamentally different in at least two aspects. First, in our setup, it is a self-chosen goal rather than expected earnings which act as the reference point. Second, we show that the crowding-out effect goes beyond offering higher-powered monetary incentives and instead stems from the interaction between goal setting and loss aversion.

2. Theoretical Framework

2.1. The Model[4]

Consider a worker who chooses to deliver a level of output $0 \leq y \leq 1$. The worker experiences disutility from producing output. We assume that this disutility is captured by the cost function $c(y, \theta)$ with the following functional form:

Assumption 1 *(Cost of output):* $c(y, \theta) = (1 - \theta)\frac{y^2}{2}$.

The parameter $0 < \theta < 1$ captures the worker's ability on the task. The higher her ability is, the lower is her associated cost of producing output. We assume that this parameter is unknown to the worker. Instead, she knows the distribution from which is drawn.[5] Specifically, we assume that this parameter is drawn from a uniform distribution that is normalized to the [0,1] interval.

Assumption 2 *(Distribution of the ability parameter):* $\theta \sim unif[0,1]$.

This assumption holds in a variety of settings. Examples include situations where workers face new tasks, or where learning about own abilities fully is not possible, either because

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[4] The proofs of all results of the model are in Appendix A.
[5] In Dalton et al. (2016a), we present a model in which the worker knows θ. The predictions of that model differ greatly from the model presented in this paper. In Proposition 2, Dalton et al. (2016a) show that when the worker knows her ability, she sets a goal ensuring that she ends up in the domain of gains and increases performance with respect to the bonus associated with reaching her self-chosen goal.

it is not in the interest of the principal to give reliable feedback (Benabou & Tirole, 2003) or because unfavorable feedback is not assimilated by the individual in order to maintain a degree of confidence that is effort-enhancing (Benabou & Tirole, 2002). Furthermore, even if reliable feedback was provided, empirical evidence shows that individuals find it difficult to estimate their own skills and may fail to update their beliefs in an unbiased way (Eil and Rao, 2011; Mobius et al., 2015 and Gonzalez-Jimenez, 2019). A manifestation of such bias in belief updating is the existence of systematic overconfidence or underconfidence (Benoit et al, 2015; Grossman and Owens, 2012 and Clark & Friesen, 2008) which reveals imperfect knowledge of own ability.

We assume that performing the task yields pecuniary benefits to the worker, which translate into utility gains. The monetary incentives are determined by the contract that the principal offers. We begin by analyzing a case, in which the principal offers a piece-rate contract, $w(y, \alpha) = ay$. The contract $w(y, \alpha)$ has the property of offering constant marginal incentives, which guarantees that the worker receives the amount $0 < \epsilon a \leq \frac{1}{2}$ when the she decides to increase her output supply on $0 < \epsilon < 1$, irrespective of how much output she may have already delivered. As described in Section 4, this type of one-dimensional piece rate contract is in effect in two of the treatments of our experiment, LOPR and HIPR.

When offered this contract, the utility of the worker is:

$$E\big(U(y)\big) = \int_0^1 ay - (1 - \theta)\frac{y^2}{2} \, f(\theta)d\theta = ay - \frac{y^2}{4}. \qquad (1)$$

The last equality uses the fact that $\int_0^1 \theta f(\theta)d\theta = \frac{1}{2}$, the worker's expectation about her ability on the task under the assumption that $f(\theta)$ is a uniform distribution on $[0,1]$. In addition, an assumption made in equation (2) is that the monetary incentives enter into the worker's utility linearly. This assumption captures the notion that individuals facing small monetary amounts do not exhibit curvature in their utility functions (see Abdellaoui, 2000; Abdellaoui et al., 2008; Wakker & Deneffe, 1996) and the discussion in Rabin, 2000).[6]

The worker chooses an output level y_p that maximizes (3), supplying a production level that satisfies the following first-order condition:

$$a - \frac{1}{2}y_p = 0. \qquad (2)$$

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[6] Later, we will show that this assumption holds for most participants in our experiment.

The output level y_p is the optimal production level under the piece rate. Thus, the optimal output level has the closed-form solution $y_p = 2a$, with the property that higher monetary incentives a yield higher output.[7]

We now study a case in which the worker is incentivized with a goal contract, which in addition to offering a piece rate a, also offers a bonus $B(y, g)$. The bonus pays a monetary amount in the event that the worker attains or surpasses a production goal, g, which belongs to the same domain as her output, so that $0 \leq g \leq 1$.

Specifically, the payoff of the agent offered the goal contract is

$$w(y, B(y, g)) = ay + B(y, g), \quad (3)$$

where

$$B(y, g) = \begin{cases} 0 \; if \; y < g, \\ bg \; if \; y \geq g, \end{cases} \quad (4)$$

and $0 > b > 1$. Thus, the worker receives a larger bonus for achieving more ambitious goals, and the bonus is not awarded if the goal is not attained. This type of contract is not novel. According to Chung et al. (2014), it is classified as a combination of linear commission and a bonus with overachievement commission at quota. Similar incentive schemes are commonly used by firms (Kaur et al, 2015; Larkin, 2014; Oyer, 1998).

For a given goal, $\hat{g}$, under the incentive scheme $w(y, B(y, \hat{g}))$, the worker must choose whether to work toward the bonus or not. She must compare her expected utility from the optimal level of output below the target level to that resulting from exceeding or just achieving the target. Denote the optimal choice of output below the goal as $\underline{y}$ and the resulting expected utility level as

$$E\left(U\left(\underline{y}, \hat{g}\right)\right) = a\underline{y} - \frac{\underline{y}^2}{4}. \quad (5)$$

Similarly, let the optimal output above or equal to the goal be $\bar{y}$ and the corresponding expected utility be

$$E\left(U(\bar{y}, \hat{g})\right) = a\bar{y} + b\hat{g} - \frac{\bar{y}^2}{4}. \quad (6)$$

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[7] The restriction $0 \leq a \leq \frac{1}{2}$ guarantees $0 \leq y \leq 1$.

When the goal is set too high, it is optimal not to try to achieve it since its achievement can be prohibitively costly, i.e. $E\left(U\left(\underline{y},\hat{g}\right)\right) \geq E(U(\bar{y},\hat{g}))$. This is the case when the marginal cost of achieving the goal, $\frac{y^2}{4} - \frac{\bar{y}^2}{4}$, is larger than the associated marginal benefit $a\bar{y} + b\hat{g} - a\underline{y}$. Thus, working toward the achievement of a high goal is more likely as b becomes larger. Also note that when $E\left(U\left(\underline{y},\hat{g}\right)\right) < E(U(\bar{y},\hat{g}))$ and $\bar{y} > y_p$, the worker exerts extra effort to attain the goal beyond the amount she would have exerted if there were no bonus in place. Hence, with the contract $w(y, B(y,\hat{g}))$, a challenging but attainable goal has the potential to increase output.

Thus far, we have examined the incentives of $w(y, B(y,g))$ under exogenous goals, that is a goal $\hat{g}$ given by the principal or a third party. However, our interest is in goals that are set by the worker herself. In Proposition 1, we show that when the contract in (3) allows for self-chosen goals, a worker with *standard preferences* will set her goal exactly equal to her optimal level of expected output. We use the term *standard preferences* to describe an individual who derives no utility from achieving or failing to achieve the goal, other than from the monetary payment that it yields.

Proposition 1: *A worker with standard preferences, who is incentivized with a self-chosen goals contract, chooses $g^* = y^*$, where $y^* = \frac{2(a+b)}{b+1}$.*

Under standard preferences, it is optimal to set a goal that is exactly equal to the expected output level. Moreover, the goal and output levels are higher, the higher the piece rate a, and the bonus b. Note that, under standard preferences, the self-chosen goal contract yields higher output than the piece rate as long as $b > 0$. When $b = 0$, the two contracts have the same monetary incentives and the worker delivers the same output $y^* = y_p$.

Reference-dependent preferences

Let us now suppose that the worker has reference-dependent preferences. This captures the notion that she does not only derive utility from the monetary incentives offered by the contract, but also that the presence of a goal induces a psychological (dis) utility from (not) achieving it. Following Wu et al. (2008) and Heath et al. (1999), we assume that the goal acquires the status of a reference point, dividing the output space into gains, which is the region of the output space where the goal is attained or exceeded, and losses, the region of the output space where the goal is not attained. Hence, a production goal induces an intrinsic, non-monetary, psychological utility that satisfies the properties of Kahneman and Tversky's (1979) value function. We assume the following representation of this psychological utility,

Assumption 3 *(Psychological utility)* $v(y,g) = \begin{cases} \mu(y-g) & if\ y \geq g \\ -\mu\lambda(g-y) & if\ y < g \end{cases}$, *with $\mu > 0$ and*

$\lambda > 1$.

The parameter $\lambda > 1$ reflects the notion that the worker is loss averse, i.e. the psychological losses of failing short of a goal by some amount looms larger than the gains from surpassing the goal by the same amount. The parameter $\mu \geq 0$ represents the weight of the psychological component on the worker's overall utility. If $\mu = 0$, the worker's utility collapses to the case of standard preferences. Finally, note that we do not include diminishing sensitivity. Not including this property is consistent with our assumption that individuals do not exhibit curvature of the utility function and implies that in our setting the degree of loss aversion is the worker's only source of risk aversion (Wakker, 2010).

