Dynamic Goal Attainment – A Formal Model and Experimental Evidence

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This paper examines the effect of externally assigned goals on dynamic effort provision. First, we develop a formal economic model to examine the timing of optimal effort provision when an agent receives a bonus for the attainment of the goal in a multiple period context. Dynamic optimization gives a precise prediction on the optimal effort levels for any given goal and bonus, conditional on the goal-attainment progress and deadline closeness. In a second step, we test the theoretical prediction in a laboratory experiment. In line with a pattern predicted by the theoretical model, subjects exert low effort in the beginning and gradually increase effort as long as the goal attainment probability is high, and decrease effort otherwise. However, we find evidence for a systematic effort overprovision which is (i) decreasing if the noise in the output process is positive and (ii) increasing with the costs already invested.

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"Briefly to illustrate some of the other elements which go to make up the science of shoveling, thousands of stop-watch observations were made to study just how quickly a labourer […] can push his shovel into the pile of materials […] With data of this sort before him […] it is evident that the man who is directing shovelers can […] assign them daily tasks which are so just that the workman can each day be sure of earning the large bonus which is paid whenever he successfully performs this task."

Frederick Winslow Taylor (1911, pp. 32-33)

1. Introduction

Since the origins of scientific management dating back to Frederick W. Taylor's (1911) famous performance studies of shovelers, linking pay to performance has become a powerful tool for motivating employees in organizations. As illustrated by Taylor, a prominent way to link pay to performance is to assign goals to employees and to promise a substantial bonus if they reach the performance standard, but provide no bonus if they do not. A key aspect of many performance targets is that they involve a dynamic decision sequence, i.e., several effort moves are required over a period of time to attain a goal. It is often at the discretion of the agents to adapt their efforts over time. Think of Taylor's shovelers, who are promised a bonus if their daily output reaches a certain performance standard. As long as they meet their targets, it is up to the shovelers whether they work with a constant effort or, for instance, provide high efforts in the morning in order to be able to relax their care during the afternoon. Other examples of dynamic goal attainment include yearly profit targets for investment bankers, quarterly sales targets for insurance sellers, or monthly targets for consultants' billable project hours. The purpose of this paper is to investigate optimal effort provision in such situations.

This paper explores to what extent a dynamic optimization model, assuming strict rationality, can contribute to understand the behavior of real decision makers. In the formal model – where an individual target is linked to a monetary bonus – we study the behavior of a rational agent who sequentially works during several periods. Within each period, the agents can advance one step towards the goal, where the probability of progress is a function of individual effort. The effort is costly, and therefore the agents constantly update their expected net utility evaluating the difference between the expected bonus and the cost of effort. The recursive solution of this dynamic optimization problem leads to precise path-dependent effort predictions. Our model suggests that balancing convex costs against the expected monetary returns, rational agents choose rather low efforts when sufficient amount of time left. As time passes, the agents will have an incentive to work more in order to achieve a desirable goal and will increase their efforts when less time remains. However, the efforts will drop when chance of reaching the performance threshold becomes low.

We then conducted a laboratory experiment to test the numeric predictions derived from our model. In each of 12 periods, participants had to choose a costly effort. This effort choice determined the probability of advancing towards the assigned goal. We systematically varied the goal size between treatments. In order to allow subjects to gain experience they repeatedly had to work on 8 identical goal attainment tasks. In the following we will refer to these consecutive tasks as *runs*.

In general, the experimental data come close to the theoretical benchmark. However, we also find systematic deviations. First, there is excessive effort provision, i.e., frequently the chosen efforts exceed the predicted efforts. Such effort overprovision is particularly strong in early periods when the deadline is remote. Having experienced task progress more often, the subjects learn to reduce their effort overprovision in the subsequent period and try to achieve successful results by working less. While those who were out of luck, increase their efforts. In addition, we find evidence for an escalation of commitment, as agents increase their effort to a stronger extent when they have already invested higher efforts for attaining the goal.

An economic literature on goals and their potential effects on employees' behavior has only recently started to emerge. Wu et al. (2004) and Heath et al. (1999) use prospect theory to explain how not-incentivized goals affect performance. Hsiaw (2011), Koch and Nafziger (2011) and Jain (2009) study the effect of intrinsic goals in the context of self-control problems and procrastination. In a randomized field experiment, Goerg and Kube (2012) find that especially self-assigned goals lead to a significant performance increase compared to a piece-rate incentive scheme. Whereas most of these studies consider personal or self-chosen goals rather than externally imposed ones (see also Crawford and Meng, 2011; Farber, 2008; Fehr and Götte, 2007; Camerer et al., 1997), some other works explore to what extent the assigned targets influence performance. For example, Murphy (2000) discussed contracts with external performance standards. In an empirical study with navy recruiters, Asch (1990) observes a significant performance increase before the goal attainment deadline and postponement of new achievements into the next period. Kivetz et al. (2006) observe increased frequency in customers' purchases when the threshold for receiving a free consumption reward is near.

In addition to motivational effects, other severe negative side effects of performance targets have been reported. Engaging in illegal and/or immoral activities to manipulate performance measures in order to meet the goals is a pertinent example of undesired behavior that seems to be fostered by goal setting. Jensen (2003), for example, emphasizes that the discontinuities of compensation schemes that promise a bonus when a goal is met create high incentives to game the system if one is close to the target. Ordonez et al. (2009) and Schweitzer et al. (2007) argue that "goals have gone wild" and emphasize the detrimental effect of goal setting.

This discussion about goal-setting on the one hand being a powerful tool to motivate employees and on the other hand a potential to harm an organization if not appropriately applied, makes it necessary to better understand how exactly individuals respond to goals and to what extent a rational model of goal attainment can predict behavior.

The remainder of the paper proceeds as follows. The next session outlines a simple model on effort provision within a dynamic context with an exogenously set target. Section 3 introduces the experimental treatments. The experimental design and procedures are described in Session 4. Section 5 presents and discusses the experimental results. Section 6 concludes.

2. Theoretical Analysis

2.1 The Model

We consider a rational agent who works on a certain task during T periods. The agent is assumed to be risk neutral and to discount future payoffs with a factor δ. In each period $t \in \{1; \dots; T\}$ the agent chooses how much effort $e_t \in [0; 1)$ to invest in the task. The performance s_t in period t is either 1 with probability $P(s_t = 1) = e_t$ or 0 otherwise. Hence, in each period the agent can advance one step towards the goal, and the effort determines the probability of such advancement. The agent has to bear costs of the effort. We assume a convex cost function of effort, i.e., $c(e_t) = \frac{a}{2} e_t^2,\ a > 0$. If the goal G is met or exceeded at the end of the last period T, the agent receives a bonus payment B.[1]

We denote the distance between the target and accumulated output with g and the remaining number of periods with τ (where $g, \tau \in N_0$). In the last period, before choosing an effort, the agent maximizes her expected utility v_T which is given by

$$v_T = v(g, \tau = 1) = \begin{cases} B, & \text{for } g = 0, \text{(i.e., the goal has been attained)} \\ 0, & \text{for } g > 1, \text{(i.e., the goal cannot be attained anymore)} \\ B \cdot P(s_T = 1) - c(e_T), & \text{for } g = 1, \text{(i.e., the goal is still attainable)} \end{cases}$$

By backward induction we derive the agent's value function $v(g, \tau)$ and characterize a recursive solution to the dynamic optimization problem. Let $e(g, \tau) = arg\max_e v(g, \tau)$ be the optimal effort chosen by an agent when the distance to the goal is g and τ periods remain. The agent's expected utility $v(g, \tau), \forall \tau \in \{0; \dots; T\}$ is given by

$$v(g, \tau) = \begin{cases} B, & \text{for } g = 0 \\ 0, & \text{for } g > \tau \\ \delta \cdot \left[e(g, \tau) \cdot v(g-1, \tau-1) + \left(1 - e(g, \tau)\right) \cdot v(g, \tau-1) \right] - \dfrac{a}{2} \cdot e(g, \tau)^2, & \text{for } 0 < g \le \tau \end{cases}$$

Solving the optimization problem we obtain the following recursive characterization of optimal effort and utility levels:

Proposition: *The agent's optimal effort level as a function of* $\boldsymbol{g}$ *and* τ *is given by*

$$e(g, \tau) = \begin{cases} B, & \text{for } g = 0 \\ 0, & \text{for } g > \tau \\ \dfrac{\delta}{a} \cdot [v(g-1, \tau-1) - v(g, \tau-1)], & \text{for } 0 < g \le \tau \end{cases}$$

[1] For a related structure with only two periods see Lizzeri et al. (2002).

and the agent's expected utility is

$$v(g,\tau)=\begin{cases} B, & \text{for } g=0 \\ 0, & \text{for } g>\tau \\ \dfrac{\delta^2}{2a}\cdot[v(g-1,\tau-1)-v(g,\tau-1)]^2+\delta\cdot v(g,\tau-1), & \text{for } 0<g\leq\tau \end{cases}$$

Proof: *The objective function is strictly concave. The optimal effort is zero if either $g=0$ (as $v(g-1,\tau-1)=v(g,\tau-1)=B$) or if $g>\tau$ (as in this case it is impossible to attain the goal and $v(g-1,\tau-1)=v(g,\tau-1)=0$). From the first order condition of the optimization problem we obtain the optimal effort level as a function of the expected utility in the subsequent period. By inserting these optimal efforts into the objective function we obtain expected utility as a function of g and τ.* ■

