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Abstract

Field studies suggest that feedback is an effective tool for promoting efficient consumption. Feedback enhances consumers' awareness of the consequences associated with consumption of those goods, such as energy, that are usually consumed indirectly and unconsciously. Yet, variations in methodologies and weaknesses of internal control in the literature studying the effect of feedback on efficient consumption make it difficult to draw general conclusions. Our study aims to isolate the mechanisms underlying the effect of feedback on consumption in a controlled environment with a neutral language. We design a laboratory experiment in which individuals are not aware of the consequences of their consumption decisions and, thus, cannot easily identify the optimal ones. We introduce feedback as a mechanism to enhance awareness of consumption consequences. We assess the efficacy of different types of feedback that include descriptive norms and framing effects to enhance search of optimal consumption. We find that feedback is most effective when we introduce a negative frame. On the contrary, feedback reduces efficiency when we introduce information about peers' inefficient behavior. Our study quantifies the effect of different types of feedback and suggests useful insights for policy makers.

JEL classification: C91; D12; Q41
Keywords: Feedback, Consumption, Laboratory Experiment

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1 Introduction

Individuals consume several types of goods and services every day. While for many of these goods and services the consequences of consumption are salient to the consumer, assessing such consequences for other kinds of goods might result in a more difficult task.[1] Examples of this latter type of goods are electricity and internet traffic. Indeed, when consumers use a fixed monthly amount of gigabytes of traffic to surf the internet or consume a fixed amount of KWh by using the most disparate appliances, they are certainly better off but, at the same time, they may fail to properly assess the costs and benefits associated to consumption. The difficulty to assess consumption consequences for these goods lies in the facts that consumers are not directly concerned about consuming KWh or gigabytes that, as Fischer (2008) points out, are invisible and partially outside their control. In this complex scenario, the decision makers' inability to make optimal choices plays a crucial role (Kahneman, 2003). Due to information costs, time, and cognitive constraints, individuals often limit their effort to reach decisions that provide a greater level of utility. This way, they may settle to satisficing utility levels and forego additional benefits.

The lack of awareness of consumption behavior combined with decision task complexity may lead individuals to be more exposed to cognitive biases and may prevent them to search for a more efficient consumption behavior. Individuals might lose the opportunity to gain additional benefits or to reduce additional costs from consuming the amount of gigabytes or KWh they are endowed each month or day. A powerful and affordable strategy that can elicit awareness of consumption and can stimulate the search for efficiency is feedback. Feedback enables to fill a "knowledge gap" that consumers face when they cannot access the level and the rate of their consumption, thus, stimulating search of efficient behavior (Cook and Berrenberg, 1981).

In this study, we test how different types of feedback, including descriptive norms and framing effects, enhances awareness of consumption consequences and stimulate the search for efficient consumption behavior. While most research on feedback has been conducted employing field experiments focusing on specific goods (e.g. energy), we isolate the mechanisms underlying feedback effects on the awareness of consumption consequences and on the search for efficiency by running an unframed laboratory experiment with a neutral language. This study aims to enrich the literature on the role of feedback in the promotion of efficient consumption behavior by exploiting the greater internal validity offered by the laboratory setting.

The rest of the paper is organized as follows. Section 2 summarizes the related literature by covering in details research on feedback. Section 3 describes the experimental design. Experimental data and results are presented in section 4. Section 5 concludes with a discussion of the results.

[1] Nelson (1970) categorized goods in *ordinary*, *search* and *experience goods*. Consumers know characteristics of ordinary goods while they need to actively inspect search goods in order to discover such characteristics (which are observable). Experience goods have unobservable characteristics which may be discovered only by consuming the good. As better explained in the next session, our experiment recalls this idea of unobservable characteristics which are revealed only through experience.

2 Literature Review

Research on the effectiveness of feedback on behavior change has a long history in psychology and behavioral economics. By providing individuals with information about their past behavior, feedback represents a powerful strategy for enhancing learning and better performance (Annett, 1969; Bandura, 1969). Feedback can be, in fact, defined as "the mechanism that directs attention to a specific goal" (McCalley, 2006).

In the consumer research field, the role of feedback has mainly been investigated in terms of effects of knowledge of results (KR) (Jones, 1910; Judd, 1905; Wright, 1906). Seminal studies report that the provision of information about past performance enhances individuals' learning of choice consequences and, thus, better consumption choices (Hutton et al., 1986; Meyer, 1987; Tellis and Gaeth, 1990). These studies investigated behavior when individuals are provided with feedback about performance and when they are not. However, by doing so, they disregarded the complex and variable nature of feedback (Ilgen et al., 1979; Kluger and DeNisi, 1996).

From an extensive analysis of 607 empirical and theoretical psychological studies on the effects of feedback, Kluger and DeNisi (1996) derived the first comprehensive theory of feedback ("Feedback Intervention Theory", from now on FIT) and highlighted that feedback might have positive effects on performance and learning only under some conditions, while it might be detrimental under others. FIT is based on the argument that feedback changes behavior through the dimensions of *standards*, *goals* and *attention.* First, individuals' behavior is mediated by comparison with pre-existing standards and goals. Individuals change behavior only if the standard suggested by feedback does not coincide with their pre-existing ones. Pre-existing standards might be personal goals (Latham and Locke, 1991) or benchmarks based on past experience or on others' experience. Second, goals and standards associated to a task are organized in a hierarchy. Therefore, feedback effectiveness on behavior change depends on how relevant is the goal to the individual. Third, individuals' attention is usually limited and directed to goals positioned at middle of the hierarchy. Feedback might shift the locus of attention on goals and standards and elicit behavior changes when a standard-discrepancy is perceived.