The expected utility of the worker with goal-dependent preferences under a set-your-own goal contract is

$$E\big(U(y,g)\big) = \int_0^1 \left(ay - (1-\theta)\frac{y^2}{2} \right) f(\theta) d\theta + \int_g^1 \big(bg + \mu(y-g) \big) f(\theta)\, d\theta$$

$$- \int_0^g \big(\mu\lambda(g-y) \big) f(\theta)\, d\theta. \qquad\qquad (7)$$

The first term of (7) is the expected monetary utility of producing y. The second term is the expected utility from producing y above the goal. Note that this term includes both monetary (if $b > 0$) and psychological gains. The third term is the expected psychological disutility from producing y below the goal. It is informative to present (7) after solving for the integrals:

$$E\big(U(y,g)\big) = ay - \frac{y^2}{4} + (1-g)\big(bg + \mu(y-g) \big) + g\mu\lambda(y-g) \qquad (8)$$

From (8) we can see that the worker faces different tradeoffs when setting a goal. These tradeoffs change with the size of the bonus offered. Let us first assume there is no bonus, i.e. $b = 0$. Then, for some given production level, $\hat{y}$, the worker will want to set a goal level such that $\hat{y} > g$ holds, since such a goal guarantees utility gains stemming from psychological utility as depicted by the last two expressions in (8). Thus, from this perspective, she has reasons to set a low goal. However, setting a too low goal will not be optimal either. To understand why, note that by setting the lowest possible goal $g = 0$, the last expression in (8) disappears, leading to the loss of a relevant source of utility if λ is large and $y > g$. Thus, the problem of the worker is to set a goal that guarantees

psychological gains and, at the same time, takes advantage of the motivational boost of λ in the last expression.

Now, if $b > 0$, then the worker does not only want to set an achievable goal such that $y > g$ holds to gain psychological utility, but she has additional reasons to set a lower goal so that she achieves the monetary bonus of bg. Again, it is important to stress that the worker will not want to set the lowest goal because then she will derive lower utility.

To solve the model, we let the worker choose output and goals simultaneously, as we did in the case with standard preferences. This implies that the worker is rational and internalizes the effect that the goal has on her expected performance and vice-versa.

The worker chooses output and goals according to the following first order conditions:

$$a - \frac{1}{2}y + (1 - g)\mu + \mu\lambda g = 0, \tag{9}$$

$$(1 - g)b - bg - (1 - g)\mu - \mu(y - g) - \lambda\mu(g - y) - \mu\lambda g = 0. \tag{10}$$

Which in turn yield:

$$y(g) = 2(a + \mu + \mu g(\lambda - 1)), \tag{11}$$

and

$$g(y) = \frac{b - \mu + \mu(\lambda - 1)y}{2(b + \mu(\lambda - 1))}, \tag{12}$$

where eq. (11) describes the optimal output for a given goal level and parameters a, μ and λ while eq. (12) describes the optimal goal for a given output level and parameters b, μ and λ. The following remarks are based on equations (11) and (12) and are useful to understand the way that goals and output relate to each other and how they respond to changes in parameters of the model.

Remark 1. Let $\mu > 0$. *Output and goals are complementary. That is, output increases with higher goals, and goals increase with higher output.*

The complementarity between goals and output presented in Remark 1 is captured in various models in the goal-setting literature, for instance in Corgnet et al. (2015) or Wu et al. (2008). However, in these models the property of diminishing sensitivity creates the complementarity. Our model shows that in the absence of diminishing sensitivity, this positive relationship between goals and output is still present under imperfect information about own ability.

Remark 2. Let $\mu > 0$. *The optimal output for a given goal level, $y(g)$, increases in the piece rate, a and loss aversion, λ. The monetary bonus, b, does not influence $y(g)$.*

Remark 2 shows how parameters of the model affect output given some goal level. The fact that the degree of loss aversion boosts performance is typically present in models where goals act as a self-control device (Koch and Nafziger, 2011; 2019). In our model, the degree of loss aversion increases performance even when the decision maker does not exhibit dynamic inconsistency.

Remark 3. *Let $\mu > 0$. The optimal goal for a given output level, $g(y)$, increases in the monetary bonus, b, and decreases in loss aversion, λ, if $b > \frac{\mu}{(1-y)}$. The piece rate, a, does not influence $g(y)$.*

Remark 3 describes how the parameters of the model affect goals given an output level. Note that the way that loss aversion affects goals for a given output depends on the magnitude of b relative to μ. In the absence of monetary bonuses (i.e. $b = 0$), highly loss averse workers will set higher goals for a given output level. However, if the monetary bonus is bigger than $\frac{\mu}{(1-y)}$, highly loss averse workers will set lower goals.

Finally, it is interesting to observe that, in this setting, a monetary bonus does not directly increase output (Remark 2). If there is an effect of a monetary bonus on output, it will come from the effect of the bonus on goals (Remark 3), and then on the subsequent effect of goals on output (Remark 1).

2.2. Solution of the Model

In this sub-section we express the optimal output and goal level in closed form and study the comparative statics at the solution with respect to the parameters we vary or measure in the experiment. These are the monetary bonus b and the loss aversion parameter λ.

Proposition 2: *A worker with the preferences given in eq. (7), with $\mu > 0$, and who is incentivized with a self-chosen goals contract, chooses an output level and a goal level equal to:*

$$y^{**} = \frac{2(\mu + a)\big(b + \mu(\lambda - 1)\big) + \mu(b - \mu)(\lambda - 1)}{b + \mu(\lambda - 1) - \mu^2(\lambda - 1)^2},$$

$$g^{**} = \frac{\frac{(b - \mu)}{2} + \mu(\lambda - 1)(\alpha + \mu)}{b + \mu(\lambda - 1) - \mu^2(\lambda - 1)^2}.$$

From Proposition 2, it is evident that when $\mu = 0$, then y^{**} collapses to y_p (the optimal output under standard preferences). We now consider the influence of the exogenous parameters of the model on y^{**} and g^{**}. The following corollary presents the comparative statics with respect to the monetary incentives of the contract.

Corollary 1: *for a worker with the preferences given in eq. (7), with $\mu > 0$, and who is incentivized with a self-chosen goals contract:*

i)   *output, y^{**}, and goals, g^{**}, increase in the piece rate, a,*

ii)   *output, y^{**}, and goals, g^{**}, are decreasing in the level of monetary bonus, b, if $\mu > \frac{\lambda}{(\lambda+1)(\lambda-1)}$.*

From Remarks 2 and 3 we know that the first part of the corollary comes from a direct effect of a on output, which, given the complementarity between goals and output (Remark 1), also raises the optimal goal in equilibrium. The positive association of piece-rate, goals and output is empirically and theoretically documented by Corgnet et al. (2015), in the context of exogenous and deterministic goals.

The second part of Corollary 1 states the main message of this paper: a monetary bonus can decrease performance. Specifically, when the worker exhibits $\mu > \frac{\lambda}{(\lambda+1)(\lambda-1)}$, she sets lower goals and attains lower performance in the presence of larger bonuses. Note that the condition $\mu > \frac{\lambda}{(\lambda+1)(\lambda-1)}$ becomes less stringent the more loss averse the worker is, or, alternatively, the more weight she gives to her psychological utility.[8] Hence, workers that give more importance to loss aversion in their utility function, either through large values of μ or through large values of λ, are more likely to set lower goals and deliver lower output the greater the bonus is.

Remarks 2 and 3 also indicate that the negative effect of bonuses on output emerges from the direct and negative effect of bonuses on goal setting, which emerges whenever bonuses are sufficiently large. This negative effect ultimately influences output by means of the complementarity between goals and output (Remark 1). Appendix B presents a graphical representation of simulations of the model to illustrate the role of loss aversion

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[8] Note that the condition $\mu > \frac{\lambda}{(\lambda+1)(\lambda-1)}$, and the condition guaranteeing that (y^{**}, g^{**}) is a local maximum, $\mu < \frac{1}{(\lambda-1)}$, can both be satisfied. That these two conditions hold simultaneously is less stringent at higher levels of loss aversion.

in moderating the effect of monetary bonuses on performance when the parameters of the model attain different values.[9]

2.3. Comparison of the Contracts

In this subsection, we compare performance when the worker faces a piece rate contract to performance when the worker faces a self-chosen goal contract. Proposition 3 shows that the self-chosen goal contract improves performance, and that output strictly exceeds the goal.

Proposition 3: *for a worker with preferences as in eq. (7) with $\mu > 0$, and who faces the same $a > 0$ across contracts:*

i) $y^{**} > y_p, \forall\, b \geq 0$

ii) $y^{**} - g^{**} > 0$ *if either* $\mu \geq b$ *and* $\mu \leq \frac{1}{2(\lambda-1)}$*, or if* $b > \mu$ *and* $\mu > \frac{1}{2(\lambda-1)}$.

In words, the self-chosen goal contract generates higher performance than the piece rate for any offered monetary bonus, b. Proposition 3 also shows that piling up, defined as the amount of output that exceeds the goal, is guaranteed when the weight given to psychological utility is larger than the bonus and when weight to the psychological utility is $\mu \leq \frac{1}{2(\lambda-1)}$.[10] This constraint is more stringent for higher levels of loss aversion. Instead, when the bonus is larger than the weight given to psychological utility, piling up appears under less stringent conditions at higher levels of loss aversion. Namely, when the weight given to psychological utility exceeds the lower bound $\mu > \frac{1}{2(\lambda-1)}$.[11]

The special case in which $b = 0$ is of particular interest. If $b = 0$, then $\mu > b$ holds even if the worker exhibits arbitrarily small $\mu > 0$. If subjects have goal-dependent preferences, this particular setting captures the condition of participants who are assigned to the GOAL treatment described in Section 4.

