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Gain and loss framing to encourage effort provision: An experiment*

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Abstract

In this paper we compare the impact of a gain framing with a loss framing on a simple and repetitive task. Based on the expectation of higher reference points in the loss framing than in the gain framing, we expected to generate higher effort in the former. Instead, we find no evidence of loss framing effect on participants' efforts over the experiment. Our results suggest that time pressure on a task kills the loss framing effect. However, experimental sessions without time pressure confirm that the potential effect of loss framing as a nudge is minimal in our context. Nowadays where nudges seem to be the king way for changing behavior we find that monetary incentives are still very powerful to incentive behaviour especially with students.

Keywords: framing effects, loss aversion, prospect theory, reference dependence, risk aversion.

JEL Classifications: C91, D91.

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1 Introduction

Environmental challenges often require people to undertake many small acts, such as switching off the lights, recycling rubbish individually, turning off the water while brushing their teeth, etc. These everyday changes of habit correspond to many small and repetitive efforts. Results of several studies suggest that loss aversion framing can be used to increase effort or to nudge people towards more sustainable behavior (Ghesla *et al.*, 2020). Several field experiments have shown that loss aversion framing can induce higher effort regarding plastic bag use, or energy saving (Bradley *et al.*, 2016, Bager and Mundaca, 2017).

This paper studies loss framing as a mean to encourage individuals to complete such small and repetitive efforts. Based on higher reference points, loss framing should increase the salience of the monetary benefit of those small and repetitive efforts "*as losses loom larger than gains*" (Kahneman and Tversky, 1979).

Loss framing of contracts amounts to prepaying individuals and reclaiming this payment if the contract is not met. Gain framing refers to paying individuals after the fact if the contract is satisfied. Furthermore, the theory posits that individuals are risk-averse in gains and risk-seeking in losses (Kahneman and Tversky, 1979). Kühberger (1998) corroborates the theory finding that risk aversion in gains and risk seeking in losses is particularly strong when reference points rather than outcomes are manipulated, i.e. when starting points rather than final earnings are manipulated.

In the present experiment, starting points are manipulated by giving individuals in loss treatments an endowment from which their losses are subtracted while giving them in gain treatments no initial endowment but they can earn additional gains. We test linear piece rate schemes with different levels of incentives playing on gain and loss framing in a risky or unrisky environment under time pressure. The main hypothesis we test is a higher effort provision in the loss treatments than the gain treatments, in the different settings of our experimental framework. Our results show no better performance under loss framing than gain framing, suggesting that such framing does not affect reference points under time pressure. We run an additional treatment relaxing the time constraint and no significant difference between loss and gain framing is found either.

2 Literature

According to expected utility theory, there is no difference in framing incentives between losses and gains as, under isomorphic framing, the two incentive types should motivate the same provision of effort. However, individuals often provide more effort to keep something that belongs to them due to the endowment effect (Kahneman *et al.*, 1991, List, 2011), or because they assess losses and gains relative to a reference point (Tversky and Kahneman, 1991) or because changes to the status quo are perceived as losses (Bateman *et al.*, 1997).

Prospect theory suggests that people will provide higher effort once they are below their reference point, i.e. they are in the loss domain. Once the reference point is reached, subjects are in the gain domain, and decrease their effort. Manipulating this reference point, can lead to higher effort provision (Kahneman and Tversky, 1979).

In the laboratory, lump-sum payoffs encourage greater effort provision under loss framing than under gain framing in both hypothetical (Hannan *et al.*, 2005) and real-life (Hossain and List, 2012) contract tasks in factories and with teachers. In an artificial, real-effort task, Imas *et al.* (2016) find that endowing subjects with a t-shirt and taking it back if they do not meet a certain target is more effective than receiving the t-shirt after having met the target. Further, in profit maximisation choice tasks, individuals prefer to retain their prepayment than to lose it even if an alternative choice leads to higher profits (Hochman *et al.*, 2014).