FIT suggests that the content of feedback is crucial for eliciting behavioral changes. If feedback directs attention to self-relevant goals instead of goals of the task, it might inhibit performance and learning. *Normative feedback* — i.e., information about what others do — can elicit behavior changes of this kind (Schultz et al., 2007; Goldstein et al., 2008; Abrahamse and Steg, 2013). The impact of feedback on behavior changes, in fact, depends on how norms are salient to individuals (Cialdini et al., 1990). FIT also suggests that the way feedback is delivered is crucial for enhancing positive behavior changes. When feedback is too frequent, it might fail to shift the locus of attention to goals of the task, since individuals would face information overload and would fail to perceive a sense of control over the task (Chhokar and Wallin, 1984). On the other hand, when feedback is designed in a way that makes salient psychologically vivid factors (Yates and Aronson, 1983; Taylor and Thompson, 1982), the locus of attention can be shifted to goals of the task. It raises the sense of control and awareness of an action that would be otherwise executed automatically. *Framing feedback* – the choice is framed as either in terms of gains or losses – can elicit behavioral responses of this kind (Kahneman and Tversky, 1979; Tversky and Kahneman, 1981). Particularly, negative frame is often associated to better choices: because individuals are loss averse, they exert more effort in the prospect of negative consequences (Ganzach and Karsahi, 1995; Levin et al., 1998; Hallsworth et al., 2014).

Kluger and DeNisi (1996) contributed to shed light on the effectiveness of feedback on enhancing performance efficiency. However, still some evidence is required to generalize the pattern of results emerged from the review the theory was built on. As mentioned by the authors, some studies might suffer from problems related to suspect methodologies, such as lack of experimental control, poor randomization of participants, and uncontrolled order effects. Such methodological and design problems might undermine the validity of conclusions on the mechanisms underlying feedback.

Several experimental studies have addressed the role of feedback on improving consumption behavior by enhancing awareness of consumption consequences. Most of these studies have been conducted using field experiments with the aim to understand how feedback contributes to improve energy consumption (Abrahamse et al., 2005; Fischer, 2008; Faruqui et al., 2010; Delmas et al., 2013; Asensio and Delmas, 2015; Lynham et al., 2016). Despite many, these studies do not converge to the same conclusion on feedback effectiveness.

Schultz et al. (2007); Allcott (2011) and Ayres et al. (2012) tested the effect of *normative feedback* on energy conservation and suggest that it is effective at increasing energy conservation. On the other hand, in reviewing several studies published in the psychological literature, Fischer (2008) notes that normative feedback elicits a mixed behavior change. To explain this inefficacy, she refers to the boomerang effect: suboptimal consumers might be motivated to change their consumption behavior towards the optimal one, while optimal consumers might feel entitled to lock-in and to avoid to change their behavior.

Other studies tested the effect of different ways of delivering feedback on improving energy consumption choices. First, McCalley and Midden (2002); Wood and Newborough (2007) and Fischer (2008) suggest that *frequency* has a positive effect on energy consumption: the more frequent is feedback, the higher is the effect on learning consumption consequences. Second, Wood and Newborough (2007) and Fischer (2008) suggest that *framing* is crucial to stimulate the search for better consumption alternatives. Conditional on how information is framed, feedback can activate different motivations and, thus, behavior changes. As an example, Asensio and Delmas (2015) show that disclosing information about negative consequences associated to consumption motivates energy conservation.

While the effect of feedback on energy consumption has been widely explored using field experiments, little has been done in the laboratory setting. A recent exception is the study by Martín et al. (2016). They simulate consumer's behavior in virtual home by asking subjects to consume energy by using seven different groups of items. They investigate energy consumption along five dimensions in which information changes. In the baseline, participants were informed about the net gain associated to their consumption choices on an invoice screen. Depending on the treatment, either they received an advice about energy saving before the choice was made, they received feedback through a smart meter display, or they received the average and minimum energy consumption level in their market. This study introduces an innovative methodology to investigate the effect of feedback on consumption behavior: by exploiting the laboratory setting it addresses a complex behavior with the benefit of a greater internal validity than that provided by field experiments. However, this study suffers from the choice of simulating a virtual energy environment in the lab. Moreover, it does not explicitly assess the role of normative feedback and framing effects.

Building on this insight and the lack of extensive laboratory investigation on feedback about consumption consequences, we aim to enrich the research by running a laboratory experiment. In our study, we simulate the problem faced by a consumer who has limited awareness of the consequences associated to her consumption choices. We provide experimental subjects with a task in which they have to choose how to allocate experimental points to five items: the number of points assigned to these items determines the final payoff of the subjects. As in the case of a consumer who has a fixed amount of a good that is consumed indirectly, such as electricity or gigabytes, our subjects do not know how items convert points in payoff but they have the opportunity to discover more efficient consumption combinations through experience. We introduce feedback as a mechanism to enhance awareness of consequences associated to consumption choices and, as better explained in the next section, we manipulate the content, the frequency and the frame of feedback about past allocation choices along six dimensions. This way, we are able to quantify the effect of different types of feedback on the search for better consumption alternatives and provide useful insights for policy makers.