When y^{**} and g^{**} from Proposition 2 are evaluated at $b = 0$ we have,

$$y^{**}|_{b=0} = \frac{\mu + 2a}{1 - \mu(\lambda - 1)} , \qquad (13)$$

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[9] Similarly, it can be shown that output, y**, and goals, g**, are decreasing in the level of loss aversion, λ, when b attains a lower bound that depends on μ.

[10] Note that the condition $\leq \frac{1}{2(\lambda-1)}$, and the condition guaranteeing that y^{**} and g^{**} are local maxima, $\mu < \frac{1}{(\lambda-1)}$, can coexist. When $\mu \leq \frac{1}{2(\lambda-1)}$ holds, then $\mu < \frac{1}{(\lambda-1)}$ is satisfied making the former condition more stringent than the latter.

[11] Note that the condition $> \frac{1}{2(\lambda-1)}$, and the condition guaranteeing that y^{**} and g^{**} are local maxima, $\mu < \frac{1}{(\lambda-1)}$, can coexist. This coexistence becomes less stringent at *lower* levels of loss aversion.

$$g^{**}|_{b=0} = \frac{(\alpha + \mu) - \dfrac{1}{2(\lambda - 1)}}{1 - \mu(\lambda - 1)}. \qquad (14)$$

Corollary 2 shows that as long as $\mu > 0$, the self-chosen goal contract yields higher performance than the piece rate, even when it does not offer a monetary bonus.

Corollary 2: *for a worker with preferences as in equation (7) with $\mu > 0$, who faces the same $a > 0$ across contracts, and who is offered a self-chosen goal contract with $b = 0$, then $y^{**}|_{b=0} > y_p$.*

Corollary 2 demonstrates that the psychological utility from letting the worker set a goal is, on its own, able to motivate the worker to a greater extent than a piece rate contract offering the same monetary incentives.

To conclude this section, we study the relationship between $y^{**}|_{b>0}$ and $y^{**}|_{b=0}$. Proposition 4 states that a worker who assigns large weights to psychological utility will perform better under a self-chosen goal contract without bonus (the GOAL treatment in our experiment) than under a similar contract with a bonus (GOAL+BONUS treatment).

Proposition 4: *for a worker with preferences as in equation (7) with $\mu > 0$, who faces the same $a > 0$ across contracts, produces greater output when $b = 0$ than when $b > 0$. That is, $y^{**}|_{b=0} > y^{**}|_{b>0}$, if $\mu > \frac{\lambda}{(\lambda-1)(\lambda+1)}$.*

Proposition 4 shows that a worker who gives sufficient weight to the psychological utility and/or is sufficiently loss averse, delivers higher output when the self-chosen goal contract is offered with $b = 0$, compared to the situation in which she was offered the same contract, but with $b > 0$. This is due to the result presented in Corollary 2: the negative relationship between output and bonuses, and the negative relationship between goals and bonuses when the worker exhibits a sufficient degree of loss aversion, so that $\mu > \frac{\lambda}{(\lambda-1)(\lambda+1)}$ holds.

Therefore, according to our analysis, offering a monetary bonus is only beneficial to the employer when the worker exhibits at most a mild degree of loss aversion. When workers are sufficiently loss averse, or alternatively give sufficiently large weight to the psychological utility, μ, offering a bonus for the achievement of a self-chosen goal backfires. In such cases, it is better for the employer to offer a contract with $b = 0$, which generates higher output at a lower cost.

3. Hypotheses

The theoretical model presented in Section 2 yields a set of hypotheses that we test in a laboratory experiment. First, according to Proposition 4, the introduction of monetary incentives in a self-chosen goal contract leads to lower goals and, consequently, lower output, if participants are sufficiently loss averse. Instead, Proposition 1 states that under standard preferences, bonuses boost output and goals. Because we expect a sizable fraction of participants to be loss averse, our first hypothesis is:

Hypothesis 1: *Goals and performance are greater under GOAL than under GOAL+BONUS.*

The second hypothesis concerns the interaction between the degree of loss aversion of individuals and the introduction of monetary bonuses. From Proposition 4 and Corollary 1, we hypothesize:

Hypothesis 2: *Goals and performance in the GOAL treatment exceed those in GOAL+BONUS by a greater difference, the more loss averse the individual is.*

From Proposition 3 and Corollary 2 we derive the third hypothesis, which states that a contract including a system of goal setting, regardless of whether it offers a bonus for the achievement of a self-chosen goal, outperforms a cost-equivalent piece rate contract:

Hypothesis 3: *Performance in GOAL and in GOAL+BONUS is greater than in LOPR.*

Proposition 1 shows that with no goal setting, output is increasing in the piece rate. This constitutes our fourth hypothesis.

Hypothesis 4: *Performance in HIPR is greater than in LOPR.*

Finally, Proposition 3 predicts that under the self-chosen goal contracts, output exceeds the goal, i.e. there exists piling up. In the presence (absence) of bonuses, piling up is more (less) likely to occur when individuals are loss averse. Because, we expect a sizable fraction of participants to be loss averse, our last hypothesis is:

Hypothesis 5: *Performance exceeds goals in GOAL+BONUS, and this is less likely to happen in GOAL.*

4. Experimental Procedures

4.1 General Procedures

The experiment was conducted at the University of Arizona's Economic Science Laboratory in May 2018. Participants were all students at the university and were

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recruited using an electronic system. The dataset consists of 12 sessions with a total of 161 subjects. On average, a session lasted approximately 70 minutes. Between 3 and 20 subjects 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. Subjects earned on average 20.7 US Dollars. The instructions of the experiment are given in Appendix E.

The experiment consisted of two parts: A and B. Upon arrival, participants were informed that their earnings from either Part A *or* Part B would be their earnings for the session, and that this would be decided by chance at the end of the session. Whether subjects faced Part A or Part B first was determined at random by the computer.

4.2. Treatment Structure: Comparison of the Contracts

In Part A, subjects 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, Gneezy et al., 2017, and Koch and Nafzinger, 2019). Subjects submitted their answers using the computer interface. Immediately after submission, a new table appeared on the computer screen and the subject was invited again to count the number of zeros in the new table.

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

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

- *LOPR*: Subjects were paid 0.20 dollars for each correctly solved table.
- *HIPR*: Subjects were paid 0.50 dollars for each correctly solved table.
- *GOAL*: Subjects were paid 0.20 dollars for each correctly solved table and were asked at the beginning of each round to set a personal goal regarding the number of tables that they aimed to solve in that round.
- *GOAL+BONUS:* Identical to the *GOAL* treatment, with the exception that subjects were offered a monetary bonus for reaching their goals. The bonus in dollars was equivalent to the goal set by the subject 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.

4.3 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 subjects' loss aversion and utility curvature. The lotteries yielded either only gains, or were mixed in the sense that either gains or losses were possible. We used the Abdellaoui et al. (2008) method, which has the advantage of eliciting risk and loss attitudes without making any assumptions about the way in which subjects evaluate outcomes or probabilities.

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 subject's choice between two initial lotteries determines the next choice problem that the subject faces. 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 subject was again invited to choose between the two available options. This process was repeated four times.

Decision sets 1 to 5 elicited subjects' 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 $j = 1,2,3,4,5$, $H_j \geq 0$, and $L_j \geq 0$. We chose the values of H_j and L_j so that the outcomes of the lottery were close to the payoffs that we expected in Part A of the experiment. This allowed us to correlate the elicited risk preferences at comparable financial stakes with their behavior in the real-effort task. The values of H_j and L_j used in each decision set are given in Table 1.

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

Panel A of Table 2 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 subject 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 was determined finally as $x_2 = 1.625$, the midpoint between 1.75 and 1.5.

Decision sets 6 to 10 elicited subjects' 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 subject would require low values of z_j to be indifferent, whereas a gain-seeking subject 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 2 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, e.g.-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 subject indifferent between the lottery $(1.625_j, 0.5; -1.40, 0.5)$ and zero.

Table 2. Example of the elicitation procedure for certainty equivalents

	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		$x_1 = 1.625$		$z_1 = -1.40$		

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 negative numbers $\{z_1 z_2, z_3, z_4, z_5\}$. The left panel presents how x_2 is elicited with the algorithm. The right panel shows how z_2 could be elicited.

Once subjects finished both parts, 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 any. Also, subjects were informed about the lottery that was chosen for potential compensation for Part B and its realization. They were also informed about which part of the experiment (Part A or B) was chosen to become their final earnings. Finally, participants completed a questionnaire about their general willingness to take risks, as well as specific risks (health, job, and driving related). These questions were taken from Dohmen et al. (2011). The questionnaire also included a measure of self-efficacy. The questionnaire can be found in Appendix E.

5. Results

5.1 Goal Setting

Our first hypothesis stated that goals would be higher in GOAL than in GOAL+BONUS. Table 3 presents the descriptive statistics regarding the goals set by subjects throughout the experiment, by treatment. Figure 1a presents the distribution of goals in these two treatments.