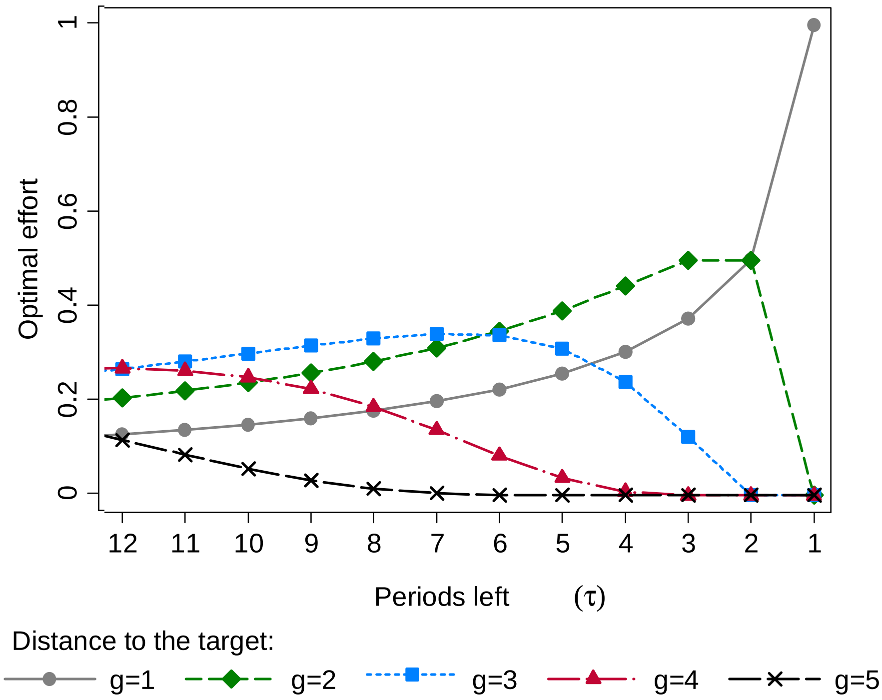
One of the main features of our mechanism is that the optimal choice only depends on the current distance to the goal and the remaining time while past progress and sunk effort costs are irrelevant for a rational decision maker. In other words, the same level of effort should be exerted by an agent who was assigned a goal of $G>g$ and achieved already a positive number of output units but still misses g steps to the target, as by some other agent who just started to work and was assigned a goal of $\hat{G}=g$.

2.2 Dynamics in Effort Provision

Using the proposition, we compute point predictions for the optimal effort levels as a function of g and τ for any bonus B and cost parameter a. Assuming $\delta=1$, Figure 1 shows the optimal effort levels for the main parameter constellation investigated in our experiment[2] as a function of the remaining time τ for five different goal distance values $g\in\{1;\ldots;5\}$. To understand this pattern, first consider a situation in which agent's effort remains without success, i.e., g remains unchanged between periods. To assess the agent's reaction we track his effort by proceeding along a respective curve in Figure 1. For example, we consider the $g=1$ curve, with the goal distance equal to one. In this case, the optimal effort levels gradually increase from 0.13 effort units in the beginning to 0.99 in the very last period. Also for $g\in\{2;3;4\}$ the efforts increase monotonically up to certain periods but then fall. The intuition for this pattern is the following: Due to the convex cost function, the agent has a basic interest to distribute the effort rather evenly across periods. However, incentives change as the remaining time decreases. As long as the goal is easy (i.e., g is relatively small compared to τ), the agent should gradually increase effort in order to achieve the goal. If, however, g is relatively large compared to τ the achievement probability becomes smaller, and as the expected probability that the goal will be attained drops the agent rationally begins to reduce effort.

[2] The parameter values that we employ in the experiment and in the figure are $G=5$, $T=12$, $B=1{,}000$, $a=1{,}001$ and $\delta=1$.

FIGURE 1: OPTIMAL EFFORT LEVELS AS A FUNCTION OF THE GOAL DISTANCE AND REMAINING TIME



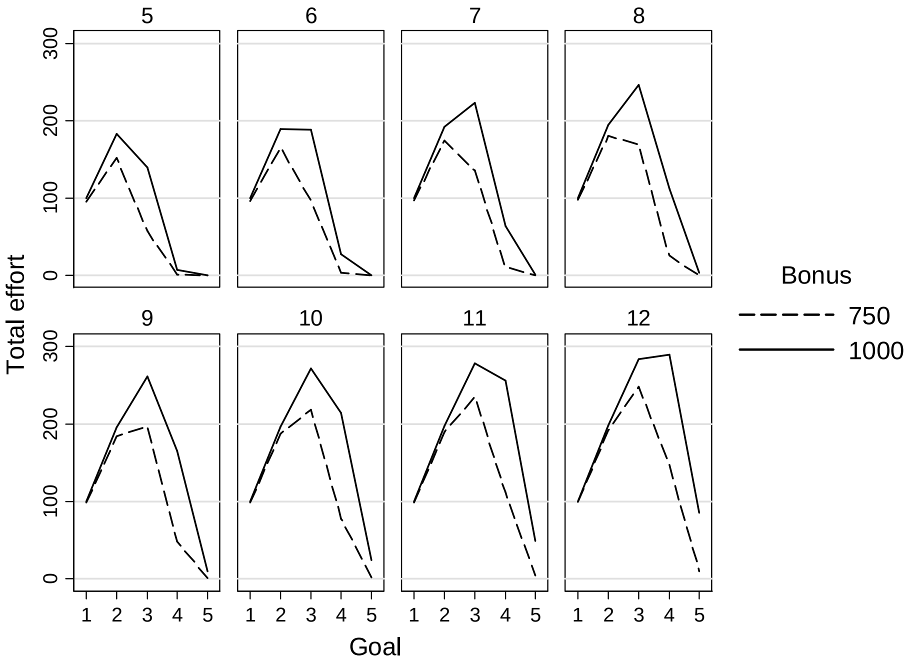
Note: For $B = 1{,}000$, $a = 1{,}001$ and $\delta = 1$.

When an agent is successful in a certain period, g is reduced by one unit. In Figure 1, this means that the optimal behavior of the agent moves from the curve g to the curve $g-1$. As can be seen from Figure 1, this move may lead either to an increase in effort (when the curve $g-1$ is above the curve g) or to a drop in effort (when the curve $g-1$ lies below the curve g). For instance, consider the curve $g = 3$ (marked with squares) when 10 periods remain. When the agent advances towards the goal by one step, this will result in a move from the curve $g = 3$ to $g = 2$ (marked with diamonds). If, for instance $\tau = 9$ the new effort on the $g = 2$ curve lies below the $g = 3$ effort: the progress towards the goal results in reduced effort during the next period as the risk of not attaining the goal has become smaller and the costs of effort to attain the goal can be distributed on a sufficiently large number of remaining periods ("The agent can relax a bit"). But when, for example, 5 periods or fewer remain, progress from $g = 3$ to $g = 2$ leads to a substantial increase in effort: In this case, a reduction in g increases the chances of attaining the goal and thus the marginal returns of advancing one step have increased while at the same time less time remains to attain the goal which makes it more important to advance towards the goal.

2.3 Incentive Effect of Goals

The point predictions for the dynamic optimal effort choices allow us to compute the expected total effort exerted across all periods. Figure 2 illustrates total effort depending on the size of the bonus (which is either 750 or 1,000), goal size (which varies from 1 to 5 on the x-axis) and number of available periods (varies from 5 to 12 between the panels).

FIGURE 2: TOTAL BENCHMARK EFFORT AS A FUNCTION OF GOAL, TIME AND BONUS



As we see, the total effort naturally increases with the bonus, as a higher bonus makes goal attainment more attractive. The total optimal effort peaks in the areas where the goal size is moderately large. The total efforts are also, ceteris paribus, higher when there are more remaining periods. When the agent has more time (and therefore trials), it is more likely that her effort will lead to successful goal attainment and thus she has in incentive to invest more. Additionally, having more periods available allows the agent to keep the effort costs low by spreading costs across several periods. Hence, the expected net payoff increases.

3. Experimental Design

To collect experimental evidence on the theoretical predictions derived above and to investigate the impact of goal size and bonus on dynamic goal achievement, we run a laboratory experiment. Our core setting comprises 3 treatments where we vary the goal size while keeping the time frame $\mathrm{T} = 12$ and bonus size $\mathrm{B} = 1{,}000$ constant. The cost parameter *a* and discount factor δ were set to 1,001 and 1 respectively. An overview of parameter combinations used in each treatment is given in Table 1. In particular, we conduct treatments with a *Low Goal* ($\mathrm{G} = 3$), *Medium Goal* ($\mathrm{G} = 4$) and *High Goal* ($\mathrm{G} = 5$). In addition, a *Medium Goal Low Bonus* treatment was designed to test the impact of the lower bonus of 750.

TABLE 1: PARAMETER VALUES AND THEORETICAL PREDICTIONS FOR A = 1,001 AND δ = 1

				Theoretical predictions regarding optimal behavior		
Treatment	Goal (G)	Available periods of time (T)	Bonus (B)	Total effort	Probability of goal achievement	Agent's net payoff
Low Goal	3	12	1,000	283.98	0.94	430.47
Medium Goal	4	12	1,000	289.23	0.68	160.36
High Goal	5	12	1,000	85.16	0.13	12.87
Medium Goal Low Bonus	4	12	750	147.68	0.30	37.34

Table 1 lists the predictions for the total expected effort, probability of goal attainment and agent's net payoff derived from the formal model. These values are computed by backward induction applying Proposition 1 in Section 2.[3] The theoretical benchmark shows that the highest level of total effort is achieved in the *Medium Goal* treatment as indeed, the goal size has a non-monotonic effect on the total optimal effort. The probability of goal attainment, when following the utility maximizing effort pattern, decreases substantially from 0.94 in the *Low Goal* treatment to 0.13 in the *High Goal* treatment.