3 Method

We design an experiment that mimics the problem faced by a consumer who has limited awareness of the consequences of her consumption choices and potentially foregoes additional benefits by undertaking a poor consumption behavior. Our aim is to quantify the effect of feedback on enhancing awareness of consumption consequences and on the search for better alternatives by manipulating three dimensions of feedback: *framing*, *frequency of delivery* and *normative content*.

We investigate consumption behavior as individuals' performance in a repeated *allocation task* of points to various items. As the simultaneous usage of different items is associated to different levels of consumption of electricity or megabytes, so experimental subjects are asked to simultaneously use five items by choosing the amount of points to allocate to each. Participants have to allocate points to five different sliders, however they cannot assess the benefits and costs associated to their allocation choices. Therefore, we introduce feedback as a way to enhance the awareness of consumption consequences and to foster the search for more rewarding allocations. Participants are told that only one allocation is optimal, i.e. is the most rewarding.

Participants earned the points they are asked to allocate to the sliders through an *effort task*. This task controls for the effect of experimental asset origin. While windfall asset has been associated to several behavioral anomalies, asset earned through effort has been associated to higher self-interested behavior (Cherry et al., 2002). The effort task was based on Abeler et al. (2011). Participants had 50 minutes to correctly count the number of zeros in 21 different tables with 150 randomly ordered zeros and ones. In our experiment, participants earned 50 points for each correctly solved table. Moreover, they were informed that they could proceed to the allocation task only upon the successful completion of all the 21 tables in the effort task. All participants managed to complete the 21 tables and, therefore, at the end of the effort task, they earned the amount of 1050 points. Individual cognitive ability might confound performance in the allocation task. Therefore, to determine a measure of individual ability, we recorded individuals' time required for completing the effort task.

In the *allocation task* participants were asked to allocate among 5 different slider $j \in \{1, ..., 5\}$ the points (1050) they earned from completing the effort task. They were told the task would be repeated for 21 rounds. In each round, participants had to allocate 50 of the 1050 points by deciding the number of points $x_j \in \{0, ..., 20\}$ to assign to each of 5 different sliders $j \in \{1, ..., 5\}$. Participants were required to use all the available points and they were allowed to allocate a maximum of 20 points to a single slider.

The first dimension of feedback that we manipulated is the *framing* of the information: when *framing* was positive, feedback was framed in terms of benefits: the j-th slider generated a payoff $\pi_j(x_j)$ that depended on the number of points x_j allocated to that slider according to the function

$$\pi_j(x_j) = c_j \exp\left(-\frac{(x_j - m_j)^2}{2s_j^2}\right)$$

where:

- c_j determines the slider's maximum payoff,
- m_j determines the number of points required for the slider's maximum payoff and
- s_j determines how fast the payoff decreases by moving away from the maximum.

The total payoff for the round was then computed as $\Pi(x_1, \ldots, x_5) = \sum_{j=1}^{5} \pi_j(x_j)$. Figure 1 shows the payoff functions and the parameters characterizing each slider.

Each slider's payoff functions were unknown to the participants, they only knew the minimum and maximum attainable total payoffs (0 and 500 ECU respectively).

When *framing* was negative, participants received a feedback framed in terms of *costs*. In this case, the j-th slider generated a cost $(C_j(x_j))$ that depended on the number of points x_j allocated to that slider according to the function

$$C_j(x_j) = c_j\left(1 - \exp\left(-\frac{(x_j - m_j)^2}{2s_j^2}\right)\right)$$

where:

- c_j determines the slider's maximum cost,
- m_j determines the number of points required for the slider's minimum cost (zero for all sliders) and
- s_j determines how fast the cost decreases by moving away from the maximum.