In contrast, the results of contract framing for piece-rate payoffs are less conclusive. Goldsmith and Dhar (2011) find that loss framing under a piece-rate payoff does not increase overall task performance but it does improve the amount of time spent searching. Abeler *et al.* (2011) and Brooks *et al.* (2017), in a case of simple piece rate contract with live feedback, have both shown how the manipulation of the reference point can increase or decrease the effort provision.

However, there is also evidence of inefficient loss aversion framing, especially in laboratory experiments with students. De Quidt *et al.* (2017) and Grolleau *et al.* (2016) do not find significant effects on effort provision due to framing in the presence of immediate feedback and piece-rate payoffs. Essl and Jaussi (2017) find reverse effect of loss framing for individuals with a high level of loss aversion and who are subject to time pressure.

Risk also influences effort provision under gain and loss framing as individuals are typically risk averse under gains and risk seeking under losses (Kahneman and Tversky, 1979). In mixed frame experiments with piece-rate payments for performing simple additions to which a known amount was either added or taken away with equal probability, both Sloof and Van Praag (2010) and Corgnet and Hernán-González (2018) find that subjects provide more effort when the additional gain or loss is higher, i.e.: when there is greater variability in the payoff. Even with the option to browse the Internet instead of adding numbers for cents, Corgnet *et al.* (2020) find that subjects continue the task for longer, despite not liking it, when faced with variable payments rather than a known amount.

3 Experimental design

We designed the experiment to test the impact of loss and gain framing on effort provision. The framing is that the participants to the experiment received a positive endowment equal to €21 in the loss framing whereas no endowment in the gain framing.

3.1 Framework and hypotheses

We run a laboratory experiment to test the impact of the gain and loss framing in a framework representing daily energy saving decisions. We retain three dimensions of such decisions: (i) repetition: this is the sum of constant everyday small efforts that decrease energy expenses and increase individuals' utility; (ii) risk: the same effort may not always lead to the same performance (*e.g.* heating decisions, because of the influence of the outside temperatures) and the payoff is sometimes revealed before the action or later; (iii) time pressure: as such efforts are made on a daily basis, it is possible that they must be done in a short period of time.

Based on Corgnet *et al.* (2018), we construct our hypotheses from a simple model with agent's binary effort where the agent receives a piece-rate linear contract and has a reference point for payment. The agent exerts a costly effort $e \in \{e_l, e_h\}$, with $c(e_h) > c(e_l)$. She can produce high of low performance $y \in \{y_l, y_h\}$, with the probability to reach some performance depending on the effort exerted: when the agent exerts effort e_l, her probability to reach low performance is π and high performance is $1 - \pi$, whereas when she exerts effort e_h, her probability to reach low performance is $1 - \pi$ and high performance is π, with $\pi > 0.5$. The agent receives a fixed wage, W, when the task is correctly completed. Depending on the treatment, this fixed wage can either take one value, w_M, or two values with equal probability, w_L and w_H. The different wages are such that $w_L < w_M < w_H$ and $w_M = \frac{w_L+w_H}{2}$. If the task is not correctly completed, the agent receives nothing.

The agent maximizes her utility function that depends positively on her *monetary utility* derived from the payment she receives for the task and on her *non-monetary utility* that is a reference-dependent function with the reference point in terms of payment expected. For simplicity, we suppose that the monetary utility of agent i is $u_i = W - c(e_i)$. The non-monetary utility is the function $v(W - g)$, with g the individual reference point. We assume that the reference point in the loss framing, g_P is different from the reference point in the gain framing, g_G, with, by definition, $g_P > g_G$. The function $v(.)$ is such that $v(0) = 0$ and $v(.) > 0$. Following Corgnet *et al.* (2018), we assume $-v(-x) = \lambda v(x)$ with $\lambda > 1$ for all $x > 0$, $v''(x) > 0$ for all $x < 0$ and $v''(x) < 0$ for all $x > 0$. When agent i exerts effort e_l, her utility function is as follows:

$$U_i(e_l) = \pi v(-g) + (1 - \pi)(W + v(W - g)) - c(e_l) \tag{1}$$

When agent i exerts effort e_h, her utility function is as follows:

$$U_i(e_h) = (1 - \pi)v(-g) + \pi(W + v(W - g)) - c(e_h) \tag{2}$$

Agent i chooses to exert effort e_h instead of e_l if $U_i(e_h) > U_i(e_l)$. When the fixed wage is w_M, agent i exerts effort e_H if:

$$w_M + v(w_M - g) + \lambda v(g) > \frac{c(e_h) - c(e_l)}{2\pi - 1} \tag{3}$$

When the fixed wage is w_L or w_H with probability one half each, agent i exerts effort e_H if:

$$\frac{w_L + w_H}{2} + \frac{v(w_L - g) + v(w_H - g)}{2} + \lambda v(g) > \frac{c(e_h) - c(e_l)}{2\pi - 1} \tag{4}$$

The first insight we deduce from inequalities (3) and (4) is that observing high effort e_H is more likely in the loss framing that in the gain framing. Indeed, $\lambda v(g)$ is higher for g_P than g_G because $\lambda > 1$. This leads to our first and major hypothesis:

Hypothesis 1: Loss framing leads to higher effort than gain framing.

Besides, inequalities (3) and (4) give additional insights. Because individuals are assumed to be risk averse in the gain domain and risk seeking in the loss domain, we find $\frac{v(w_L - g) + v(w_H - g)}{2} < v(w_M - g)$ in the gain domain and $\frac{v(w_L - g) + v(w_H - g)}{2} > v(w_M - g)$ in the loss domain. In the gain domain, inequality (3) is easier to satisfy than inequality (4) while in the loss domain, inequality (4) is easier to satisfy than inequality (3). We deduce our second hypothesis:

Hypothesis 2: High and low payment with equal probability decrease effort compared to average payment in the gain domain, but the reverse occurs in the loss domain.

We also note that the likelihood of observing a high effort will be higher as the probability of producing high performance when making a high effort, π, is high, or as the fixed payment is high. Instead, when the increase in cost from exerting a low to a high effort is higher, the likelihood of observing a high effort will be lower.

In order to test these predictions, we implemented 3 treatments that we will detail below. We ran an additional fourth treatment to test for the impact of time pressure that characterizes a specific environment of daily energy saving decisions. Time pressure may alter the impact of reference-dependent points on effort (Essl and Jaussi, 2017).

Hypothesis 3: Time pressure limits the effect of loss framing.

3.2 Experimental task

We ask subjects to complete an artificial, real-effort task involving counting the number of 1 in 9 by 9 tables of randomly ordered 0 and 1 (similar to the tasks in Abeler *et al.* (2011) and Essl and Jaussi (2017)). Subjects are informed that they will see up to 140 tables[1] in 28 periods of 5 tables. In each period, subjects have 80 seconds to count the number of 1 in 5 tables.

The advantages of this task are that no special knowledge is required, learning possibilities are limited, and effort is easily measurable. There is little intrinsic motivation for subjects to complete the task and so they should complete it only for extrinsic gains. In addition, experimenter demand effects are minimized as the task is artificial and the outcome is of no intrinsic value to the experimenter.

3.3 Treatments

We conducted different treatments and used a between-subjects design. We conducted 3 treatments: the *Fixed* treatment (n=60) where the participant receives w_M when the task is correctly completed, the *Random* treatment (n=98) where the participant receives either w_L or w_H with equal probability when the task is correctly completed and she knows the amount of the fixed

[1] The number of 1 in each tables was drawn randomly between 28 and 45 for all periods prior to the first experimental session and the same sequence was applied to all subjects.

wage when she makes her effort, and the *Risky* treatment (n=103) that is the same as the later but the participant does not know the fixed wage when she makes her effort. We added a fourth treatment to assess the role of time pressure and run the *Time* treatment with a fixed wage (n= 95).

We first carry out a 2 by 3 design to create 6 treatment groups: gain and loss framing versus fixed, random, and risky incentives. We then include an additional treatment: time, which removes the time constraint. Table 1 summarises the different treatments.