The impact of the bonus reduction is in line with incentive theory. Overall, a 25% reduction in the bonus in *Medium Goal Low Bonus* reduces the total effort by almost one half. The lower effort results in a reduced probability of goal attainment. Also the expected net payoff is lower when the bonus is low.

4. Experimental Procedures

We ran the experiment in the Cologne Laboratory for Economic Research at the University of Cologne using the experimental software zTree (Fischbacher, 2007). In total, 4 sessions were conducted with 120 participants (46% females), who were recruited with ORSEE (Greiner, 2004). Each subject was assigned to one treatment and participated in the experiment only once. Instructions were shown on the screen and handed out on paper at the beginning of the experiment. Each participant received a one-time endowment of 5,000 experimental currency units (ECU), equivalent to €15.

In every period participants had to choose an effort level from the set {0; …; 99}, which determined the costs of effort to be subtracted from their experimental account.[4] Immediately after each effort choice a random device decided with probability equal to the effort (divided by 100)

[3] Note that the predicted effort patterns illustrated in Figure 1 are unaffected by G. Therefore, the prediction is relevant for all core treatments with $B = 1{,}000$. The *Medium Goal Low Bonus* treatment is the only one in which effort allocation comprises different values but qualitatively follows a similar pattern (for comparison see Figure A1 in Appendix).

[4] Participants learned their goal, bonus size and number of periods at the beginning of the experiment. For information about values of these parameters see Table 1.

whether the performance output was increased by 1 or not. The participants precisely knew the remaining distance to the goal and the incurred costs. If the total output met or exceeded the goal G at the end of the last period T, a bonus B was awarded. The identical goal-attainment task was repeated 8 times.

At the end of the experiment the subjects took part in two lottery choice experiments for loss and risk preferences (Gächter et al., 2007; Holt and Laury, 2002). Additionally, they had to answer a 10-items Big Five Inventory (Rammstedt and John, 2007), as well as general questions concerning their motivation. The participants earned on average €17.50, plus a show-up fee of €2.50. They were paid anonymously at the end of the experiment. The sessions lasted for about 1 hour and 20 minutes. The total sample size was 120 subjects, i.e., 30 independent observations per treatment.

5. Results

5.1 Goal Attainment and Effort

Observation 1: *The goal attainment frequency decreases with the goal size.*

First, we focus on the goal attainment rates – defined as relative frequency of successfully achieved goals. Figure 3 demonstrates the average goal attainment rate per run, standard errors, theoretical benchmark and total average. The higher the goal the less frequently it is attained. The difference in individual goal-attainment rates (individual average over 8 runs) is statistically highly significant between the three treatments (p-value < 0.001, Jonckheere-Terpstra test for descending alternatives) - see also the regression analysis reported in Table 2.[5] The relative goal attainment frequencies come very close to the predicted rates of the optimal effort path in the Low Goal (0.95 vs the benchmark of 0.94) and the Medium Goal (0.72 vs. the benchmark of 0.68) treatments (p-values > 0.55, two-sided Fisher-Pitman permutation test for paired replicates[6]). In the High Goal treatment, participants achieve the performance standard substantially more often than a utility maximizing agent would (0.39 vs. the benchmark 0.13, p-value < 0.001). However, there are substantial learning effects as attainment frequencies converge towards the prediction. As the goal attainment naturally depends on the amount of the exerted effort, we look in the next step at the effort provision in details.

[5] For all non-parametric tests, unless something different is mentioned, we calculate one average value per subject.
[6] See Kaiser (2007) for more details.

FIGURE 3: GOAL ATTAINMENT

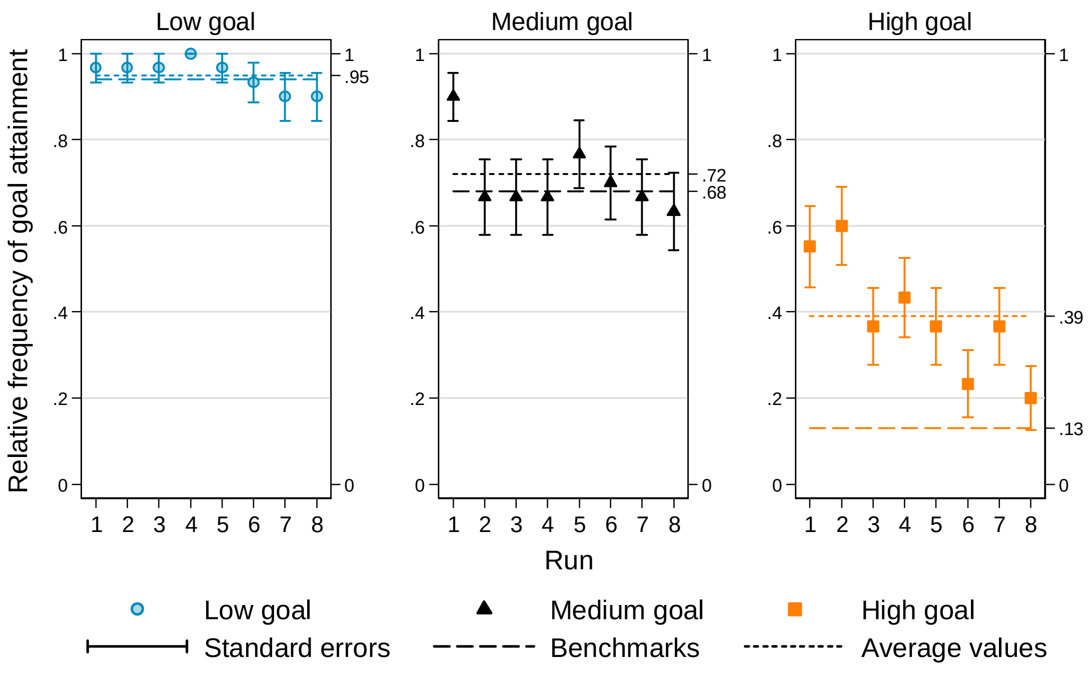


TABLE 2: GOAL SIZE AND GOAL ATTAINMENT

	(1) Probit marginal effects		(2) Random effects panel regression	
	Coef.	SE	Coef.	SE
Low goal	0.32***	(0.05)	0.25***	(0.05)
High goal	-0.26***	(0.08)	-0.30***	(0.08)
Run 1	0.15***	(0.04)	0.14***	(0.05)
Run 2	0.08	(0.06)	0.08	(0.06)
Run 4	0.04	(0.05)	0.03	(0.05)
Run 5	0.04	(0.05)	0.03	(0.04)
Run 6	-0.05	(0.06)	-0.04	(0.05)
Run 7	-0.03	(0.05)	-0.02	(0.04)
Run 8	-0.11*	(0.06)	-0.09*	(0.05)
Constant	0.34	(0.20)	0.55***	(0.20)
R^2	0.25		0.05	
N of obs.	719		719	
N of subjects	90		90	

Note: The dependent variable in both specifications is goal attainment (0/1). The reference group is the *Medium Goal* treatment. Controls are gender and age and are not significant. Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Observation 2: *Subjects exert less effort when the goal is high.*

Figure 4 demonstrates the average total effort per run, standard errors and theoretical benchmark. In line with the theoretical prediction, we observe a non-monotonic relation between the goal size and overall contributions: While working on average 280.09 units per run in the *Low Goal* treatment, the subjects provide on average total effort of 309.74 units in the *Medium Goal* and of 244.38 in the *High Goal* treatments. Testing the difference in means of goal-attainment efforts (individual average over 8 runs) between treatments with a two-sided Fisher-Pitman permutation test for independent samples reveals that subjects work significantly more in the *Medium Goal* than in the *High Goal* (*p*-

value = 0.059). Especially in the last 4 rounds, the detrimental effect of the high goal becomes clear: With 177.22 units the average effort in the High Goal treatment is significantly smaller compared to the Medium Goal treatment (287.18, *p*-value = 0.012) and to the Low Goal treatment (268.78, *p*-value = 0.015). The average total effort in the *Low Goal* does not significantly differ from the *Medium Goal* treatment (*p*-values > 0.15). The regression reported in Table 3 supports these observations.