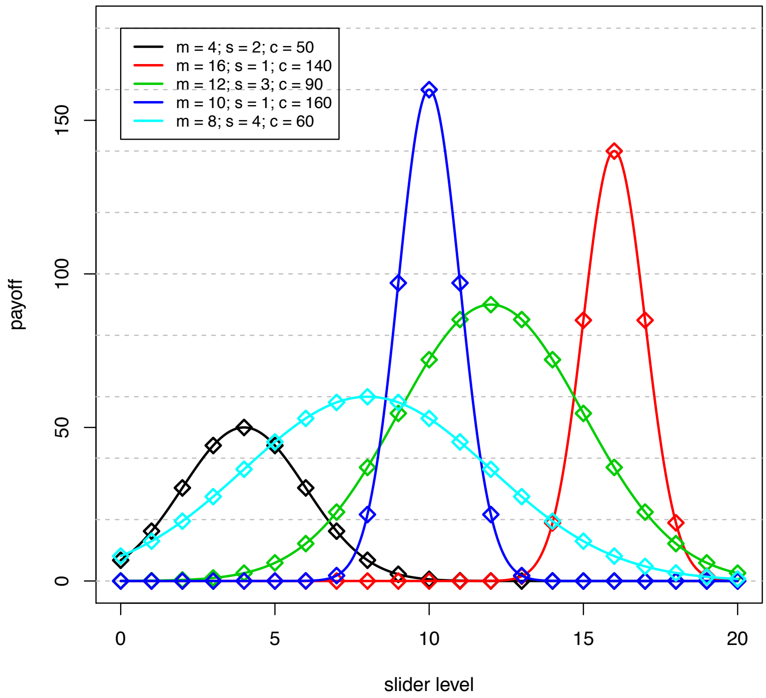


Figure 1: Sliders' payoff functions

Obviously, the cost of each allocation is computed to keep the final payoff unchanged across frames: figure 2 shows the cost functions and the parameters characterizing each slider in the negative framing. For maintaining the opportunity of performance comparisons in different frames, at the beginning of each round, participants were endowed with 500 ECU and were informed about the costs they have to pay for the chosen allocation. The payoff is determined by subtracting the cost of the allocation from the endowment of 500 ECU.

The second dimension of feedback that we manipulated is *frequency*: participants received information about the allocation outcome either at the end of each round, or every three rounds (thus, only at the end of round 3, 6, 9, 12, 15, 18, and 21). In the second case, when participants received information every 3 rounds, they were informed about the outcome of all the previous three rounds, so that at period 3, 6, 9, 12, 15, 18, and 21 the amount of information available to the participants was the same across conditions.

By combining *framing* and *frequency* in a 2x2 design we obtain four experimental treatments.

- In Treatment *straight*-×1, the sliders generate payoffs and the participants receive feedback every round.

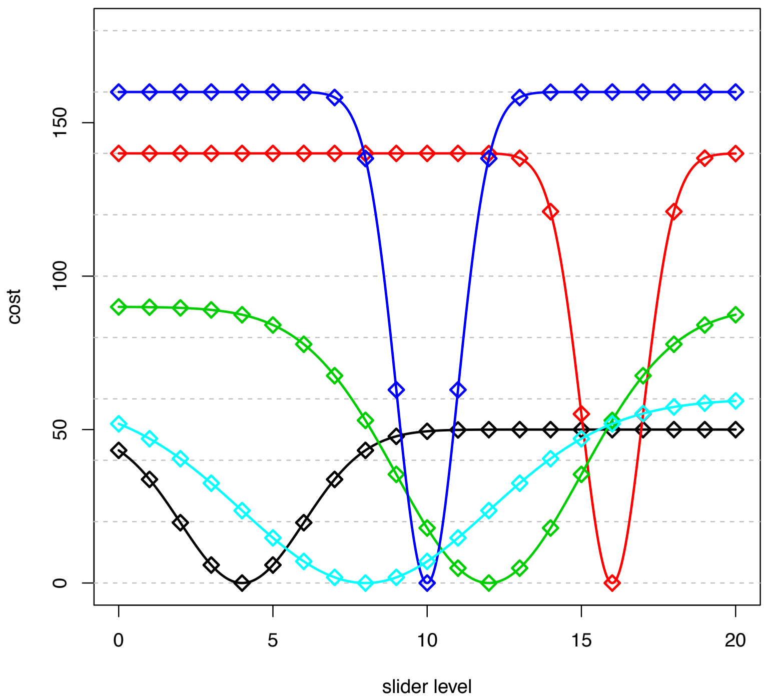


Figure 2: Sliders' cost functions

- In Treatment *straight*-×3, the sliders generate payoffs and the participants receive feedback every three rounds.
- In Treatment *reverse*-×1, the sliders generate costs and the participants receive feedback every round.
- In Treatment *reverse*-×3, the sliders generate costs and the participants receive feedback every three rounds.

As a third experimental dimension, we manipulated the content of feedback by including *normative information*. Treatments on *normative content* followed the basic structure of treatment *straight*-×1, in addition we provided participants not only with information about the outcome they obtained in each round, but also with information about the outcome obtained by another subject in each round. We designed two *normative feedback* treatments, *info-eff* and *info-ineff*. In both treatments participants received feedback about the payoff obtained by the *best-performer* of a group of subjects that participated to a pilot session of the *straight*-×1 treatment.[2] The two treatments, however, differ in the best-performer's category: in *info-eff* participants were informed about the past performance of an efficient best-performer, i.e., the best performer of a group in which participants reached the optimal allocation; while in the *info-ineff* participants were informed about the past performance of an inefficient best-performer, i.e., the best-performer of a group in which none reached the optimal allocation.[3]

Table 1 summarizes our experimental treatments. All treatments were run in a between subjects design. To provide transparent incentives for revelation of truthful consumption decisions in each round, one round was randomly selected for being paid out at the end of the experiment.

Table 1: Experimental treatments

Treatment	*Frame*	*Frequency*	*normative content*
straight-×1	Positive	every round	none
straight-×3	Positive	every 3 rounds	none
reverse-×1	Negative	every round	none
reverse-×3	Negative	every 3 rounds	none
info-eff	Positive	every round	efficient best-performer
info-ineff	Positive	every round	inefficient best-performer

[2] The pilot session was conducted to collect data on best-performers. In this session, participants were arranged into groups of five or six participants. In addition to receiving information about individual past performance, participants were informed about the past performance of the best-performer of their group. For the sake of completeness, we compared performance in treatment *straight*-×1 and in the pilot treatment without finding, in aggregate, any significant differences. This is not surprising given that different types of best-performers emerged from each group. The effects of providing heterogeneous normative feedback cancel out each other.