In the fixed treatment, the payoff is €0.15. Under gain framing, subjects earn €0.15 per correct answer, i.e. when they have given the exact number of 1 in the table. Under loss framing, subjects lose €0.15 per wrong answer or incomplete answer. Prior to the start of the loss treatment, €21 was distributed to each subject to increase the salience of the potential earning and of the feeling of losing the money. In the gain treatment, no mention of how much could be earned in total was made, even if this could be easily calculated.[2] We wished to establish a higher reference point in the loss treatment than in the gain treatment.

At the end of each period, subjects received feedback on the number of correctly completed tables, the payoff for each correct answer, the money made in this period and the updated earnings of the experiment, either counting up from €0 or down from €21.

In the random treatment, the payoff for a correct table was drawn randomly between €0.05 and €0.25 with equal probability at the beginning of each period. Subjects were informed of the draw at the beginning of each period, prior to counting. Everything else is identical to the fixed treatment.

In the risky treatment, the payoff for a correct table was drawn randomly between €0.05 and €0.25 with equal probability at the beginning of each period. Subjects were informed of the draw at the end of each period after having counted the number of 1 in 5 tables. Everything else is identical to the fixed treatment.

We also ran a treatment in which we removed the time constraint. This treatment is identical to the fixed treatment with a loss and gain framing. Subjects could gain or lose €0.15 per table. The only difference is that subjects could spend as much time as they desired counting the number of 1 in each of the 140 tables.

[2]It was quite easy for subjects to calculate that they could earn €0.75 per period and for 28 periods, that the maximum payoff is €21.

		Gain	Loss
	Endowment	€0	€21
Incentive	Fixed	€0.15	€-0.15
	Random	€0.05 or €0.25	€-0.05 or €-0.25
	Risky	€0.05 or €0.25	€-0.05 or €-0.25
	Time	€0.15	€-0.15

Table 1: Payoffs by treatment

3.4 Participants and Procedure

In total, 354 students took part in the experiment. The experiment was programmed using zTree software (Fischbacher, 2007). Table 2 details the characteristics of subjects in each treatment. In addition to the amount earned during the experiment, subjects received a €5 show-up fee.

Treatment	n	Age	Female (%)	Undergrad. (%)	Avg. earnings (€)
Gain-Fixed	31	21.03	54.84	70.97	13.55
Loss-Fixed	29	20.59	65.52	79.31	12.86
Gain-Random	48	20.69	54.17	79.17	14.13
Loss-Random	48	21.25	58.33	68.75	13.20
Gain-Risky	52	21.15	57.69	80.77	13.27
Loss-Risky	51	21.61	43.14	72.55	12.70
Gain-Time	46	20.22	73.91	80.43	18.30
Loss-Time	49	20.63	75.51	79.59	19.10

Table 2: Description of sample by treatment

At the beginning of their session, subjects chose a subject number at random and a computer post. All instructions were read aloud by the experimenter and were displayed on two screens at the front of the room. Subjects were told that the experiment would consist in two phases: (1) the experimental task, (2) a questionnaire.[3] The first phase began with comprehension questions which were corrected collectively before subjects started the experimental task. Instructions for the second phase were read aloud once all subjects had completed the first phase.

[3]The questionnaire included questions pertaining to subjects' appreciation of the task and standard sociodemographic questions.

4 Results

The main variable of interest is the average number of tables correctly counted by subjects in each period. This variable is used as a proxy for the effort provided by subjects. Table 3 provides the average, the standard deviation, and average minimum and maximum number of correct tables by period for each treatment.

	Number of correct tables per period			
Treatment	Avg	Sd	Min	Max
Gain-Fixed	3.23	0.69	1.75	4.50
Loss-Fixed	3.06	0.91	1.07	4.68
Gain-Random	3.27	0.68	1.36	4.64
Loss-Random	3.10	0.80	0.89	4.54
Gain-Risky	3.10	0.75	0.54	4.29
Loss-Risky	3.01	0.61	1.64	4.57
Gain-Time	4.36	0.80	1.11	4.96
Loss-Time	4.55	0.53	1.71	5.00

Table 3: Descriptive statistics by period and treatment

First, we compare subjects' effort provision as proxied by the average number of tables correctly completed per period across framing and within an incentive structure. Subjects perform better in the gain frame for fixed, random, and risky incentive structures. When the time constraint is removed, subjects perform better in the loss frame. However, none of these differences are significant.