FIGURE 4: TOTAL EFFORT PER RUN

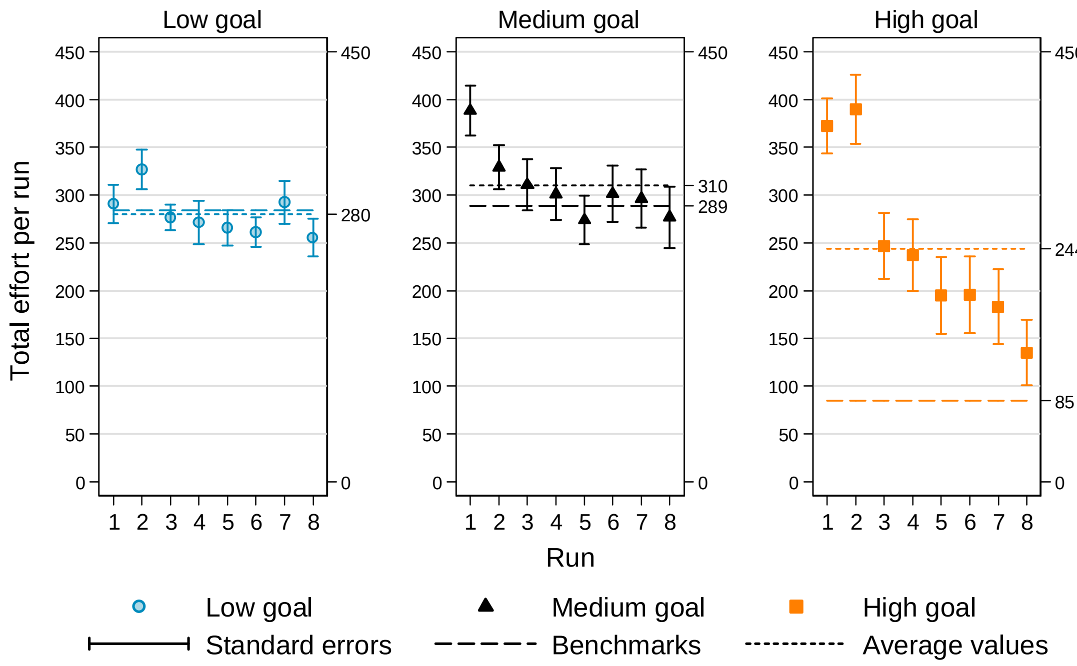


TABLE 3: GOAL SIZE AND EFFORT

	(1) Random effects panel regression (All runs)		(2) Random effects panel regression (last 4 runs)	
	Coef.	SE	Coef.	SE
Low goal	-27.87	(20.31)	-16.14	(26.18)
High goal	-58.78*	(35.05)	-104.25**	(43.99)
Run 1	72.43***	(19.33)		
Run 2	70.47***	(17.65)		
Run 4	-8.16	(15.92)		
Run 5	-33.16*	(17.27)		
Run 6	-25.29*	(14.50)	7.87	(14.04)
Run 7	-20.70	(17.12)	12.46	(17.90)
Run 8	-55.61***	(16.29)	-22.46	(17.10)
Constant	265.50***	(87.10)	298.46***	(101.07)
R^2	0.13		0.02	
N of obs.	720		360	
N of subjects	90		90	

Note: The dependent variable in both specifications is the total level per run. The reference group is the *Medium Goal* treatment. Controls are gender and age and are not significant. Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Observation 3: *When the goal is high the total effort is significantly higher than would be expected from the theoretical benchmark.*

Although the comparison between treatments delivers results consistent with the theoretical prediction discussed in section 3, we observe some significant deviations from the benchmark in the *High Goal* treatment. Here, participants provide significantly more total effort than predicted by the theory in all except the last run (p-values ≤ 0.018, two-sided Fisher-Pitman permutation test).

The subjects thereby exert an inefficiently large amount of effort to achieve the high target. A potential explanation for this rests on the idea that the subjects have a desire to attain the goal beyond the pure monetary considerations. As in the *High Goal* treatment the goal attainment probability based on the benchmark effort is low, subjects invest too much effort at the cost of their payoff while striving to meet a performance standard and to avoid failure. Hence, the results indicate that overly ambitious targets may lead to inefficient self-exploitation at least in the short run.

In the *Low* and *Medium Goal* treatment it is very likely that subjects reach the goal by remaining on the payoff-maximizing effort path In the *Low* (*Medium*) *Goal* treatments, effort overprovision occurs only in the first (first 2) run(-s) (p-values ≤ 0.096) and vanishes afterwards.

5.2 Determinants of Effort Overprovision

More insightful evidence can be found when examining the effort overprovision on a more detailed level within a single period. In every period subjects face particular (g,τ)-constellations when making their decisions. Whereas the parameter τ (the number periods left) diminishes from period to period at an equal pace for all subjects, the change in the parameter g (the actual distance to the target) depends on individual effort and exogenous luck. According to our framework, for any fixed bonus only the remaining goal distance and the number of remaining periods affect the effort size. In other words, rational agents who face identical (g,τ)-combinations should exert the same amount of effort regardless their initial goal and previous progress. To detect systematic deviations from the predicted path we now bring all data points with the respective (g,τ)-combinations together and compare them between treatments.

Observation 4: *The theoretical benchmark explains the observed average behavior quite well, with one exception: Efforts systematically exceed the predictions when the number of remaining periods is large.*

Figure 5 is divided into 5 panels, one for each value of $g \in \{1, 2, ..., 5\}$, and shows the average effort contributions exerted for any particular (g,τ)-combination, where g is fixed within every panel and τ varies along the x-axis. The dashed lines depict the benchmark effort derived from our model (recall that these are identical for all three treatments). The connected lines show the average effort levels chosen by subjects who are in a particular (g,τ)-constellation. As only subjects in the *High Goal* treatment can be in a constellation where $g = 5$, the respective panel presents only one line. Similarly,

$g = 4$ can be experienced either in the *High Goal* or *Medium Goal* treatments but not in the *Low Goal* treatment. Therefore there is no line representing the *Low Goal* treatment in the panel $g = 4$. On the other hand, in the *High Goal* treatment no subject can be confronted with (g,τ)- constellation such as (4,12), (3,12), (3,11), (2,12), (2,11), (2,10) etc. as it is impossible to attain this level of progress toward the goal in such a limited number of periods.

FIGURE 5: EFFORT FOR DIFFERENT DISTANCES FROM THE GOAL

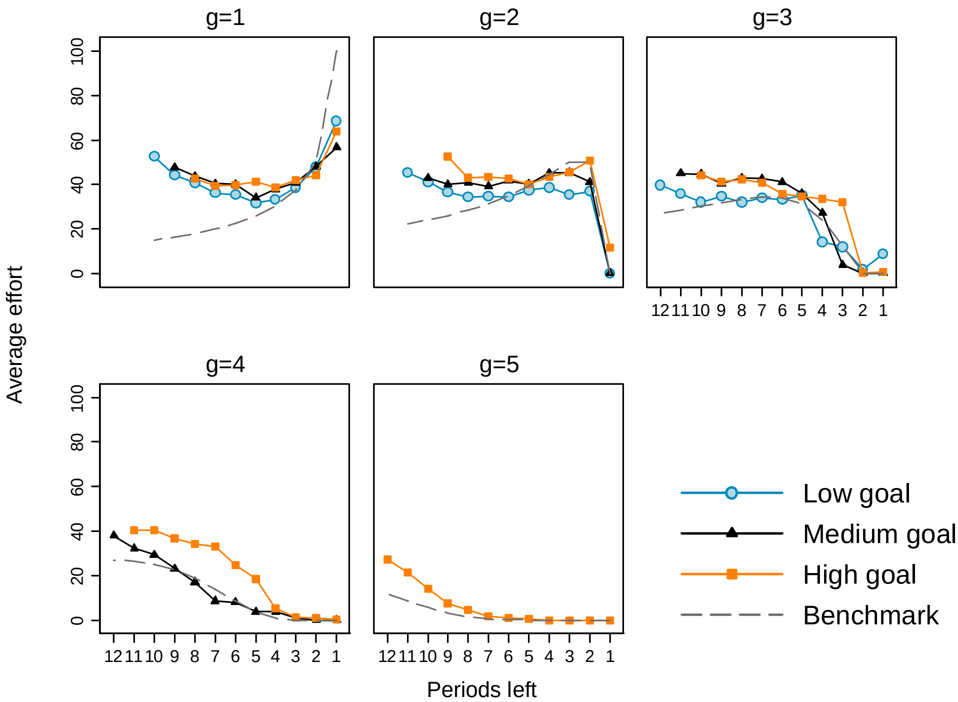


Figure 5 reveals that the pattern of behavior is qualitatively similar to the theoretical prediction, especially for values of $g \geq 3$ and when the number of remaining periods is rather small. But it appears to be different from the prediction for $g \leq 2$ if the number of remaining periods is large, indicating that subjects exert too much effort when they have many periods remaining to achieve only one or two more goal steps. When g is large (see panels for $g = 4$ and $g = 5$) effort decreases as the number of remaining periods decreases, which is in line with the theoretical prediction. For $g = 3$ the effort remains almost stable when $\tau \geq 6$ and then slowly approaches zero. Thus, the most notable deviations from theory is observed when $g = 1$ and $g = 2$ for large values of τ, in which a strong overprovision of effort occurs. The non-parametric statistical analysis confirms in all three treatments that the effort is indeed often significantly higher than in the theoretical prediction, especially when many periods remain (for *p*-values see Table A1 in Appendix).[7]

[7] Nevertheless, the situation for $g = 1$ and $\tau = 1$ appears different: In our setting it is possible to attain the goal with near certainty when it is only one step away, and in the core treatments it is always worthwhile to make the investment of 99.9 units to guarantee that the goal is attained. However, agents do not exert enough effort in this respect and provide on average not more than 69.35% of the required effort. This difference is significant at the 0.1% level in all three treatments. This might be due to a ceiling-effect, as the optimal effort for $g = 1$ and $\tau = 1$ was also the highest possible input in the experiment. However, this effect is also pronounced in the *Medium*

In all three treatments we observe a reduction in the deviations from the prediction with the progress of periods. So why is there effort overprovision especially at the beginning of a run? It might partially result from a selection issue: The data points with low g and high τ represent subjects that come close to the target in very early periods.[8] Some subjects might systematically try to attain the goal early on and therefore exert excessively high efforts in early periods, while it would be optimal to smooth out the costs of effort and start with lower effort levels. Indeed, out of the 34 cases observed in the *Low Goal* treatment where subjects arrived at $g = 1$ in the earliest possible period (here $\tau = 10$), 91.18% exert above median effort in the very first period of the respective run. In the *Medium Goal* and *High Goal* treatments, this measure amounts to 83.33% (out of in total 18 cases) and 100% (from 4 cases), respectively. Similarly, in the *Low Goal* (*Medium Goal*, *High Goal*) treatment when $g = 2$ and $\tau = 11$ (10, 9), the share of the initial above-median contributors is 62.70% (66.67% and 92.31%) respectively. Hence, a large share of participants who tend to overprovide efforts is reflected in the means of early periods with low *g*. In other words, subjects who spread their efforts more evenly, and thus behave more in line with our theory, are much less likely to come close to the goal at such an early point. Indeed, considering only those observations where subjects provide not more than the 50th percentile of effort in the very first period of a run, we observe efforts that are more in line with the theory (see Figure A2 in Appendix).