[3] Participants in the *info-eff* and *info-ineff* were not informed about the best-performer's category (e.g., efficient or inefficient).

3.1 Participants and Procedures

The experiment was run at CEEL (Cognitive and Experimental Economic Laboratory) of the University of Trento (Italy). Participants were students of the same university. The experiment was conducted using both the z-Tree software (Fischbacher, 2007, used for the effort task) and a software developed at CEEL (for the allocation task). In total, 207 participants took part in the experiment.

Each experimental session was conducted on two subsequent days: the recruitment message informed participants that they had to guarantee their availability in both days. The first day was dedicated to the effort task (solved on average in 27.76 minutes) and the second to the allocation task (one session lasted on average 60 minutes). In addition to a show-up fee of 4 Euro, participants received the result of one randomly selected round of the allocation task.[4] On average, individual total earnings amounted to €16.21.

4 Results

In order to investigate how different types of feedback enhance individuals' awareness of consumption consequences and, thus, increase the effort exertion to search for alternative consumption allocations, we consider two different measures of performance: (i) the round in which subjects reach the optimal allocation and (ii) the fraction of rounds in which subjects make optimal allocation choices. There would be a third natural candidate measure of performance: the payoff obtained by the subjects in the experiment. However, in our design payoffs are bounded to be between 0 and 500 ECU. Since many subjects hit the upper bound, this additional measure would not allow to properly identify differences in performance among treatments. Indeed, performances tend to converge at the end of the experiment when progressively subjects reach the efficient payoff.[5] For this reason, we provide only descriptive information about the payoff dynamic in the experiment and we test treatment effects using the measures of performance mentioned above.

To analyze the first measure of optimal consumption choices, i.e., the round in which subjects reach the efficient allocation, we use a duration model, while to analyze the second measure, i.e., the fraction of optimal choices, we employ a fractional response model.[6]

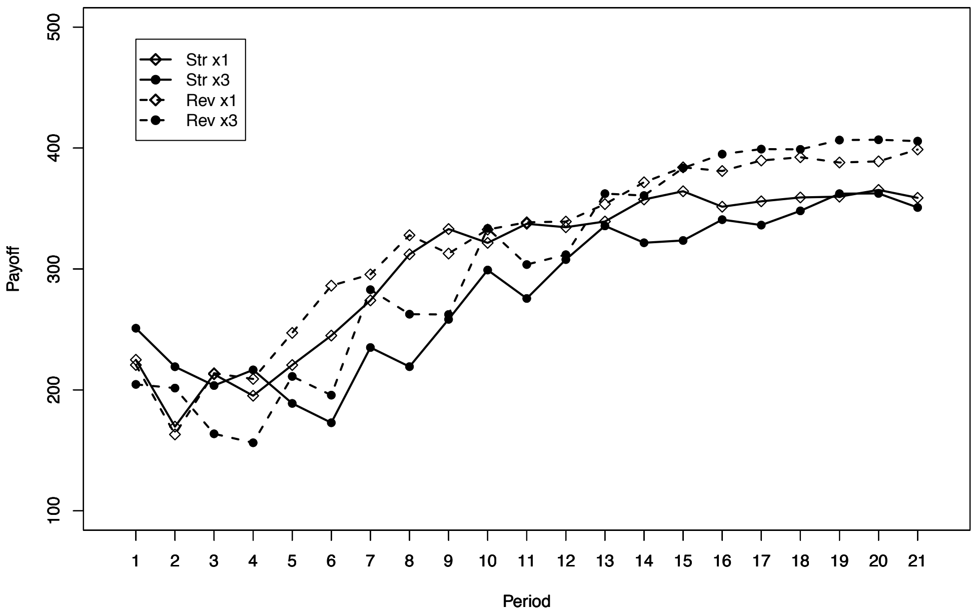
In the following, we describe the results with the aim to isolate and quantify the effect of the three dimensions of feedback (*framing*, *frequency*, and *normative content*) we manipulated in our six treatments. In particular, we first discuss the impact of framing effects and frequency of feedback and, then, we move to the effect of normative feedback.

[4] The exchange rate was 25 ECU = 1 Euro.

[5] A workaround to the problem is to employ a censored regression model to identify the effects. However, this strategy implies that the dependent variable is censored and can theoretically assume values above (below) the threshold. This is not the case in our setting. Payoffs higher than the optimal one have no meaningful interpretation and cannot be obtained.