We find indeed that subjects assigned to GOAL set significantly higher goals than subjects assigned to GOAL+BONUS (t(53.069)= 2.61297, p=0.005).[12] Participants assigned to GOAL set an average goal of 48.82 tables, while those in the GOAL+BONUS treatment averaged 37.48 tables. This represents a difference of 30.2%, or 0.57 standard deviations, between the two treatments. This result supports the first part of Hypothesis 1: *Goals are higher under GOAL than under the GOAL+BONUS.*

Table 3. Goals 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**	**44.3**	**40**	**22.758**	**31**	**48.5**	**180**	**18**

Figure 1a. Distribution of Goals by Treatment
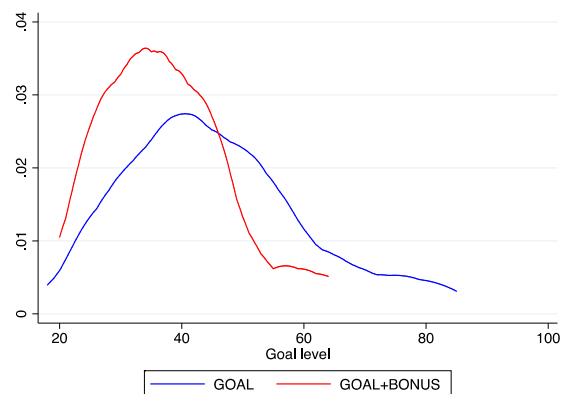
In Appendix D, we show that the difference between the treatments becomes greater over the rounds, indicating that not only do subjects adjust their goals after being provided with

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

feedback, but also that this adjustment induces a larger difference in goal setting between the treatments.

We regress the goal level set by individuals on assignment to the treatments, while controlling for loss aversion for some specifications. We use Poisson count regressions to account for the count nature of the goals data. The estimates confirm Hypothesis 1: subjects set higher average goals when goals are not monetarily rewarded with a bonus. Table 4 (col. 2 and 3) also shows that loss averse individuals set on average higher goals, another pattern predicted by our model.

Table 4. Goals as Function of Treatment and Preference Parameters

	(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 regressions of the statistical model $\text{Goal Level} = \beta_0 + \beta_1 \text{GOAL} + \Gamma'\text{Controls} + \varepsilon_i$ with $\varepsilon_i \sim \text{Poisson}(\omega)$. "Goal Level" equals the sum of a subject's goals in the real-effort task. Subjects 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 subject is loss averse or not. A subject 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 subjects 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.

5.2 Performance

Hypothesis 1 also asserts that performance in the GOAL treatment would be higher than in GOAL+BONUS. Also, Hypothesis 3 states that GOAL and GOAL+BONUS leads to higher performance than LOPR, and Hypothesis 4 proposes that performance would be higher in HIPR than in LOPR. In this subsection, we examine how performance compares across treatments. Recall that we define performance in the experiment as the total number of tables an individual solves correctly.

Table 5 reports the descriptive statistics of performance by treatment. Figure 1b also shows the distribution of performance in GOAL and GOAL+BONUS. We find that paying a monetary bonus for achieving a goal does indeed backfire. Subjects assigned to GOAL

solve a higher average number of tables, on average 47.58 tables, than subjects assigned to GOAL+BONUS, who solve 42.897 tables on average (t(77.88)= 1.485, p=0.07).[13] The size of this effect is 11.1%, or 0.36 standard deviations.[14] According to our model, this implies that most of our subjects are loss averse. We consider, in Section 6, whether this is the case, using the data from our independent measure of loss aversion.

Table 5. Performance by treatment

Treatment	N	Mean	Median	S.D.	25th	75th	Max	Min	Mean Cost
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 1b. Distribution of Performance in the Treatments with Goal Setting
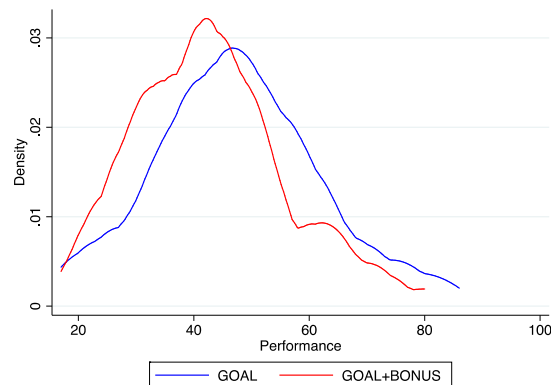
In addition, we observe that subjects assigned to GOAL display higher average performance than those assigned to either of the piece rate treatments, LOPR (t(75.99)= 1.520, p= 0.066) or HIPR (t(73.69)= 1.805, p=0.037).[15] The effect size of the mean differences between the treatments is 0.401 standard deviations and 0.406 standard deviations, respectively. The fact that output is higher under GOAL than under HIPR shows that an employer setting up a GOAL contract rather than a higher piece rate can

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

[14] The power of this test is 0.671. The design of the experiment aimed at a power of 0.8 with an effect size of 0.5 standard deviations. However, the sizeable variation in performance on the task, evident in larger-than anticipated standard deviations of performance, led to lower power.

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

extract higher output from workers at lower cost. Overall, these results partially support Hypothesis 3.

However, Hypothesis 3 is not fully supported in our data. We do not find significant differences in average performance between GOAL+BONUS and LOPR (t(72.24)= -0.0477, p= 0.962), GOAL+BONUS and HIPR (t(73.668)= -0.316, p= 0.752) or LOPR and HIPR (t(73.668)= -0.316, p= 0.752).[16] Raising the piece rate or adding a set-your-own-goal contract with a bonus did not improve performance over LOPR. These findings are similar to those in Fehr & Goette (2007).

We also perform Poisson count regressions of individual performance on treatment dummies and relevant controls. Table 6 presents the regression estimates, which confirm the aforementioned findings. Specifically, the coefficient associated with GOAL is significant at the 5% level for all specifications: subjects in GOAL exhibit higher average performance than subjects in GOAL+BONUS. Similarly, the coefficient of GOAL is significantly larger than the coefficient associated with LOPR ($\chi^2 = 13.28$, p= 0.001) and also larger than that for HIPR ($\chi^2 = 16.79$, p= 0.001).[17]

Table 6. 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***	0.176***
	(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 regressions of the statistical model $\text{Performance}_i = \beta_0 + \beta_1\text{GOAL} + \beta_2\text{HIPR} + \beta_3\text{LOPR} + \beta_4\text{Loss Averse} + \varepsilon_i$ with $\varepsilon_i \sim \text{Poisson}(\omega)$. "Performance" measures the total number of tables a subject solves correctly over the six rounds of the real-effort task. Subjects 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 subject is loss averse or not. A subject 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. Model (3) presents estimates of a regression including only those subjects 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

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

[17] We use the estimates of column (2) in Table 6 for statistical inference.

Additionally, the coefficients for the LOPR and HIPR treatments are not significant for the specification in columns (1) and (2), corroborating the findings of the pairwise tests that performance in LOPR, HIPR and GOAL+BONUS are statistically indistinguishable ($\chi^2 = 0.16$, p= 0.6887).[18]

However, when the regression is performed including only subjects with linear utility, significant differences among the treatments emerge.[19] Column (3) of Table 6 shows that subjects with linear utility assigned to GOAL+BONUS exhibit higher average performance than those in LOPR. This suggests that a system of goal setting with monetary bonus is more effective than increasing the piece rate. Thus, when all assumptions of the model hold, including the requirement that workers are risk neutral for monetary payments, there is support for Hypothesis 3.[20] As in the analyses reported previously, these estimates show that subjects assigned to GOAL exhibit higher average performance than those assigned to any other treatment.

Table 7. Difference between Performance and Goals by Round

	Round 1	Round 2	Round 3	Round 4	Round 5	Round 6	Average
GOAL+BONUS							
Mean	0.410	0.948	1	0.641	1.282	1.128	0.901
Median	0	1	1	1	1	1	1
S.D.	2.435	1.848	1.933	2.590	1.972	2.154	1.141
GOAL							
Mean	-1.463	-1.073	0.073	0.317	0.512	0.536	-0.207
Median	0	0	0	1	1	1	0.166
S.D.	5.532	4.880	4.797	4.687	4.675	4.135	4.123

Furthermore, Hypothesis 5 predicts pilling-up in GOAL+BONUS, as well as to a lesser extent in GOAL. Table 7 shows that for subjects in GOAL, the average piling up is negative in the first round and becomes not significantly different from zero in subsequent

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[18] These results and those presented in Subsection 5.1 are robust to adding an ability variable in the regression, measured by the number of correct tables that subjects completed in the 5-minute practice round.

[19] Details of these classifications are given in Section 6 and Appendix C. To classify subjects according to their curvature we constructed variables $\Delta_{ij} \equiv x_{ij} - EV_j$, where x_{ij} is the certainty equivalent of subject i for lottery j, EV_j stands for the expected value of the lottery, and $j = \{1,...,5\}$ is an indicator of the used lottery. A subject was 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.