The observation that also in the *Low Goal* treatment the effort choices are significantly higher than the benchmark values may at first look seem contradictory to observation 3. However, this results from subjects exerting more effort early on instead of distributing it more equally over several periods. As a result, the goal is reached within a shorter time, and effort is reduced afterwards to zero. Therefore there is no significant difference between the total effort and the theoretical prediction, but there is a significant effort overprovision in the early periods of a run at inefficiently high costs.

To gain a deeper understanding of the reasons for potential deviations from the benchmark we investigate the following regressions. The dependent variable is the actual effort *minus* the theoretical effort in the respective (g, τ)-constellation. The predicted effort for a particular (g, τ)-combination is the same in all three treatments. Thus, the dependent variable can also be interpreted as a *ceteris paribus* increase in effort. As the optimal (and in the majority of cases the actual) efforts in situations when the goal is either attained or cannot be attained anymore are equal to 0, we exclude these (g, τ)-combinations from our analysis. We also include dummy variables for each possible (g, τ)-combination. We cluster the data on the individual level and control for gender and age.

Observation 5: *Above-average luck leads to a decrease in effort (relative to the benchmark effort).*

Our first explanatory variable of interest is defined as a ratio of successfully attained performance units and cumulative effort exerted in the past periods (henceforth referred as "experienced luck").

Goal Low Bonus treatment (see below), where the optimal choice is 75 but the observed mean effort 54.11 (*p*-value<0.01).

[8] There is a lower number of observations behind each data point.

Recall that the probability of receiving one additional performance unit is equal to chosen effort divided by 100. Therefore, on average the expected return to effort is equal to the effort itself, and the ratio equals one. However, actually realized returns differ because of the random draw and thus there is exogenous variation in past "success". When the realized performance lies above the exerted effort, the "experienced luck" variable is above one and the subject can be considered as "lucky". To the contrary, an "experienced luck" below one means that the subject received fewer units than the expected value of the invested efforts would predict. By definition, on average the "experienced luck" is equal to 1. Indeed, the mean value of this variable in the very last period is 0.97.

A rational decision maker would not condition the decision on past luck but only on the current (g, τ)-constellation. Any systematic deviation thus represents a behavioral bias. As Table 4 reports, "experienced luck" indeed has a significantly negative effect on effort. A rough interpretation is that subjects who are rewarded with twice as much performance units than they should have received according to their efforts reduce effort by 6.46 units compared to those individuals who progressed along the expected performance given their efforts.[9] One potential explanation is due to a systematic attribution error. To explore this further we estimate in model (2) whether subjects react symmetrically to being "lucky" or "unlucky", i.e., achieving a performance above or below its expected value given the exerted efforts. The variable "luck" is equal to $min\{1, Experienced\ Luck\}$ and "no luck" to $max\{1, Experienced\ Luck\}$. Interestingly, agents reduce their efforts when having experienced above average luck but do not increase them when being unlucky. A potential explanation is related to the fundamental attribution bias: potentially subjects understand than below average luck is just a result of the randomization process, while they (erroneously) attribute above average successes to their own efforts and thus reduce these efforts.

[9] Consider as example two agents provide in three consequent periods 33 effort units. One agent succeeded in two out of three periods and his "luck"-measure is equal to 2*100/(3*33) ≈ 2. Another agent experienced success only in one period and his "luck" measure equals to 1*100/(3*33) ≈ 3.

TABLE 4: PAST SUCCESS AND EFFORT OVERPROVISION

	(1)		(2)	
	Coef.	SE	Coef.	SE
Experienced luck in previous periods	-6.46***	(1.91)		
Luck			-8.38***	(2.77)
No luck			-1.70	(3.51)
Low goal	-0.34	(2.43)	-0.62	(2.34)
High goal	-0.90	(2.50)	-0.52	(2.38)
Constant	-37.48***	(8.94)	-33.13***	(9.42)
Runs	yes		yes	
Dummies for *(g, τ)*-combinations	yes		yes	
R^2	0.29		0.29	
N of obs.	5970		6060	
N of subjects	90		90	

Note: The dependent variable in both specifications is $\Delta = e(g, \tau) - e^{opt}(g, \tau)$. The reference group is the *Medium Goal* treatment. Controls are gender and age and are not significant. The observations are restricted to data points where g > 0 and g ≤ τ. Standard errors in parentheses; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

A final conjecture is that we may see an escalation of commitment effect as a further reason for the overprovision of effort. To explore this possibility, we investigate to what extent the costs already invested in the goal attainment affect efforts in a given run. Again we run regressions with the difference between actual and theoretical effort as the dependent variable. We include individual fixed effects to account for heterogeneity in the general propensity to exert effort. We conduct separate regressions for each τ, as cumulative costs naturally increase from period to period. In this case, our main independent variable of interest is the costs per period accrued in the current run. In other words, we control for average incurred goal attainment expenditures.

Observation 6: *Efforts increase with the costs already invested in the goal attainment.*

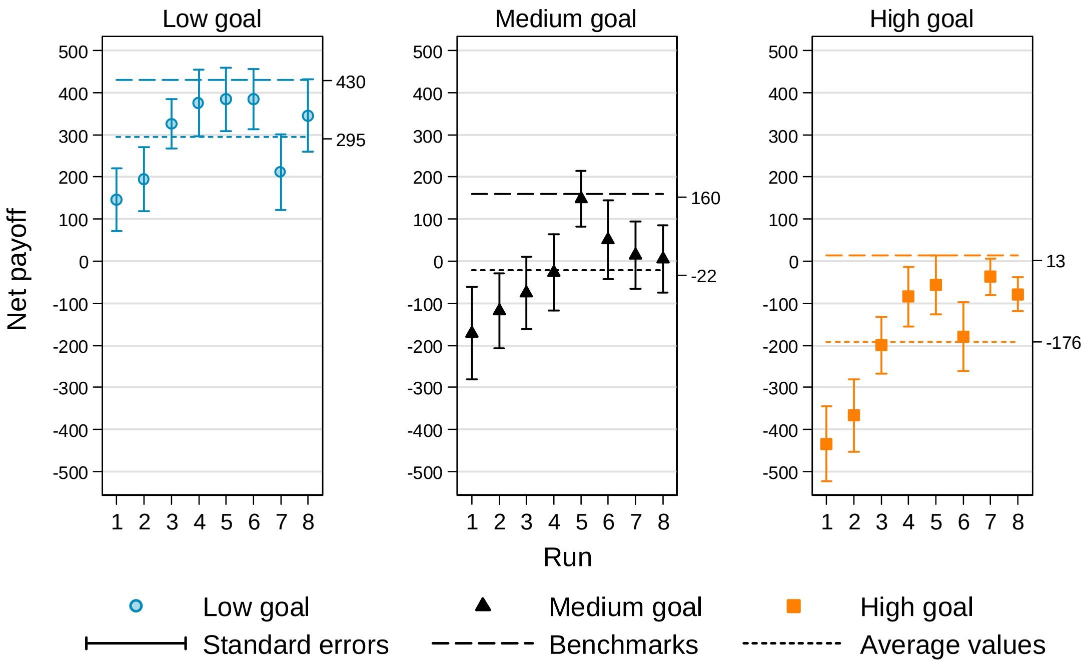
For a rational decision maker previously invested costs are irrelevant for the effort and goal attainment since only the *(g,τ)*-constellation should matter for the optimal effort choice. This would imply that the estimated coefficient of the invested costs should be zero. However, we find positive and, in a vast majority of cases, highly significant coefficients of the costs invested. The results are reported in Tables A2 and A3 in the Appendix. Thus agents' effort on average increases with the previous monetary investment in the goal attainment. Hence, sunk costs significantly affect behavior, and participants indeed show behavior that can be interpreted as an escalation of commitment.