[6] Compared to OLS regression with logit transformed data, the fractional response model has the advantage to naturally allow for observations with values of 0 and 1. For details about these models see Papke and Wooldridge (1996) and Ramalho et al. (2011)

Figure 3: Average payoff by round and treatment



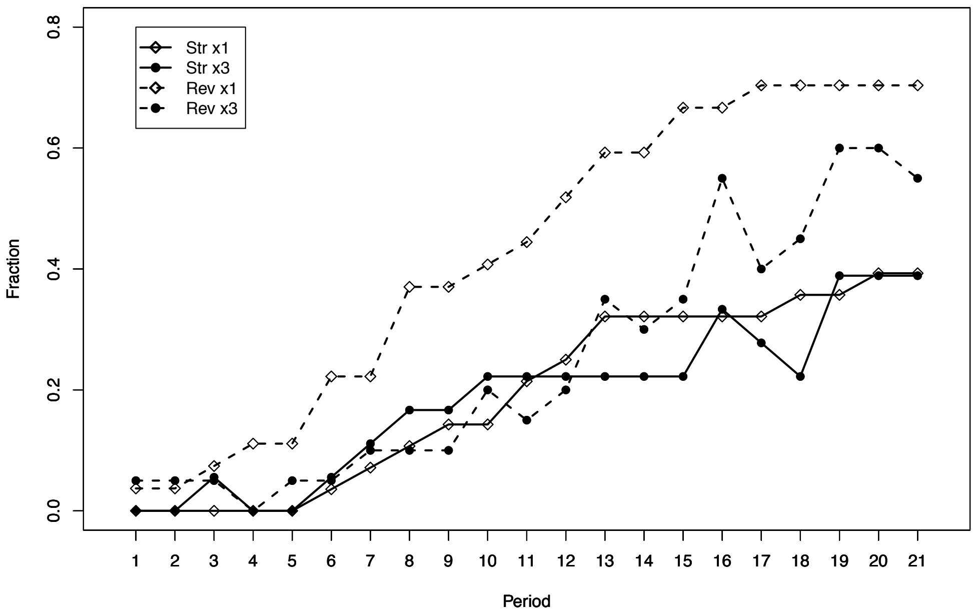
4.1 Framing effects and frequency of feedback

In this subsection, we consider behavior in the treatments *straight* and *reverse* with feedback every round (×1) and every three rounds (×3).

Figure 3 shows the average payoff by round and treatment. As it is apparent from the figure, the average payoff increases over rounds in all treatments and, in the final rounds, it reaches a higher level in the *reverse* compared to the *straight* treatments. To have a clearer picture about the level of efficiency across treatments, we can look at the figure 4 that shows the fraction of subjects making optimal choices by round and treatment. From the figure we can observe that the frequency of efficient subjects reaches much higher levels in the *reverse* treatments compared to the *straight* ones. In the *reverse* treatments, 70% of the subjects reach efficiency in the final round when the frequency of feedback is ×1, while 55% of the subjects reach efficiency when the frequency of feedback is ×3. In the *straight* treatments, independently of the frequency of feedback, only 39% of the subjects reach the efficient allocation in the final round. Both figures suggest that *framing* more than *frequency* of feedback drives the difference in performance among treatments.

To better identify the type of feedback which is most effective at enhancing the awareness of consumption consequences and fostering the search for better allocations, we ran regression models (Table 2). Model 1 is a fractional response probit model with the fraction of rounds in which subjects are efficient as dependent variable, while Model 2 is a proportional hazard Cox model with the first round in which subjects reach efficiency as dependent variable. Both models share the same set of explanatory variables: (i) two

Figure 4: Fraction of efficient choices by round and treatment



treatment dummies d(*reverse*) and d(×3) and their interaction d(×3)×d(*reverse*); (ii) a dummy variable controlling for gender d(female), (iii) the average mark obtained in the exams (demeaned), and (iv) the time in minutes spent in the laboratory to complete the real effort task.

Starting with the results about the fraction of efficient choices in Model 1, we confirm the insight that *negative frame* significantly fosters a behavior change toward the search of an efficient combination of allocation choices. In fact, the variable d(*reverse*) is positive and significant. This shows that the expected fraction of rounds in which subjects make optimal choices is higher in the *reverse* treatments than in the *straight* ones. As a second result, the lack of significance of the variable d(×3) suggests that the diluted frequency of feedback does not impact subjects' performance. More precisely, the fraction of efficient choices when the feedback about the payoff is given every three rounds does not differ from when it is given every round. Finally, looking at the estimate of the term d(×3)×d(*reverse*) we can exclude the presence of interaction effects between framing and frequency of feedback. Among the control variables we find a weakly significant effect of the gender dummy suggesting that the fraction of efficient choices made by women is lower than the one by men.

Moving to the results on the duration of the search before reaching the optimal allocation in Model 2, we observe that the estimated parameter of d(*reverse*) is positive and significant. This estimate implies that, at each round, the expected hazard of reaching the optimal allocation in the *reverse* treatment is 202% higher than the expected hazard in the *straight* one (the estimated parameter implies an expected hazard

Table 2: Regressions' estimates with s.e. in parentheses

	Mod. 1 FRM probit (robust se)	Mod. 2 Cox PH durat. mod.
(Intercept)	-0.7465***	—
	(0.2211)	—
d(×3)	-0.0368	0.1004
	(0.3028)	(0.4896)
d(*reverse*)	0.7203**	1.1078**
	(0.2535)	(0.3882)
d(×3)×d(*reverse*)	-0.5188	-0.6668
	(0.4353)	(0.6272)
d(female)	-0.3699°	-0.6364*
	(0.2139)	(0.3112)
exam_mark	0.0141	0.0496
	(0.0353)	(0.0567)
time_effort_task	-0.0174	-0.0271
	(0.0118)	(0.0190)
R^2	0.163	0.167
Concordance	—	0.669