[20] The estimates presented in column (3) of Table 6 confirm that there is no empirical evidence in our data to support the notion that higher-powered piece rates yield higher output, even if only individuals who have linear utility are considered. This corroborates the results of the pairwise tests and the regression estimates using the full sample.

rounds. This finding implies that subjects in the treatment in which goals are not incentivized on average meet their self-chosen goal. In contrast, for subjects in GOAL+BONUS, piling up is positive after round 1. The average piling up level over is significantly positive for subjects in GOAL+BONUS (t(38)= 4.934, p<0.001) and not different from zero for participants in GOAL (t(40)=-0.322,p=0.749) When comparing piling up between these treatments, we find a significant difference (t(78)=-1.62, p= 0.054). These findings support Hypothesis 5.

6. Risk Attitudes and their Relationship to Crowding out

The aim of this section is to describe the attitudes of participants toward risk and losses, and to test Hypothesis 2, which proposes that the crowding-out effect of the monetary bonus is more pronounced for more loss averse participants.

6.1. Risk Attitudes

To measure subjects' attitudes towards risky monetary payments, we use data from part B of the experiment, where we elicit the certainty equivalents of five lotteries that offer positive payments, $\{x_1, x_2, x_3, x_4, x_5\}$, and the sequence of negative outcomes, $\{z_1, z_2, z_3, z_4, z_5\}$, each of them making subjects indifferent between receiving zero and a mixed lottery $(x_j, 0.5; z_j, 0.5)$ for any $j = \{1,2,3,4,5\}$. We classify participants according to the curvature of their utility function, e.g. concave, convex or linear, as well as according to their sensitivity toward losses.

We find that the majority of subjects in our sample have linear utility functions in the domain of gains. Specifically, 91 subjects are classified as having a linear utility function (proportion test against 0.5, p=0.048), while 65 have a concave utility function, and only five have a convex utility function. Details of this classification are included in Appendix C. When a power utility function is assumed, $x_{sj} = EV_{sj}{}^\theta$ where EV is the expected value of lottery j and s indicates the individual, we find the pooled estimate across participants to be $\hat{\theta} = 0.95$, reflecting that the majority of individuals in the sample have linear utility and that those classified as having a concave utility typically have only modest concavity. In Appendix C, we show that similar conclusions are reached when other families of utility functions are assumed. These results confirm that our assumption that subjects have linear utility functions is reasonable.

In addition, we find that most subjects are loss averse. Specifically, 134 subjects are classified as loss averse and only 27 are gain-seeking (more sensitive to gains than

losses of the same magnitude). Appendix C 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.[21]

Table 8 presents descriptive statistics of the loss aversion coefficients, λ_j, obtained by computing $\lambda_j = x_j / z_j$, for $j = 1, ... ,5$. Following Abdellaoui et al. (2008), we compute one loss aversion coefficient for each mixed lottery that we implement. We find that, on average, subjects exhibit loss aversion for every mixed lottery. The null hypothesis that the loss aversion coefficient is equal to one is rejected for each lottery. Moreover, we cannot reject the null that the five loss aversion coefficients are equal to each other (F(4,805)=0.26, sphericity-corrected p-value=0.613), corroborating the notion that sign-dependence, rather than the magnitude of the loss, determines loss aversion.

Table 8. Loss Aversion Estimations

	λ_1	λ_2	λ_3	λ_4	λ_5	$\lambda_{average}$
Mean	3.459	3.676	3.712	3.548	3.945	3.668
Median	1.777	1.777	1.777	1.777	2.285	2.136
S.D.	4.798	4.716	4.699	4.166	4.566	3.752
25th perc.	0.516	1.066	1.066	1.230	1.066	1.208
75th perc,	3.2	3.2	3.2	5.333	5.333	4.48

Aggregating the coefficients across lotteries and individuals, subjects exhibit an average loss aversion coefficient of 3.7 and a median coefficient of 2.13. This implies that, for our subjects, losses loomed on average 3.7 times larger than equally-sized gains. Previous studies that used the same definition of loss aversion found a median loss aversion parameter of similar magnitude. For instance, Tversky and Kahneman's (1992) median estimate was 2.25, Abdellaoui et al. (2007) reported a median estimate of 2.54, Abdellaoui et al. (2016) observed a median estimate of 1.88, and Abdellaoui et al. (2008), using the same method to elicit loss aversion, obtained a median loss aversion parameter equal to 2.61. As in our study, Abdellaoui et al. (2008) found considerable heterogeneity,

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[21] The proportion of loss averse subjects 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 t-tests (LOPR vs. GOAL (p= 0.7046), HIPR vs. GOAL (p= 0.889), GOAL+BONUS vs. GOAL (p= 0.564)).

reflected in the size of the interquartile range (the difference between the 25th and 75th percentile).

6.2. Interaction of Loss Aversion with the Bonus Treatment

Next, we examine the role of loss aversion in explaining the treatment effects. We first evaluate the strength of the treatment effects among loss averse subjects. According to Hypothesis 1, sufficiently loss averse subjects would set higher goals and exhibit higher performance when assigned to GOAL than to GOAL+BONUS. Moreover, according to Hypothesis 2, more loss averse subjects would exhibit a larger positive difference in both goals and performance between GOAL than to GOAL+BONUS.

To perform a conclusive test of Hypotheses 1 and 2, we extend the OLS regression specifications presented in Tables 4 and 6 by adding an interaction dummy for whether a subject is both loss averse and is assigned the GOAL treatment. In this manner, we evaluate whether relatively loss averse subjects display greater positive differences in performance and the goals they set when assigned to GOAL rather than to GOAL+BONUS.

Table 9 presents results of these regressions. Columns (1) and (3) show that the estimates of "GOAL", as well as those of the interaction between ``Loss averse'' and ``GOAL'', are positive and significant. Hypothesis 1 is supported by the estimates on the interaction term: Loss averse subjects assigned to GOAL exhibit higher performance and set higher goals compared to those assigned to GOAL+BONUS, and the treatment difference is larger than for individuals in GOAL who are not loss averse (($\chi^2(1) = 7.76$, p=0.005) and ($\chi^2(1) = 15.37$, p<0.001), respectively).

To distinguish participants with a high degree of loss aversion from those who are only mildly loss averse, we use a median split. That is, we classify subjects as having a high degree of loss aversion if their average loss aversion coefficient is above the median (of 2.136). Subjects with an average loss aversion coefficient below the median but higher than 1 are classified as mildly loss averse. We use the same count regression specifications as in Tables 4 and 6 but we replace ``Loss Averse'' with dummies for "High Loss Averse" and "Mild Loss Averse". Also, we interact the dummy variables for the different degrees of loss aversion with GOAL treatment.

Table 9. Heterogeneity of Treatment Effects by Participant Loss Aversion Level

	(1) Performance	(2) Performance	(3) Goal Level	(4) Goal Level
GOAL	0.093*	0.136**	0.148**	0.159*
	(0.056)	(0.064)	(0.067)	(0.083)
GOAL*Loss Averse	0.236***		0.351***	
	(0.043)		(0.054)	
GOAL*High Loss Averse		0.188***		0.327***
		(0.054)		(0.076)
GOAL* Mild Loss Averse		0.136**		0.151**
		(0.063)		(0.060)
Loss Averse	0.131***		0.045	
	(0.033)		(0.057)	
High Loss Averse		0.144***		0.074
		(0.043)		(0.079)
Mild Loss Averse		0.051		-0.015
		(0.045)		(0.078)
HIPR	-0.034	-0.013		
	(0.034)	(0.034)		
LOPR	-0.020	-0.014		
	(0.035)	(0.035)		
Constant	3.666***	3.663***	3.593***	3.602***
	(0.034)	(0.043)	(0.048)	(0.067)
Log-Likelihood	-834.808	-836.584	-467.624	-470.959
N	160	160	80	80

Note: This table presents the estimates of the Poisson regression of the specification $\text{Performance}_i = \beta_0 + \beta_1 \text{GOAL} * \text{Loss Averse} + \beta_2 \text{GOAL} + \beta_3 \text{LOPR} + \beta_4 \text{LOPR} + \beta_5 \text{Loss Averse} + \mathcal{E}_i$ with $\mathcal{E}_i \sim \text{Poisson}(\omega)$ as well as 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 $\mathcal{E}_i \sim \text{Poisson}(\omega)$. "Performance" is the total number of correctly solved tables by a subject over all rounds and "Goal level" is the sum of the goals set by the subject over all rounds. Subjects were assigned either to the GOAL, HIPR, LOPR, or the GOAL+BONUS treatment. GOAL+BONUS is the benchmark category for the regression. ``Loss Averse'' is a dummy variable that captures whether a subject is loss averse or not. A subject is loss averse when at least four of her variables $\lambda_j$, where $\lambda_j \equiv x_j/z_j$, are greater than one, ``Mild Loss averse' equals 1 if a subject is loss averse and her average λ is lower than the median subject in the sample, and equals 0 otherwise. ``High Loss averse' equals 1 if a subject is loss averse and her average λ is lower than the median participant in the sample and 0 otherwise. See Appendix C 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.

The estimates in Columns (2) and (4) of Table 9 show that subjects with a high degree of loss aversion set relatively higher goals when assigned to GOAL than to GOAL+BONUS ($\chi^2(1) = 22.30$, p= 0.001). As with goals, there is a difference in performance between the two treatments for subjects with high degrees of loss aversion ($\chi^2(1) = 4.89$, p=

0.027), with those in GOAL exhibiting better performance. Mildly loss averse subjects also exhibit a treatment difference, but the coefficient is smaller and less significant. Thus, the superior performance and higher goals under GOAL compared to GOAL+BONUS are primarily driven by highly loss averse individuals.