5.3 Payoffs

Observation 7: *Actual payoffs are in general lower than predicted because participants exert inefficiently large efforts. However, payoffs increase over rounds as the agents' choices converge towards the predicted efforts.*

By definition an overprovision of effort must lead to lower expected payoffs, as the marginal effort costs exceed the marginal monetary benefit. Indeed, as can be seen in Figure 6, in every treatment the average net payoffs in all 8 runs lie below the predicted values, which are depicted with dashed lines. Interestingly, the average net payoffs are negative in the *High Goal* treatment: In this treatment payoffs are significantly lower than predicted in all runs but 4, 5 and 7 (p-values < 0.1, two-sided Fisher-Pitman test). The average net payoff in the *Medium Goal* treatment is only positive after run 4, and payoffs are significantly lower than the predicted value of 160.36 (p-values < 0.1 in all but run 5 and 6). The *Low Goal* treatment is the only one in which the net payoffs remain positive during the whole experiment, but also here in runs 1, 2, 3 and 7 the payoffs are significantly lower than predicted (p-values < 0.1).

FIGURE 6: AVERAGE NET PAYOFFS AND 95% CONFIDENCE INTERVALS



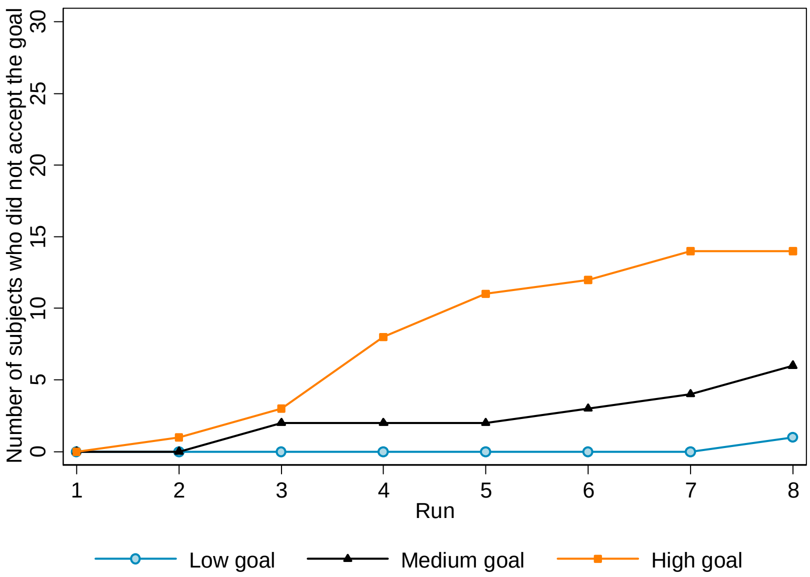
Note: Dashed lines are a-priori expected net payoffs conditional on optimal effort.

5.4 "Goal Acceptance" and Drop-Outs

While the dynamic optimization model would predict that agents should always exert some effort early on (and as long as the goal is in principle attainable), Locke and Latham (1990) have stressed that a goal has to be "accepted" beforehand, as otherwise individuals will not work towards the goal. According to goal-setting theory, the more difficult the goal, the lower the number of subjects that will accept it. Also in our setting one could expect that the acceptance rate falls with the goal difficulty, especially because of the strongly decreasing expected net payoffs. If subjects have not provided any effort in a particular run, we characterize them as "not accepted the goal" in this run. We classify those subjects who have exerted any positive effort at least in one period of a run, as "accepted the goal" in this particular run. Figure 7 shows the number of participants in the group "not accepted the goal". In the *Low Goal* treatment the agents almost always work towards the goal. In the *High Goal* treatment the picture looks different. In the first three runs, the vast majority of the participants provide some positive effort, while in the runs 5 to 8 approximately 40% of subjects choose no effort at all. Although the expected net payoff from goal attainment in the *High Goal* treatment is very low (ECU 12.86 = €0.04), approximately two thirds of subjects work toward the goal. Taken together, this suggests that the goal attainment is not driven merely by monetary incentives but also by some intrinsic goal achievement drive or feelings of obligation which is reduced only in later runs as individuals experienced losses.

Observation 8: *The more difficult the goal and the lower the expected payoff, the more likely participants are to drop out from the goal attainment task and exert no effort at all. Even though the expected net utility from attaining the goal is very low in the High Goal treatment, more than 50% of subjects work to reach it.*

FIGURE 7: NUMBER OF "NOT ACCEPTED" GOALS



Note: The number of independent observations in each treatment is N=30.

Table 6 reports Probit regressions clustered on the level individuals, which aim to study the determinants of "goal acceptance". Taking the treatment *Medium Goal* as a reference group and controlling for the average costs per run, we observe a significantly positive coefficient of the *Low Goal* treatment dummy on the goal attainment and a significantly negative coefficient of the *High Goal* treatment dummy on the goal acceptance. However, when we control for the experienced goal attainment success, the treatments' coefficients become insignificant. On the one hand, the goal size is highly correlated with achievement, as the low goal could be easily achieved (it was attained in 94% of cases), whereas goal achievement in the high goal treatment was rather rare (13% of cases). Nonetheless, goal acceptance depends on previous individual experience. Hence, the lack of goal acceptance is indeed mainly driven by reactions to the past experience of failing to reach the goal.

Observation 9: *Not only the goal difficulty, but also previous success affects the goal acceptance.*

TABLE 5: PAST SUCCESSES AND GOAL ACCEPTANCE

	(1) Coef.	SE	(2) Coef.	SE
Low goal	0.079***	(0.03)	-0.00	(0.12)
High goal	-0.067**	(0.04)	-0.004	(0.01)
Average costs per run	0.0001***	(0.00)	-0.00	(0.00)
# Achieved goals / # Played runs			0.06***	(0.04)
Dummies for sequences				
Controls				
Pseudo R^2	0.42		0.56	
N of obs.	623		623	
N of subjects	89		89	

Note: The dependent variable is goal acceptance (Yes=1, No=0). Marginal effects orobit regression estimates. Clustered by individuals. Robust standard errors are reported in parentheses. The reference group is the *Medium Goal* treatment. . Controls are gender and age and are not significant. Significance levels based on the Probit estimationa are denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.5 Effect of the Bonus

We have focused so far only on the core treatments in which the goal difficulty was varied. In this section, we discuss an additional treatment where we lowered the bonus paid for goal attainment.

Observation 10: *The average individual effort is significantly smaller when the bonus for goal attainment is low. Nevertheless, there is also a significant amount of effort overprovision in the Medium Goal Low Bonus treatment.*

Table 2 shows the descriptive statistics of the key outcome variables in this *Medium Goal Low Bonus* treatment. The model predicts an average total effort of 147.68 for the *Low Bonus*, as opposed to 289.23 for the *High Bonus* treatment. Indeed, the difference in the expected total effort is significant: The participants provide on average 32% less effort in the treatment *Medium Goal Low Bonus* (*p*-value = 0.015, two-sided Fisher-Pitman test for independent samples).

It is, however, interesting to note that the overprovision of effort is also significant in the *Medium Goal Low Bonus* treatment. This again supports the conjecture laid out above that the agents have an intrinsic motivation or feel an obligation to attain the goal, which in turn leads to overprovision of effort. Indeed, recall that under the *high* bonus the probability of attaining the goal is, with about 72% across all rounds, very close to the prediction. But under the low bonus this probability is, at 46%, by far higher than the prediction of 30% (*p*-values < 0.10 for runs 2-4 and 6, *p*-values < 0.05 for runs 1, 5 and 7-8, one-sided Binomial test, N = 30).

5.6 Personal Characteristics and Effort Overprovision

In Tables A3 and A4 in the Appendix we replicate the regression models presented above, including personal characteristics such as gender, the Big Five personality dimension measures, risk and loss aversion measures and running regression estimations with individual clusters pooled over treatments. The Big Five personality traits were measured with a 10-item scale introduced by Rammstedt and John (2007). The risk aversion measure was derived from the lottery choices suggested by Holt and Laury (2002) and varies from 0 to 10. The loss aversion was measured on the scale from 0 to 6 (Gächter et al., 2007).

These personal characteristics are not significant in any of the models.

6. Conclusion

We investigated a stylized formal model of dynamic goal attainment in which agents receive a bonus payment when attaining a predetermined goal within a given time frame. Dynamic optimization provides a precise prediction regarding optimal effort choices. We have tested this setting in a laboratory experiment, and we find that the dynamic optimization model qualitatively explains patterns of the experimental data quite well. According to our prediction, the relationship between goal size and the amount of provided effort is non-monotonic, as subjects exert the most effort when facing medium challenging goals. But we also find evidence for systematic deviations from the rational prediction. For instance, participants provide too much effort as compared to the prediction in treatments where the goal is hard to attain without making losses. This indicates that participants to some extent feel an intrinsic motivation or obligation to attain the goal, even when it is too costly from a purely economic perspective.

Moreover, we find that past luck affects effort provision and also observe substantial evidence for an escalation of commitment, as agents increase their effort to a stronger extent when they have already invested higher amounts of money in attaining the goal.

We conclude that the investigation of dynamic optimization models indeed helps to understand the intertemporal behavior of agents faced with a goal. However, behavioral phenomena lead to systematic deviations from the optimal effort path that yield interesting challenges for future research on optimal goal setting.