Signif. codes: 0 < '***' ≤ 0.001 < '**' ≤ 0.01 < '*' ≤ 0.05 < '°' ≤ 0.1 < ' ' ≤ 1

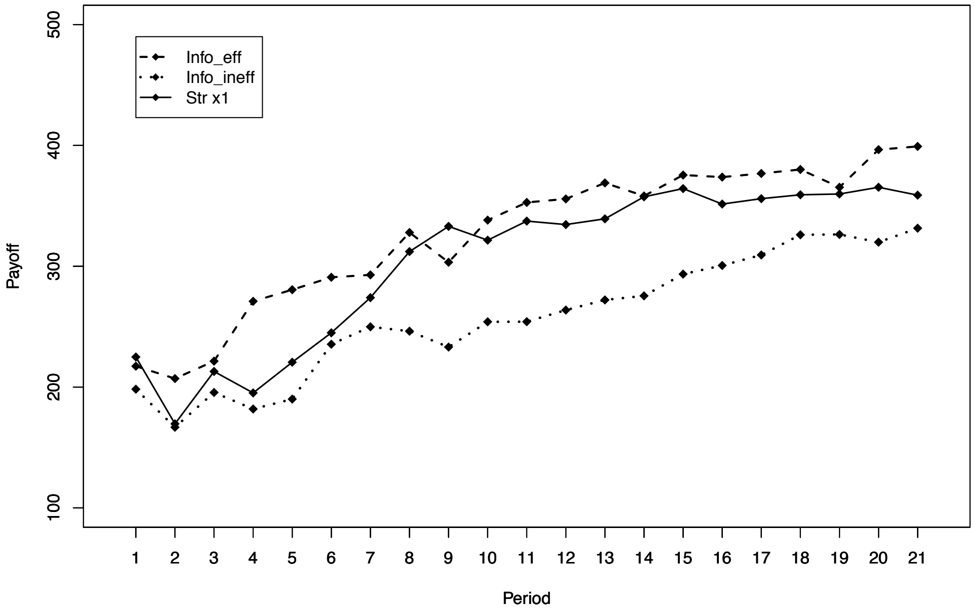
ratio of 3). In other words, subjects exposed to a negative frame are significantly more willing to exert effort to search for an alternative efficient allocation compared to those exposed to a positive frame. Model 2 confirms that the diluted frequency of feedback has no significant effect on the number of rounds needed to reach the optimal combination of allocation choices (d(×3) is not significant). Finally, Model 2 confirms the effect of gender on search of efficiency: women show a lower hazard of reaching the optimal allocation compared to men (47% lower).

4.2 Normative feedback

In this subsection, we analyze the impact of normative feedback on efficient consumption behavior. Looking at Figure 5, which reports the average payoff by round and treatment, we can see that in the second half of the experiment payoffs are ranked as expected: the average payoff in the *info eff* treatment is higher than that in the *straight*-×1 treatment that, in turn, is higher than that in the *info ineff* treatment. Figure 6 shows the fraction of efficient choices by round and treatment and provides similar insights about how feedback about the best performer's past allocation choices affects performance. We observe that the fraction of efficient choices in the last rounds is 39% in the *straight*-×1 and 44% in the *info eff* treatments, while it is only 18% in the *info ineff* treatment.

These results suggest that feedback about the best performer's performance represents an anchor for consumers to exert effort and, thus, to change their consumption behavior toward search for efficiency. Table 3 shows results from an econometric test of this insight. Model 3 and Model 4 parallel the two models reported in Table 2. More precisely, Model 3 is a fractional response probit model with the fraction of rounds in

Figure 5: Average payoff by round and treatment

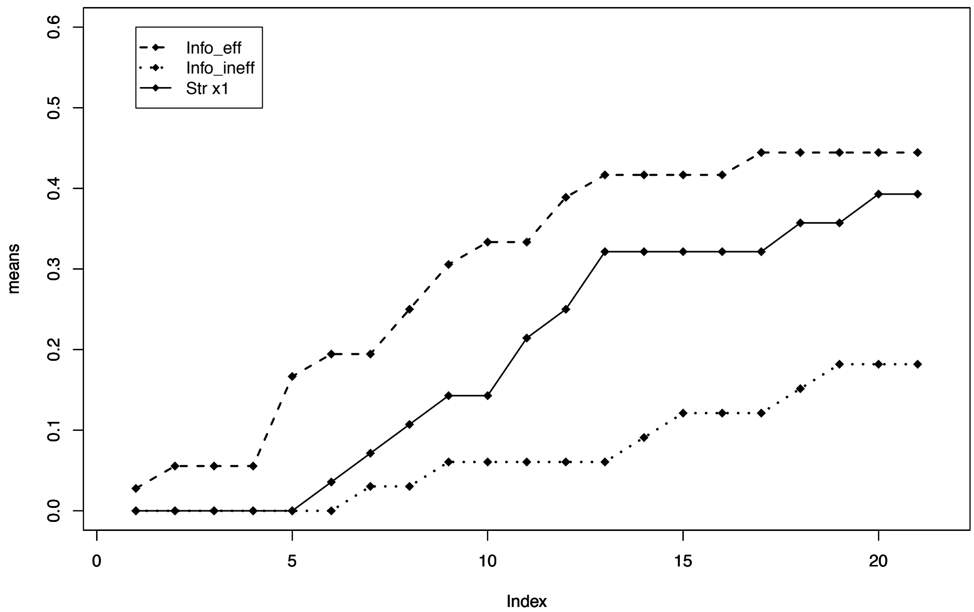


which subjects are efficient as dependent variable, and Model 4 is a proportional hazard Cox models with the first round in which subjects reach efficiency as dependent variable. As for the dependent variables, these models differ from Models 1 and 2 only for the treatments dummies. The variables d(*no info*) and d(*info ineff*) capture the effect of providing no information about the best performer's performance and the effect of providing information about an inefficient best performer compared to the baseline of providing information about an efficient best performer.