Moreover, Table D.2 in Appendix D corroborates the pattern that subjects with both a linear utility for money and a high degree of loss aversion exhibit a stronger treatment effect. Overall, these findings are all supportive of Hypothesis 2. Additionally, in Table D.3 of Appendix D, we present evidence suggesting that there is no interaction between exhibiting a concave utility function for money and the presence of monetary bonuses in explaining goal levels. Thus, if concave utility functions have an effect in performance, this effect is not driven by the influence of concave utility on goal setting.

7. Conclusion

This paper shows that offering monetary bonuses for the achievement of self-chosen goals can significantly reduce performance. If a worker exhibits loss aversion and does not have perfect knowledge about her own ability, setting an ambitious goal can boost performance since she would exert high effort to avoid the psychological losses from falling short of her goal. The introduction of monetary bonuses for meeting a self-chosen goal crowds out this motivational effect, since the worker will prefer setting lower goals to increase the likelihood that the monetary bonus is achieved. This behavior is detrimental to performance since lower goals correlate with lower effort. Thus, a goal contract with no monetary payment can lead to better performance than one where achieving the goal comes with a monetary bonus. The results of the experiment demonstrate that this theoretical possibility can be observed in a real, incentivized task that requires cognitive effort.

The theoretical framework allows us to pin down the conditions guaranteeing these results. The presence of loss aversion determines whether introducing bonuses is detrimental to performance. The experiment corroborates the theoretical proposition that loss averse individuals set lower goals and perform particularly worse when their self-chosen goal carries monetary consequences. Moreover, the theory also predicts that more loss averse individuals exhibit this crowding out effect more strongly. Indeed, in our sample, participants who exhibit a greater degree of loss aversion display a larger difference in performance between the GOAL and GOAL+BONUS treatments.

Insofar as our empirical findings generalize to less controlled non-laboratory environments, this paper suggests that including monetary bonuses in a worker's compensation scheme does not necessarily guarantee better worker performance.

Similarly, increasing the piece rate may also not improve performance. A scheme in which individuals set their own goals, when achieving the goal carries no monetary bonus, is the most effective incentive scheme that we have studied. From an employer' s point of view, given that there is already a piece rate in place, a GOAL scheme dominates all others in that it extracts the highest output with no increase in unit wage costs. It is plausible that these results hold for a broad class of environments, though obviously further research would be required in order to make stronger claims about the generality of our results.

This paper opens promising avenues for future research. First, although laboratory experiments ensure internal validity, it would be interesting to replicate our experiment in a more natural environment with different pools of subjects. Second, future research could study the emergence and size of the crowding out effect under more general conditions. This may require giving-up on closed-form theoretical solutions and require the use of other methods to derive predictions. Finally, we restricted our study to the optimal choice of goals and output when monetary incentives are kept constant. It would be relevant to examine the optimal choice of monetary incentives (i.e. magnitude of the piece rate and eventual combination with bonus) in light of the crowding out effect that we have documented here.

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Appendix A. Proofs

Proposition 1

PROOF: We first show that at an optimum, it must be the case that $y^* = g^*$. Second, we show that y^* must satisfy $y^* = \frac{a+b}{2b+\frac{1}{2}}$. First, when $y \neq g$ either y or g is not optimal. Consider y_l such that $y_l < g$. Then, $E(U(y_l,g)) = ay - \frac{y_l^2}{4}$. By reducing her goal and setting $y_l = g$ the agent achieves a strictly greater payoff, $E(U(y_l,g)) = ay_l + g_l - \frac{y_l^2}{4}$. Now consider a given y_h, such that $g < y_h$, The agent's payoff is $E(U(y_h,g)) = ay_h + bg - \frac{y_h^2}{4}$. By increasing the goal to $g = y_h$ the agent's payoff increases to $E(U(y_h,y_h)) = ay_h + g_h - \frac{y_h^2}{4}$. Therefore, y must be set to be equal to g.

The second step is to derive the optimal goal. By the first step of the proof, we know that the agent will always work exactly as much as needed to receive the bonus. Her expected utility is then

$$E\big(U(y,g)\big) = \int_0^1 ay - (1-\theta)\frac{y^2}{2}f(\theta)d\theta + \int_y^1 by f(\theta)d\theta \qquad (A.1)$$

$$= E\big(U(y,g)\big) = ay - \frac{y^2}{4} + by(1-y) \qquad (A.2)$$

To derive the optimal goal, we consider the first order condition for the maximization of earnings with respect to output,

$$a + b - \frac{y^*}{2} - 2by^* = 0. \qquad (A.3)$$

The above implies that $y^* = g^*$, with $y^* = \frac{a+b}{2b+\frac{1}{2}}$. Note that $\frac{\partial y^*}{\partial a} = \frac{\partial y^*}{\partial a} > 0$ and $\frac{\partial y^*}{\partial b} = \frac{\partial g^*}{\partial b} = \frac{1-2a}{(b+1)^2}$, which is non-negative as long as $0 \leq a \leq \frac{1}{2}$, the piece rate interval that guarantees $0 \leq y_p \leq 1$. ∎

Proposition 2

PROOF: The expected utility of the worker facing the self-chosen goals contract is given by eq. (8). The optimal output and effort are given by the first order conditions depicted by eq. (9) and eq. (10) respectively.

We first show that the solution to the system of equations is a local maximum. To that end we compute the second derivatives with respect to y and g, which are $\frac{\partial^2 E(U(y,g))}{\partial y^2} =$

$-\frac{1}{2}$ and $\frac{\partial^2 E(U(y,g))}{\partial g^2} = -2(b + \mu(\lambda - 1))$. The cross derivative between goals and output is $\frac{\partial^2 E(U(y,g))}{\partial y\,\partial g} = \mu(\lambda - 1)$. Thus, the Hessian matrix of this system of equations is

$$D = \begin{pmatrix} -\dfrac{1}{2} & \mu(\lambda - 1) \\ \mu(\lambda - 1) & -2(b + \mu(\lambda - 1)) \end{pmatrix} \qquad (A.4)$$

The determinant of D is $|D| = b + \mu(\lambda - 1) - \mu^2(\lambda - 1)^2$. Therefore, a sufficient condition for $|D| > 0$ is $\mu < \frac{1}{(\lambda-1)}$, and the necessary condition for this system to yield a global maximum is $b + \mu(\lambda - 1) > \mu^2(\lambda - 1)^2 > 0$.

We are now in a position to solve the system of equations. Substituting eq. (10) into eq. (9) yields

$$y^{**} = \frac{2(\mu + a)(b + \mu(\lambda - 1)) + \mu(b - \mu)(\lambda - 1)}{b + \mu(\lambda - 1) - \mu^2(\lambda - 1)^2} \qquad (A.5)$$

Substituting eq. (9) in eq. (10) yields:

$$g^{**} = \frac{\dfrac{(b - \mu)}{2} + \mu(\lambda - 1)(\alpha + \mu)}{b + \mu(\lambda - 1) - \mu^2(\lambda - 1)^2}. \qquad (A.6)$$

The sufficient condition for the tuple (y^{**}, g^{**}) to be a local maximum, $\mu < \frac{1}{(\lambda-1)}$ guarantees that $y^{**} \geq 0$ and $g^{**} \geq 0$. ∎

Corollary 1.

PROOF: From y^{**} presented in eq. $(A.5)$ and g^{**} given in eq. $(A.6)$, we show that $\frac{\partial y^{**}}{\partial a} > 0$ and $\frac{\partial g^{**}}{\partial a} > 0$, for all $a > 0$. The partial derivative of y^{**} with respect to a is

$$\frac{\partial y^{**}}{\partial a} = \frac{2(b + \mu(\lambda - 1))}{b + \mu(\lambda - 1) - \mu^2(\lambda - 1)^2}, \qquad (A.7)$$

and the partial derivative of g^{**} with respect to a is:

$$\frac{\partial g^{**}}{\partial a} = \frac{\mu(\lambda - 1)}{b + \mu(\lambda - 1) - \mu^2(\lambda - 1)^2}. \qquad (A.8)$$

Note that (A.7) ad (A.8) are always positive since $\lambda > 1$ and $b + \mu(\lambda - 1) > \mu^2(\lambda - 1)^2$. The latter is the necessary condition guaranteeing that y^{**} and g^{**} are local maxima, as shown in Proposition 2.

Similarly, from y^{**}, given in equation $(A.5)$ and g^{**} presented in equation $(A.6)$, we show that $\frac{\partial y^{**}}{\partial b} < 0$ and $\frac{\partial g^{**}}{\partial b} < 0$ conditional on μ and λ attaining certain values. The partial derivative of y^{**} with respect to b is:

$$\frac{\partial y^{**}}{\partial b} = \frac{-2\mu^2(\lambda-1)^2(\alpha+\mu) - \mu^3(\lambda-1)^3 + \mu^2(\lambda-1)\lambda}{[b + \mu(\lambda-1) - \mu^2(\lambda-1)^2]^2}, \qquad (A.9)$$

and the partial derivative of y^{**} with respect to b is:

$$\frac{\partial g^{**}}{\partial b} = \frac{\lambda\mu - \mu^2(\lambda-1)(\lambda+1) - 2a\mu(\lambda-1)}{2[b + \mu(\lambda-1) - \mu^2(\lambda-1)^2]^2}. \qquad (A.10)$$

A necessary condition for $(A.9)$ to be negative is that $\mu^2(\lambda-1)\lambda - 2\mu^3(\lambda-1)^2 - \mu^3(\lambda-1)^3 < 0$, which can be rewritten as $\mu > \frac{\lambda}{(\lambda+1)(\lambda-1)}$. A necessary condition for equation $(A.10)$ to be negative is that $\lambda\mu - \mu^2(\lambda-1)(\lambda+1) < 0$, which can be rewritten as $\mu > \frac{\lambda}{(\lambda+1)(\lambda-1)}$. $\blacksquare$

Proposition 3.