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Appendix

FIGURE A1: OPTIMAL EFFORT FOR B=1,000 COMPARED TO B=750

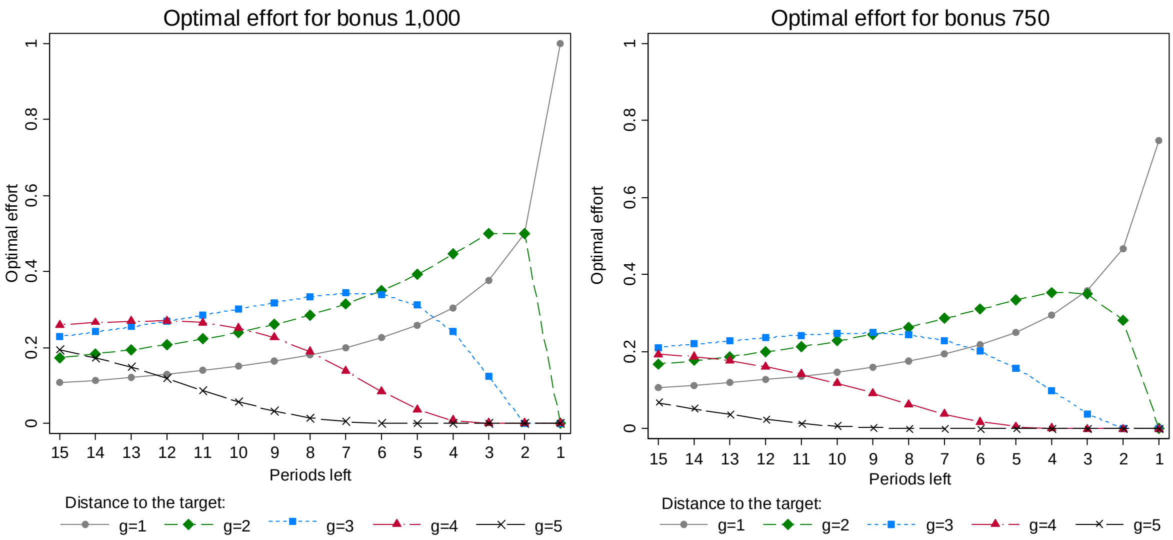

FIGURE A2: BEHAVIOR IF THE EFFORT IN THE FIRST PERIOD OF A RUN WAS EQUAL OR BELOW MEDIAN

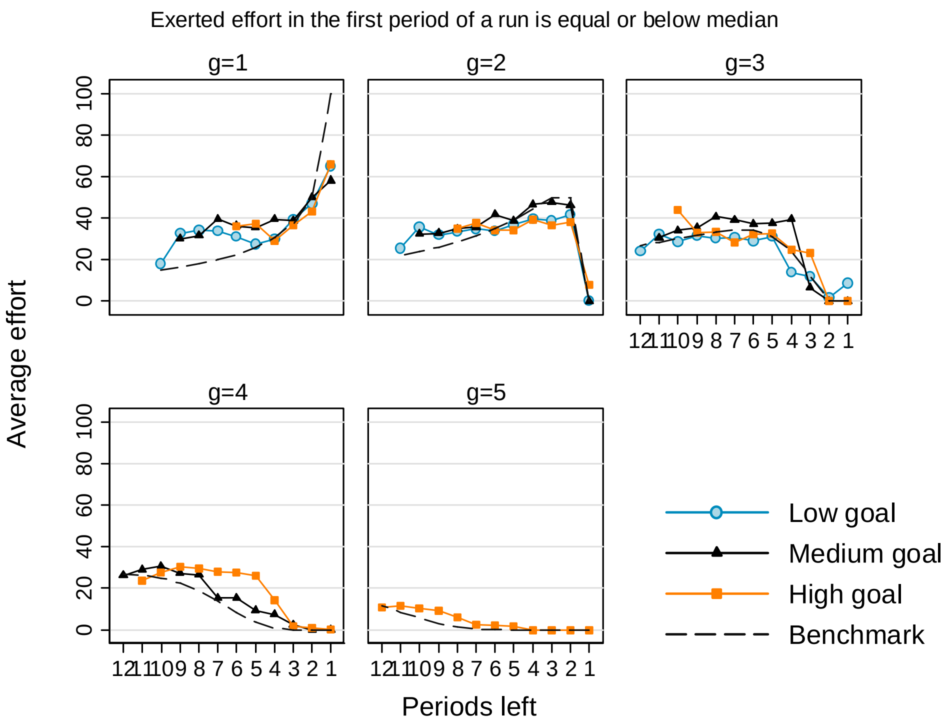

TABLE A1: EFFORT OVERPROVISION

	Low Goal											
	τ											
g	12	11	10	9	8	7	6	5	4	3	2	1
1			***°	***°	***°	***°	***°	**	*			(***°)
2		***°	***°	***°	***	**				(**)		
3	***°	***										

	Medium Goal											
	τ											
g	12	11	10	9	8	7	6	5	4	3	2	1
1				***	***°	***°	***°	***	**			(***°)
2			***°	***°	***	***	***°					
3		***°	***°	***	***	**	*					
4	***°	**	***	**	*		*					

	High Goal											
	τ											
g	12	11	10	9	8	7	6	5	4	3	2	1
1						***	***°	***°	**		(***)	(***°)
2				**	***°	***	***					
3			**	***°	***°	**				*		
4		***°	***°	***	***°	***°	***	**	*			
5	***°	***°	***°	***°	**	**		***				

Note: The table denotes for any (*g*, *τ*)-combination the significance levels for rejecting the null hypothesis that effort is equal to the benchmark as tested with the two-sided Fisher-Pitman permutation test for paired replicates. We average efforts for each (*g*, *τ*)-combination of each agent across all runs for this agent. Through this approach we generate a data set with statistically independent observations for the different (g, *τ*)-combinations, which correspond to economically identical choice problems. Possible parameter constellations are highlighted in grey; Significant discrepancies are indicated with ***°$p < 0.001$; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; The parenthesis indicate that the observed effort level is significantly lower than the predicted; The number of indipendent observations varies between 7 and 31 per cell.

TABLE A2: PAST COSTS AND EFFORTS IN THE MAIN TREATMENTS

Low Goal											
τ	1	2	3	4	5	6	7	8	9	10	11
Average costs spent per period	-0.12	-0.30	-0.10	0.09	0.17***	0.18***	0.17***	0.19***	0.20***	0.14***	0.10***
	(1.01)	(0.67)	(0.30)	(0.09)	(0.04)	(0.04)	(0.05)	(0.03)	(0.03)	(0.02)	(0.02)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
g dummies	-	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.956	0.520	0.803	0.470	0.710	0.721	0.693	0.732	0.727	0.808	0.696
Adj. R2	0.129	-0.441	0.566	0.079	0.559	0.609	0.600	0.663	0.669	0.771	0.639
N of subjects	16	22	26	28	28	29	30	30	30	30	30
N of obs.	21	46	65	88	109	134	168	193	222	240	240

Medium Goal											
τ	1	2	3	4	5	6	7	8	9	10	11
Average costs spent per period	0.27**	0.11	0.07	0.17**	0.14**	0.18***	0.13**	0.17***	0.19***	0.16***	0.13***
	(0.12)	(0.13)	(0.08)	(0.07)	(0.06)	(0.04)	(0.05)	(0.04)	(0.03)	(0.03)	(0.02)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
g dummies	-	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.987	0.777	0.651	0.506	0.397	0.542	0.565	0.695	0.684	0.653	0.687
Adj. R^2	0.941	0.561	0.417	0.319	0.208	0.418	0.462	0.631	0.621	0.585	0.627
N of subjects	17	25	26	29	29	30	30	30	30	30	30
N of obs.	32	68	88	143	164	189	209	230	240	240	240

High Goal											
τ	1	2	3	4	5	6	7	8	9	10	11
Average costs spent per period	-0.05	0.21*	0.28***	0.23***	0.15***	0.11**	0.11***	0.04	0.06	0.20***	0.22***
	(0.06)	(0.11)	(0.04)	(0.06)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
g dummies	-	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.998	0.790	0.671	0.615	0.480	0.427	0.528	0.453	0.534	0.646	0.683
Adj. R^2	0.989	0.573	0.455	0.425	0.367	0.306	0.429	0.340	0.440	0.577	0.623
N of subjects	18	23	27	29	30	30	30	30	30	30	30
N of obs.	32	62	92	119	231	236	239	240	240	240	240

Note: Dependent variable: $\Delta=e(g, \tau) - e^{opt}(g, \tau)$; Fixed effects regression clustered by individualswith robust standard errors in paranthesis; Controlled for runs (with dummies); The observations are restricted to data points where g>0 and $g \leq \tau$; Significance levels denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

TABLE A2: PAST COSTS AND EFFORTS IN THE *MEDIUM GOAL LOW BONUS* TREATMENT

	Medium Goal Low Bonus										
τ	1	2	3	4	5	6	7	8	9	10	11
Average spentcosts	-0.0785	0.3876**	0.22	0.0851	0.1313**	0.1524***	0.1818***	0.2078***	0.1673***	0.1979***	0.1633***
	(0.1307)	(0.1403)	(0.1484)	(0.0672)	(0.0538)	(0.0567)	(0.0471)	(0.0297)	(0.0336)	(0.0357)	(0.0228)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
g dummies	-	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.952	0.7544	0.598	0.4468	0.368	0.4899	0.5153	0.6698	0.6613	0.6167	0.6395
Adj. R^2	0.8938	0.5986	0.4073	0.2858	0.2136	0.3813	0.424	0.6142	0.607	0.5575	0.5858
N of obs.	32	68	88	143	164	189	209	230	240	240	240

Note: Dependent variable: Δ=e(g, τ) - e^{opt}(g, τ); Fixed effects regression with robust standard errors in paranthesis; The observations are restricted to data points where g>0 and g$\leq\tau$; Significance levels denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