On average per period, subjects correctly completed most tables in the two treatments without time constraint. The average performance of these treatments is towards the maximum performance of all other treatments with time constraint. In the fixed and time treatments, the incentive structures are identical. Subjects complete significantly more tables under both types of framing when the time constraint is removed (p<0.001, Wilcoxon rank-sum test).

Figure 1 shows the average number of correct tables per period by treatment. On average, subjects complete significantly more tables per period in the time treatments for both frames, thus confirming the descriptive statistics above in Table 3. In the fixed, random and risky treatments, we see an upward trend in the evolution of the number of correct tables over the experiment. Subjects appear to improve in their ability to count the number of 1 within the 80 seconds time constraint. On the other hand, we see a downward trend in the time treatments, particularly for the gain-time treatment. This suggests a fatigue effect as the experiment goes on.

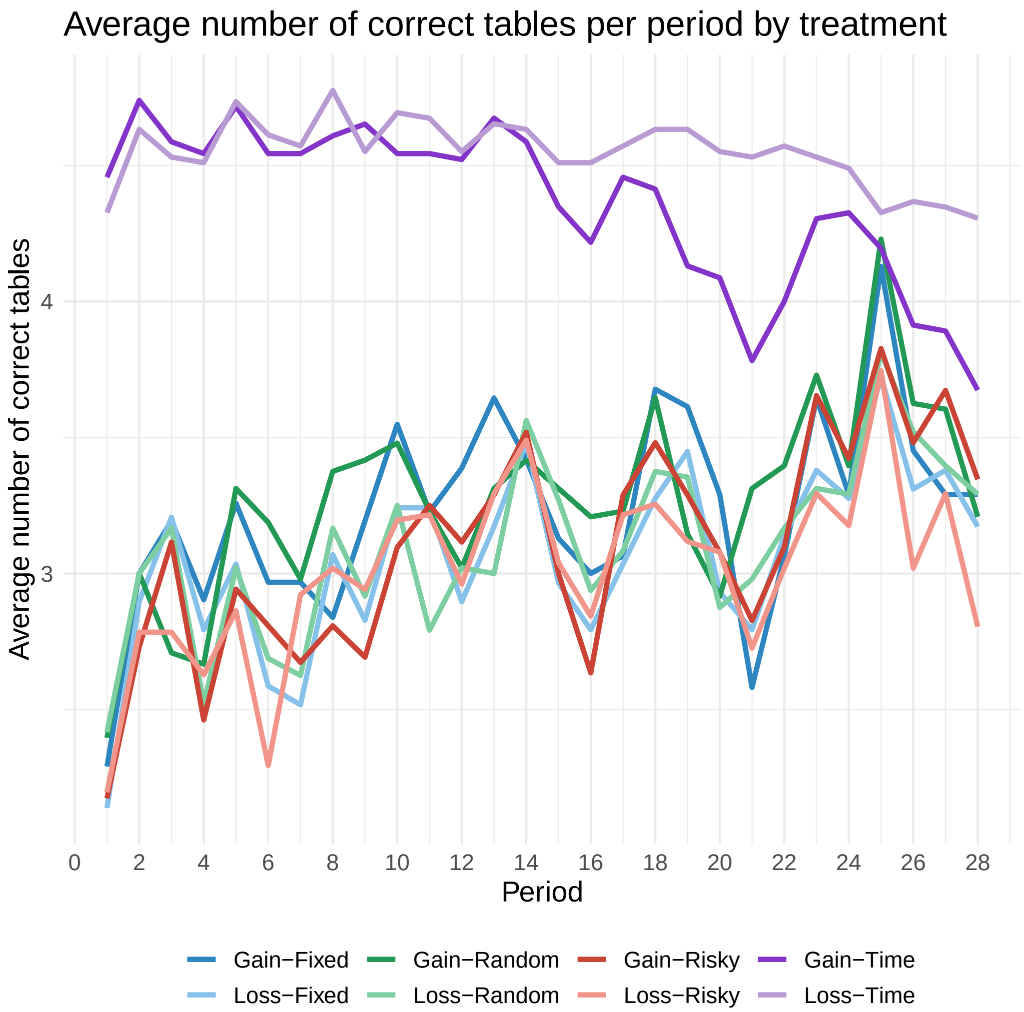

Figure 1: Average number of correct tables per period by treatment

We estimate the impact of the different treatments thanks to an OLS regression clustered by subject, with the number of 1 counted correctly for a period as dependant variable. We choose this variable rather than the average number of tables correctly counted by subjects in each period as it allows also to account for the difficulty of the task. We run several specifications and our results are robust.[4] All treatments with time constraint lead to

[4]We run several estimations with different dependent variables to measure efforts such

the same effort as there are no significant differences. The two treatments without time pressure lead to an increase in the subject performance as compared to the former treatments but still, no difference between the gain and loss framing appears. Table 4 presents three models adding controls sequentially. Model 1 presents the regression with only the effect of the treatments: we observe that all treatments with time constraint have the same impact on subject effort, but the treatments with no time pressure are inducing a higher performance. Model 2, controlling for the specification of the treatment, exhibits an increasing performance over time. This shows that people tend to get better along the experiment, suggesting a learning effect. A positive draw, *i.e.* a lucky draw of payoff in the random and risky treatments, increases subject effort. Results from model 3 suggest a positive correlation between liking to play games such as playing with words or sudoku and the subject's effort as well as between the subject's grade at her high school diploma and her effort. By contrast, female subjects seem to underperform at the task.