PROOF: We start by demonstrating part i). Suppose instead that $y^{**} \leq y_p$. Using $(A.5)$ and $y_p = 2a$, the assumed inequality yields $\frac{2(\mu+a)(b+\mu(\lambda-1)) + \mu(b-\mu)(\lambda-1)}{(b+\mu(\lambda-1)) - \mu^2(\lambda-1)^2} \leq 2a$. This inequality can be rewritten as $2\mu b + \mu^2(\lambda-1) + \mu b(\lambda-1) + 2a\mu^2(\lambda-1)^2 \leq 0$, which is an impossibility given that $\lambda > 1$. Then, it must be the case that $y^{**} > y_p$.

Now we demonstrate ii). We subtract $(A.5)$ from $(A.6)$, which yields

$$y^{**} - g^{**} = \frac{(\mu+a)(\mu(\lambda-1) + 2b) + (b-\mu)\left(\mu(\lambda-1) - \frac{1}{2}\right)}{b + \mu(\lambda-1) - \mu^2(\lambda-1)^2}. \qquad (A.11)$$

First, note that the denominator in $(A.11)$ is always positive, since $\mu < \frac{1}{(\lambda-1)}$ is a necessary condition to guarantee that (y^{**}, g^{**}) is a local maximum. If $b > \mu$ and $\mu \geq \frac{1}{2(\lambda-1)}$, then $y^{**} - g^{**} > 0$. Additionally, $y^{**} - g^{**} > 0$ if $\mu \geq b$ and $\mu < \frac{1}{2(\lambda-1)}$. Note that $\mu < \frac{1}{2(\lambda-1)}$ is more stringent than $\mu < \frac{1}{(\lambda-1)}$. Thus, more stringent conditions are required to guarantee piling up when $\mu \geq b$.

In contrast, $y^{**} - g^{**} < 0$ holds if $\frac{a+\mu}{\mu-b} < \frac{\mu(\lambda-1) - \frac{1}{2}}{\mu(\lambda-1) + 2b}$, which requires $\mu \geq b$ to maintain the

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inequality, and, as is evident from the left-hand side of the inequality, it becomes less stringent as b decreases. However, for $b = 0$, the smallest value that b can attain, the condition becomes $\frac{a+\mu}{\mu} < \frac{\mu(\lambda-1)-\frac{1}{2}}{\mu(\lambda-1)}$, which never holds since $\frac{a+\mu}{\mu} > 1$ and $\frac{\mu(\lambda-1)-\frac{1}{2}}{\mu(\lambda-1)} < 1$. When $b > \mu$, the condition for negative piling up becomes $\frac{a+\mu}{\mu-b} > \frac{\mu(\lambda-1)-\frac{1}{2}}{\mu(\lambda-1)+2b}$. Then, if $\mu < \frac{1}{2(\lambda-1)}$ holds, which is a more stringent condition than $\mu < \frac{1}{(\lambda-1)}$, it is possible to find values of b and μ such that negative piling up occurs. Hence, negative piling up is only possible when $b > \mu$ together with $\mu < \frac{1}{2(\lambda-1)}$. ∎

Corollary 2

PROOF: We first demonstrate i). Suppose that $y^{**}|_{b=0} < y_p$. Using equation (13) and $y_p = 2a$, the assumed inequality yields $y^{**}|_{b=0} = \frac{(\mu+2a)}{1-\mu(\lambda-1)} < 2a$, and some rewriting leads to $\mu + 2a\mu(\lambda-1) < 0$, which is a contradiction since $\lambda > 1$. Then, it must be the case that $y^{**}|_{b=0} > y_p$.

To prove ii) we subtract (13) from (14), which yields

$$y^{**}|_{b=0} - g^{**}|_{b=0} = \frac{a + \dfrac{1}{2(\lambda-1)}}{1-\mu(\lambda-1)}. \qquad (A.12)$$

For the feasible values that these parameters can attain, and since the tuple $(y^{**}|_{b=0}, g^{**}|_{b=0})$ is a local maximum guaranteed by $\mu < \frac{1}{(\lambda-1)}$, it must be that $y^{**}|_{b=0} - g^{**}|_{b=0} > 0$. ∎

Proposition 4.

PROOF: Suppose instead that $y^{**}|_{b=0} \leq y^{**}|_{b>0}$, while $\mu > \frac{\lambda}{(\lambda-1)(\lambda+1)}$. Using equations (16) and (17), the assumed inequality yields $\frac{2(\mu+a)(b+\mu(\lambda-1))+\mu(b-\mu)(\lambda-1)}{(b+\mu(\lambda-1))-\mu^2(\lambda-1)^2} \geq \frac{\mu+2a}{1-\mu(\lambda-1)}$. Rewriting, we get $\lambda - 2(\lambda-1)(\mu+a) - \mu(\lambda-1)^2 \geq 0$, which is a contradiction since it requires $\lambda > (\lambda-1)\mu(1+\lambda)$, which cannot hold for $\lambda > 1$ and $\mu > 0$. Therefore, it must be that $y^{**}|_{b=0} > y^{**}|_{b>0}$ if $\mu > \frac{\lambda}{(\lambda-1)(\lambda+1)}$. ∎

Appendix B. Simulation of the Model

In this appendix, we report the results of simulations to illustrate the role of loss aversion in moderating the effect of monetary bonuses on performance. We plot y^{**} against different levels of b and we let λ take different values. We keep $a = 0.2$ fixed.

We start by assuming low values of μ, so that the psychological utility has a small weight relative to the utility of the monetary payments. Figure B.1 shows that for $\mu = 0.01$ and $\mu = 0.1$, the higher the level of the bonus, b, the greater the output, for $1 < \lambda \leq 2$.
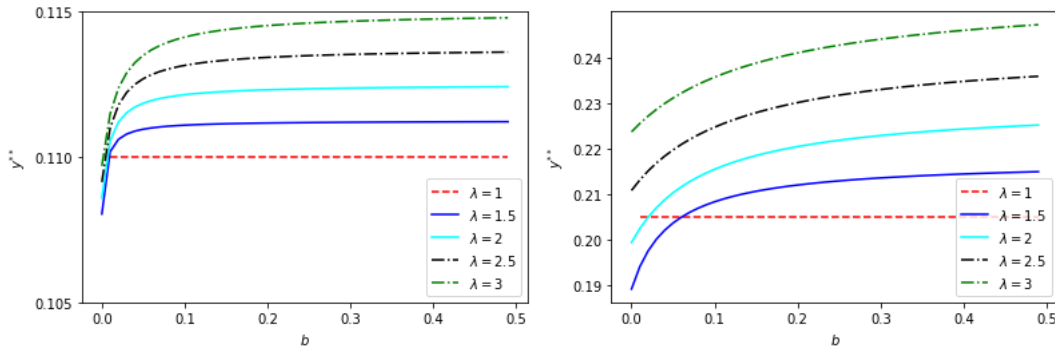

Figure B.1. a) Simulation with $\mu = 0.01$ b) Simulation with $\mu = 0.1$

In contrast, Figure B.2 shows that for relatively high values of μ, namely $\mu = 0.2$ and $\mu = 0.3$, it is possible that output decreases as the bonus offered increases. Specifically, when the worker has $\lambda \geq 3$ in Figure 2a and $\lambda \geq 2.5$ in Figure 2b, higher bonuses yield lower output than lower bonuses.