TABLE A3: EFFECT OF PERSONALITY TRAITS ON EFFORT OVERPROVISION

	(1) Total effort		(2) Total effort		(3) Δ=e(g, τ) - e^{opt}(g, τ).		(4) Δ=e(g, τ) - e^{opt}(g, τ).	
Low goal	-27.17	(21.66)	-12.57	(25.96)	-0.38	(2.39)	-0.52	(2.33)
High goal	-62.10*	(37.55)	-105.79**	(46.60)	-2.26	(2.73)	-1.97	(2.62)
Experienced luck in previous periods					-6.51***	(1.91)		
Luck							-8.18***	(2.77)
No luck							-2.22	(3.45)
Female dummy	0.68	(2.54)	0.95	(3.31)	2.95	(2.69)	2.90	(2.59)
Age	0.19	(0.30)	0.10	(0.36)	0.23	(0.31)	0.22	(0.30)
Risk aversion	0.00	(0.50)	-0.27	(0.62)	-0.07	(0.51)	-0.08	(0.48)
Loss aversion	-0.45	(0.78)	0.09	(1.00)	-0.10	(0.74)	-0.08	(0.72)
Extroversion	0.38	(0.75)	0.11	(0.91)	0.51	(0.70)	0.44	(0.68)
Agreeableness	-0.20	(0.72)	-0.53	(1.05)	0.11	(0.67)	0.13	(0.64)
Neuroticism	0.58	(0.57)	0.77	(0.76)	0.97	(0.61)	0.95	(0.60)
Conscientiousness	-0.38	(0.59)	-0.73	(0.80)	-0.70	(0.63)	-0.68	(0.60)
Openness	-0.92*	(0.51)	-1.36*	(0.69)	-0.77	(0.54)	-0.75	(0.52)
R^2	0.13		0.02		0.29		0.29	
N of obs.	720		360		5970		6060	
N of subjects	90		90		90		90	

Note: The reference group is the Medium Goal treatment. Controls are gender and age and are not significant. The observations are restricted to data points where g > 0 and g ≤ τ. Standard errors in parentheses; * *p* < 0.1, ** *p* < 0.05, *** *p* < 0.01.

TABLE A4: GOAL ATTAINMENT, GOAL ACCEPTANCE AND PERSONALITY TRAITS

	(1) Bonus received (0/1)		(2) Goal accepted (0/1)		(3) Goal accepted (0/1)	
Low goal	1.19***	(0.24)	1.46***	(0.54)	-1.18	(0.72)
High goal	-0.87***	(0.26)	-1.06***	(0.36)	-0.97*	(0.52)
Average costs per run			0.00***	(0.00)	-0.00	(0.00)
# Achieved goals / # Played runs					5.48***	(0.73)
Female dummy	0.10	(0.24)	0.24	(0.37)	0.30	(0.42)
Age	0.04	(0.03)	0.03	(0.06)	0.03	(0.06)
Risk aversion	-0.04	(0.05)	0.05	(0.07)	0.10	(0.09)
Loss aversion	-0.11	(0.08)	0.01	(0.15)	0.20	(0.17)
Extroversion	0.06	(0.07)	0.05	(0.09)	0.12	(0.11)
Agreeableness	-0.04	(0.07)	-0.22*	(0.13)	-0.23*	(0.12)
Neuroticism	0.08	(0.06)	0.09	(0.10)	0.11	(0.13)
Conscientiousness	-0.04	(0.07)	-0.16	(0.11)	-0.28**	(0.12)
Openness	-0.09	(0.05)	0.03	(0.08)	0.12	(0.10)
R^2						
N of obs.	719		623		623	
N of subjects	90		89		89	

Note: Probit regression estimates. Clustered by individuals. Robust standard errors are reported in parentheses. The reference group is the *Medium Goal* treatment. Significance levels denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

SUPPLEMENTARY MATERIALS FOR MANUSCRIPT

‘DYNAMIC GOAL ATTAINMENT – A FORMAL MODEL AND EXPERIMENTAL EVIDENCE’

Instructions

Translation from German:

General information

At the beginning of the experiment, for every participant receives an endowment of 5.000 tokens.
The experiment consists of 8 parts. In no part of the experiment your income depends on the decisions of another participant. Each part consists of 12 periods.

Decision in each period

In each part you can win a bonus of 1.000 tokens. You get this bonus if your result is at least as high as the objective. This amounts to 5 units in every part.
At the beginning of the first period of a part your result is zero.
In each period your result can go up by exactly one unit or remain unchanged. To do so, you can choose an effort from the set [0, …, 99]. This effort causes you costs that will be subtracted from your account. The exact amount of costs is presented in the attached table and can be computed with the “costs calculator” on the screen.
After you choose your effort, the computer will determine if your result is raised by one unit. The probability that your result will be raised by 1 unit equals your input (in %).
At the end of each period you learn whether your result went up by one unit or not, and the updated score.

Bonus at the end of a part

If your result is at least as high as the objective of 5 units you receive a bonus of 1.000 tokens. Otherwise you do not receive any bonus.

Information at the end of a part

At the end of a part you will receive a message whether you met the objective, how many tokens are left on your account, and an overview on the calculation of your income.

Total income

Your total income from the experiment results as follows:

Endowment of 5.000 tokens
minus accumulated cost for the provided efforts
plus bonuses received in each of the 8 parts.

At the end of the 8th part your earnings will be paid to you at an exchange rate of € 0.30 for 100 tokens.

Please note

After the experiment another very short experiment will take place. Subsequent to this we will ask you to answer a few questions concerning your own person.

During the whole experiment no communication is permitted. If you have a question, raise your hand out of the cabinet. All decisions are taken anonymously, i.e., none of the other participants will come to know the identity of anyone having taken a particular decision. The disbursement will also be carried out anonymously, i.e., no participant will come to know which amount is paid to another participant.

Original instructions in German:

Allgemeine Informationen

Zu Beginn des Experiments bekommt jeder Teilnehmer ein Startkapital von **5000 Talern** auf seinem Konto gutgeschrieben.
Das Experiment besteht aus **8 Teilen**. In keinem Teil ist Ihr Einkommen von den Entscheidungen eines anderen Teilnehmers abhängig.
Jeder Teil besteht aus **12 Perioden**.

Entscheidung in jeder Periode

In jedem Teil können Sie einen Bonus in Höhe von **1000 Talern** gewinnen. Diesen Bonus bekommen Sie, wenn Ihr Ergebnis mindestens so hoch wie das Ziel ist. Das Ziel beträgt in jedem Teil **3 Einheiten**.
Zu Beginn der ersten Periode eines Teils ist **Ihr Ergebnis Null.**
In jeder Periode eines Teils kann sich Ihr Ergebnis um **genau eine Einheit** erhöhen oder unverändert bleiben.
Hierzu wählen Sie in jeder Periode einen ganzzahligen **Einsatz aus der Menge [0, ..., 99].**
Der gewählte Einsatz verursacht Ihnen **Kosten**, welche Ihnen von Ihrem Konto abgezogen werden. Die Kosten für jeden Einsatz können Sie der beigelegten Tabelle entnehmen oder mit Hilfe eines Kostenrechners ausrechnen, den Sie unten auf dem Bildschirm finden.
Nachdem Sie einen Einsatz gewählt haben, bestimmt ein Zufallszug, ob sich Ihr Ergebnis um eine Einheit erhöht. Die Wahrscheinlichkeit, dass Ihr Ergebnis sich um 1 Einheit erhöht, ist gleich **Ihrem Einsatz (in %).**
Am Ende einer Periode erfahren Sie, ob sich Ihr Ergebnis um eine Einheit erhöht hat oder nicht, sowie das aktuelle Ergebnis am Ende dieser Periode.

Bonus am Ende eines Teils

Ist Ihr Ergebnis am Ende eines Teils mindestens so hoch wie das Ziel **von 3 Einheiten**, erhalten Sie den Bonus in Höhe von 1000 Talern. Ansonsten erhalten Sie keinen Bonus.

Information am Ende eines Teils

Nach einem Teil erhalten Sie eine Mitteilung, ob Sie das Ziel erreicht haben, wie hoch Ihr Gesamtkontostand im Experiment ist, sowie eine Übersicht über die Berechnung Ihres Einkommens.

Gesamteinkommen

Das Gesamteinkommen aus dem Experiment ergibt sich wie folgt:

Startkapital in Höhe von 5000 Talern
minus Summe der angefallenen Kosten für die geleisteten Einsätze
plus Summe der Boni aus jedem der 8 Teile.

Am Ende der 8 Teile wird Ihnen Ihr Gesamteinkommen zu einem Wechselkurs von €0.30 pro 100 Taler ausgezahlt.

Bitte beachten Sie

Nach diesem Experiment findet noch ein anderes sehr kurzes Experiment statt. Im Anschluss daran werden wir Sie bitten, einige Fragen zu Ihrer Person zu beantworten.

Während des gesamten Experiments ist keine Kommunikation gestattet. Wenn Sie eine Frage haben, strecken Sie bitte die Hand aus der Kabine. Sämtliche Entscheidungen erfolgen anonym, d.h. keiner der anderen Teilnehmer erfährt die Identität desjenigen, der eine bestimmte Entscheidung getroffen hat. Auch die Auszahlung erfolgt anonym, d.h. kein Teilnehmer erfährt, wie hoch die Auszahlung eines anderen Teilnehmers ist.