Hence, our results confirm that loss framing does not lead to higher effort than gain framing. Treatments including a random payoff or a risky payoff do not induce significant differences in subject effort. Besides, when there is no time pressure, although the subjects performance seems higher in the loss framing than in the gain framing in the second half of the experiment according to Figure 1, we find no significant difference between the gain and loss framing.[5] We let subjects have as much time as they wished, which allowed to raise significantly the number of 1 counted. We note that in the treatments with no time pressure several subjects had every table correct. These subjects were very likely verifying their counting when they were not sure of their result. Recalling that the payoff for a table is only €0.15, we did not expect such kind of behavior with a task that we found so unpleasant.

5 Discussion

We find no effect on effort of our different incentive schemes. Our results are thus in line with recent work that challenge the conditions under which loss

as the average number of correct tables in the period, the total number of tables solved, the time spent solving the table, the number of guess made, the money earned, etc. They all lead to the same result. We also made a panel regression analysis, which leads to the same result.

[5]In fact, according to the round selected to define the second part of the experiment, one can find a significant effort. However, this result is very sensitive to the choice of the round considered as the final one delimiting the first and second period. Therefore we find that the result was not robust and choose not to present it.

	Model 1	Model 2	Model 3
(Intercept)	**115.744*****	**73.678*****	43.925
	(4.489)	(16.241)	(23.349)
Loss-Fixed	−5.745	−5.745	−8.216
	(7.547)	(7.547)	(7.285)
Gain-Random	1.563	1.563	−1.444
	(5.740)	(5.659)	(5.661)
Loss-Random	−4.302	−4.503	−4.199
	(6.131)	(6.147)	(6.080)
Gain-Risky	−4.647	−4.863	−4.611
	(5.837)	(5.820)	(5.881)
Loss-Risky	−7.596	−7.722	−6.483
	(5.430)	(5.401)	(5.371)
Gain-Time	**42.643*****	**42.643*****	**42.084*****
	(6.206)	(6.206)	(6.374)
Loss-Time	**49.890*****	**49.890*****	**48.956*****
	(5.273)	(5.273)	(5.253)
Period		**0.578*****	**0.596*****
		(0.088)	(0.087)
Positive draw		**224.532***	197.633
		(104.194)	(103.747)
Risk averse			0.456
			(1.664)
Hot hand			−0.071
			(0.105)
Sudoku			**2.642***
			(1.087)
Word games			**2.712***
			(1.203)
Female			−5.278
			(2.865)
Age			−0.058
			(0.410)
Engineer			−1.474
			(3.993)
HS diploma grade			**1.937****
			(0.650)
R^2	0.218	0.231	0.249
Adj. R^2	0.217	0.231	0.248
Num. obs.	49560	49560	49000