Finally, Figure B.3 shows that for large values of μ, such as for the value of 0.5 shown in the figure, output is greater when the bonus offered b is lower, even when the loss aversion coefficients are not too large.
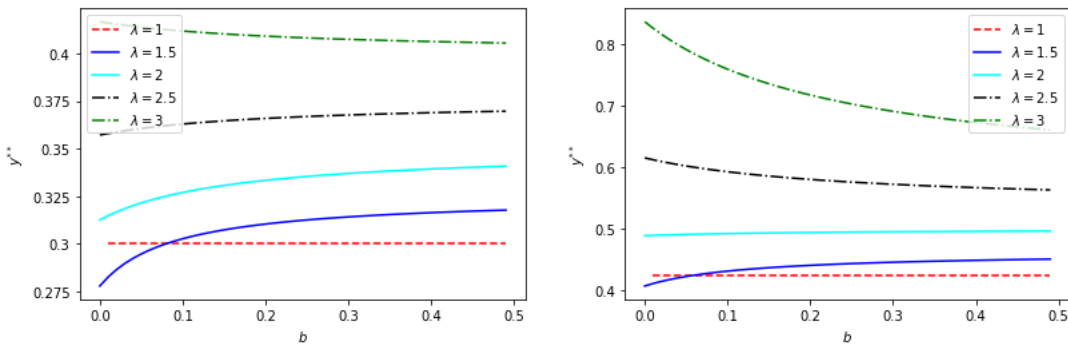
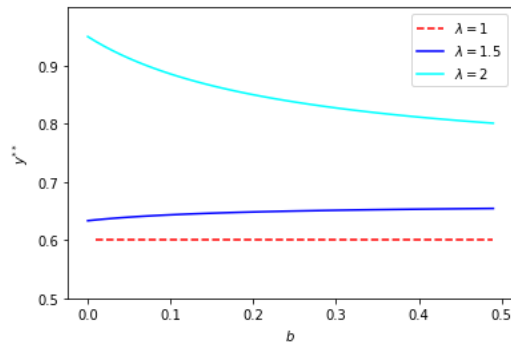**Figure B.2.** a) Simulation with $\mu = 0.2$ b) Simulation with $\mu = 0.3$

Figure B.3. Simulation with $\mu = 0.5$

Appendix C. Details of the Risk Attitude Classifications

In this appendix, we report some additional analysis of the data of part B of the experiment, in which utility curvature and loss-aversion are measured. These elicited data consist of a vector of certainty equivalents $\{x_1, x_2, x_3, x_4, x_5\}$ for five different lotteries, and the vector of offsetting loss outcomes $\{z_1, z_2, z_3, z_4, z_5\}$ for each subject. These values can be analyzed to understand (1) the risk attitudes of subjects when outcomes are restricted to the gain domain, (2) whether risk attitudes have a sign-dependent component as proposed in prospect theory, and (3) how loss averse a participant is.

C.1. Risk attitudes towards 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 subjects in the domain of gains. We classify each subject 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. Formally, $EV_j = 0.5H_j + 0.5L_j$. The sign of Δ_{ij} is a non-parametric measure of the risk attitude of subject i with respect to lottery j. If the subject 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 subject has a risk averse attitude toward that lottery. Also, whenever $\Delta_{ij} = 0$, the subject is risk neutral.

We perform a classification of subjects 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 subject 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, then at least 50% of the data must lie within this confidence interval. Furthermore, to account for response error, we classify a subject to have a risk averse attitude when at least four of her Δ_{ij}s are negative. A subject is risk seeking when at least four of her Δ_{ij}s are positive, and a subject 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 C.1 shows that, by this criterion, the majority of subjects, 57%, are classified as having linear utility (proportions test against 0.5 results in p=0.048). While 40% of participants are classified as having concave utility (proportions test against 0.5 yields p=0.003) and only five as having convex utility.

Table C.1 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. subjects	**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 subjects 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 subject i is classified as having concave utility for lottery j whenever the difference $\Delta_{ij} \equiv x_{ij} - EV_j < 0$. A subject i is classified as having convex utility for lottery j whenever the difference $\Delta_{ij} > 0$. A subject 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 subjects classified as having concave, convex, and linear utility over all lotteries. A subject is classified to have concave utility if she displays risk averse attitudes toward at least four lotteries. A subject 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 subject as having linear utility.

The second analysis we conduct on these data assumes that the utility function of subjects follows a particular functional form. We fit the certainty equivalents to these functionals to examine the subjects' risk attitudes. Specifically, we assume that the utility of subjects is of the power utility form, $x_{ij} = EV_j^{\alpha}$, which belongs to the CRRA family, or of the exponential utility form, $x_{ij} = 1 - \exp(-\rho EV_j)$, 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 C.2 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 subjects in aggregate display slight 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 were also some subjects more appropriately classified as risk averse.

C.2 Loss aversion

Next, we analyze the sequence of negative outcomes $\{z_1, z_2, z_3, z_4, z_5\}$ that made the subjects 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 this data reveals the degree of a subject'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 subject 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 subject 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.

Table C.2 Estimates of parameters of the utility function of the representative participant

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

We first analyze the loss aversion coefficients at the individual level. A subject is classified as loss averse when at least four (out of five) of her loss aversion coefficients satisfy $\lambda_i > 1$. A subject is classified as gain-seeking when at least four (out of five) of her loss aversion coefficients have $\lambda_i < 1$. Finally, a subject is classified as having mixed attitudes toward losses if she cannot be classified as either loss averse or gain seeking. Table C.3 shows that the large majority of subjects is loss averse. Specifically, 72% of participants are classified as loss averse and 14% as gain-seeking.

Table C.3 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**
Averaged	**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 C.3 shows that according to this analysis, 134 subjects, or 85% of participants, are loss averse and the remaining 27 subjects are gain-seeking. Thus, both analyses conclude that the great majority of the subjects are loss averse.

Appendix D. Additional Tables and Analyses

Table D.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	7	7	8
S.D.	4.908	4.345	4.353	4.399	4.371	4.549

Table D.2 Effect of treatment and loss aversion on performance and goals for subjects with linear utility only

	(1) Performance	(2) Performance	(3) Goal Level	(4) Goal Level
GOAL* Loss Averse	0.346***		0.555***	
	(0.058)		(0.073)	
GOAL* High Loss Averse		0.231***		0.543***
		(0.077)		(0.107)
GOAL*Mild Loss Averse		0.048		0.176*
		(0.093)		(0.097)
Loss Averse	0.170***		0.134*	
	(0.045)		(0.077)	
High Loss Averse		0.220***		0.114
		(0.056)		(0.109)
Mild Loss Averse		0.048		-0.038
		(0.093)		(0.111)
GOAL	0.181**	0.309**	0.218**	0.211
	(0.082)	(0.099)	(0.095)	(0.1306)
HIPR	0.098***	0.145***		
	(0.044)	(0.044)		
LOPR	-0.134**	-0.129***		
	(0.048)	(0.048)		
Constant	3.584***	3.588***	3.505***	3.564***
	(0.464)	(0.056)	(0.065)	(0.097)
Log-Likelihood	-442.008	-437.376	-278.999	-282.066
N	91	91	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 subject solves correctly over all rounds and "Goal setting" is the sum of the goals set by the subject over all rounds. Subjects were assigned either to the GOAL, HIPR, LOPR, or GOAL+BONUS treatment. GOAL+BONUS is the benchmark category for the regression. ``Loss Averse'' is a dummy variable that captures whether a subject is loss averse or not. A subject is loss averse when at least four variables $\lambda_j$, where $\lambda_j \equiv x_j/z_j$, are greater than one, ``Loss averse Mild' equals 1 if a subject is loss averse and her average λ is lower than the median subject in the sample, and 0 otherwise. ``Loss averse High' equals 1 if a subject is loss averse and her average λ is lower than the median subject in the sample and 0 otherwise. All models include only subjects 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.

Table D.3 Association of concave utility, loss aversion and treatment, with goals and performance

	(1)	(2)	(4)	(5)
	Performance	**Performance**	**Goal Level**	**Goal Level**
GOAL*Concave Utility	-0.024	-0.021	0.014	0.015
	(0.021)	(0.021)	(0.027)	(0.026)
Concave Utility	-0.019*	-0.012	-0.013	-0.01
	(0.011)	(0.011)	(0.020)	(0.072)
GOAL	0.073*	0.075*	0.280***	0.280***
	(0.042)	(0.042)	(0.046)	(0.046)
LOPR	-0.016	-0.019		
	(0.034)	(0.034)		
HIPR	-0.020	-0.033		
	(0.034)	(0.034)		
Loss Averse		0.123***		0.139***
		(0.028)		(0.039)
Constant	3.735***	3.657***	3.61***	3.552***
	(0.027)	(0.033)	(0.035)	(0.043)
Log-Likelihood	-841.956	-832.509	-475.665	-469.368
N	160	160	80	80

Note: This table presents the estimates of the Poisson regression of the specification $\text{Performance}_i = \beta_0 + \beta_1 \text{GOAL} * \text{Concave Utility} + \beta_2 \text{GOAL} + \beta_3 \text{LOPR} + \beta_4 \text{LOPR} + \beta_5 \text{Loss Averse} + \varepsilon_i$ with $\varepsilon_i \sim \text{Poisson}(\omega)$, as well as the Poisson regression of the statistical model $\text{Goal level}_i = \beta_0 + \beta_1 \text{GOAL} * \text{Concave Utility} + \beta_2 \text{GOAL} + \beta_3 \text{LOPR} + \beta_4 \text{LOPR} + \beta_5 \text{Loss Averse} + \varepsilon_i$ with $\varepsilon_i \sim \text{Poisson}(\omega)$. "Performance" is the number of tables a subject correctly solves over all rounds and "Goal setting" the sum of the goals set by the subject over all rounds. Subjects were assigned either to the GOAL,"HIPR, LOPR, or GOAL+BONUS treatment. The last is the benchmark category for the regression. ``Loss Averse'' is a dummy variable that indicates whether a subject is loss averse or not. A subject is loss averse when at least four of her $\lambda_j$, where $\lambda_j \equiv x_j/z_j$, are greater than one. ``Concave Utility" is a dummy variable that equals 1 if a subject exhibits concave utility and zero otherwise. A subject exhibits concave utility when at least four of her variables Δ_j, where $\Delta_j \equiv x_j - EV_j$, are less than zero. Standard errors are in parenthesis. * indicates a p-value <0.1, ** indicates a p-value <0.05, ***indicates a p-value <0.01.

Appendix E. Experimental Instructions

E.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.

E.2 Part A: Counting task

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)

Payments

(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 * 20 cents.**

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

E.3 Part B: decision-making part

 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

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.

E.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?