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 4: Statistical models

framing generates higher efforts than gain framing (Gal and Rucker, 2018) and suggest that different mechanisms may reduce the effect of loss framing. We can think of too high monetary incentives relatively to the difference in cost of effort between a high and a low effort (W and $c(e_h) - c(e_l)$ in the model) or also to a link between effort and performance too strong (π in the model). Further experiments should be run to determine the conditions under which loss framing improves behavior. We discuss some points below.

5.1 Feedback

De Quidt *et al.* (2017) argue that live feedback tends to decrease the incentive power of loss framing. They also find no significant effect of their treatment with loss framing. However, Abeler *et al.* (2011), Brooks *et al.* (2017) and Goldsmith and Dhar (2011) conduct experiments with students, very low payoffs and live feedback and find a significant effect of the loss framing. Thus, we think this is probably not the main reason of our result. Another potential explanation for our result is the set up of our reference point.

5.2 Reference point

One can argue that subjects were not from the beginning in the loss domain in our loss treatment due to a much smaller reference point than the €21. Students may expect to earn between €10 and €15 when participating in our experiment. Therefore, even if they loose money for each table, they mat remain in the gain domain as compared to their reference point. However, we should observe different trajectories according to the gain and loss treatments. In the gain framing treatments, the subjects should be in the loss domain until they reached their reference point and then feel to be in the gain domain, suggesting a decreasing curve over the periods. By contrast, in the loss framing treatments, for any reference point smaller than €21, we should observe smaller effort when the subjects are below their reference point and then higher effort once they have reached it, suggesting an increasing curve over the experiment. We do not observe any difference in the subjects' trajectories when there is time pressure. The only sign of such an effect is in the last periods of the treatments without time pressure (see figure 1), Our results point in the direction that time pressure tends to decrease the efficacy of a loss framing, as in Essl and Jaussi (2017).

5.3 Future leads

We think that there are two main reasons why all our incentive schemes lead to the same result. First, our monetary incentives are too strong. Second, our opportunity costs are too weak. In both the paper of Abeler *et al.* (2011) and Brooks *et al.* (2017), which find a significant effect of the loss framing, the opportunity cost was higher. In Abeler *et al.* (2011), participants were alone in a room, with a push bottom allowing them to stop whenever they wanted and leaved. In Brooks *et al.* (2017), subjects were also able to leave the experiment when they wanted and they were online, probably at home, which makes the opportunity cost even more salient. It is also worth noting that in Abeler *et al.* (2011) experiment, the treatment with no manipulation of the reference point lead to a higher number of subjects staying until the end of the experiment (about 1/3). This result is in line with our experiment.

6 Conclusion

The effect of loss framing seems not to be cumulative with sufficient incentives. Once the monetary incentives are high enough as compared to the opportunity cost, the loss framing is not inducing higher effort than the gain framing or has a much smaller effect that is difficult to observe in laboratory experiments with students. Several meta-analysis are starting to emerge, gathering experimental evidences on nugdes. The recent meta-analysis of DellaVigna and Linos (2020) analyses the result of random controlled trials of unpublished nudge units[6] and academic experiments[7]. They estimate that nudges have an effect of around 1 to 2 percents as compared to the control group. If this is the case, it may be that we do not have enough statistical power to detect an effect of this kind of magnitude.

[6]Their final sample is constituted of 126 trials, involving 243 nudges and collectively impacting over 23 million participants

[7]A final sample of 26 random controlled trials, including 74 nudge treatments with 505,337 participants for the academic paper

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