Looking at the fraction of efficient consumption choices in Model 3, we find that subjects informed about the payoffs of an inefficient best performer show a significantly lower fraction of efficient choices compared to those informed about the payoffs of an efficient best performer (d(*info ineff*)). We also observe no significant difference in performance between subjects that do not receive information and subjects that receive information about the efficient best performer (d(*no info*)). These results show that the type of normative content embedded in the information provided to the subjects is crucial for enhancing or inhibiting the search for better consumption alternatives. In particular, we observe that not always more information is better than less. While receiving information about past performance of virtuous subjects seems to have no impact on performance, receiving information about inefficient ones seems to have a detrimental effect on performance. Among the control variables the gender dummy is negative and weakly significant, confirming the effect observed in the other treatments.

Looking at the number of rounds necessary to reach the optimal allocation in Model 4, we observe that the estimated parameter of d(*info ineff*) is negative and significant.

Figure 6: Fraction of efficient choices by round and treatment



Therefore, the hazard of reaching an efficient allocation when receiving information about the inefficient best performer is lower than when receiving information about the efficient best performer (the expected hazard is 68% lower). As a second result, we find no significant difference in the hazard of reaching an optimal allocation when information about past performance is not provided compared to when information about the efficient best performer is provided. Overall, the results obtained with the duration analysis confirm the results observed when looking at the fraction of efficient choices: information about past performance of an inefficient best performer reduces the willingness, i.e. measured in terms of increase in the number of rounds, to find the efficient allocation. As a final observation, we find a significant gender effect with women showing a lower hazard of reaching efficiency compared to men (57% lower).

Table 3: Regressions' estimates with s.e. in parentheses

	Mod. 3 FRM probit (robust se)	Mod. 4 Cox PH durat. mod.
(Intercept)	-0.3939**	—
	(0.1844)	—
d(*no info*)	-0.2517	-0.3072
	(0.2500)	(0.3956)
d(*info ineff*)	-0.8097***	-1.1357*
	(0.2927)	(0.4893)
d(female)	-0.5981**	-0.8420*
	(0.2480)	(0.3949)
exam_mark	0.0230	0.0504
	(0.0443)	(0.0746)
time_effort_task	-0.0150	-0.0150
	(0.0095)	(0.0175)
R^2	0.216	0.134
Concordance	—	0.696

Signif. codes: $0 <$ '***' $\leq 0.001 <$ '**' $\leq 0.01 <$ '*' $\leq 0.05 <$ '$^\circ$' $\leq 0.1 <$ ' ' ≤ 1

5 Conclusions

In this study, we investigated how different types of feedback enhance individuals' willingness to explore alternative better consumption choices. In particular, we focused on the decision problem faced by a consumer who has limited awareness of the consequences of her consumption choices, as the case in which the good is consumed via various items.

To isolate and quantify the effect of feedback on consumption behavior, we ran a laboratory experiment. Differently from previous studies which adopted field experiments on energy consumption, we exploited the laboratory setting to have internal control over the mechanisms underlying feedback in a complex decision context, such as the one in which consumers are not aware of the consequences associated to their consumption behavior. We mimicked the consumer's problem of consuming a fixed amount of a commodity through several items. This is the case of consumers who are monthly endowed with a fixed amount of KWh, battery or gigabytes to be allocated to various items. We designed a setting in which individuals are endowed with a fixed amount of points to allocate to five items in order to extract a certain level of utility. Participants were asked to obtain the highest level of utility associated to different combinations of allocation choices. We introduced feedback as a mechanism to enhance awareness of consumption consequences and to foster search for better allocations. We varied feedback along three dimensions: framing, frequency and normative content. We created six treatments to isolate the effect of each of the three types of information feedback on consumption behavior.

Our first finding relates to framing. When information feedback is negatively framed, it elicits the highest incentive to exert effort to search for optimal consumption. This pattern reflects the widely known phenomenon of *loss aversion* (Kahneman and Tversky, 1979). When feedback makes salient negative aspects of past consumption choices, compared to when it is positively framed, individuals become significantly more sensitive to the consequences of their consumption choices and more willing to engage in a search for better consumption options. The second finding concerns frequency. Diluting the frequency of feedback about past allocation choices does not elicit a significant behavioral change. This suggests that feedback on consumption is effective only if it makes salient other psychologically vivid factors (Yates and Aronson, 1983; Taylor and Thompson, 1982). Individuals become significantly more sensitive to consumption consequences and more willing to search for alternative options when they are given a continuous or a diluted feedback which is negatively framed compared with the case in which they receive a positively framed feedback. To be effective on behavior, feedback has to activate the loss aversion bias irrespectively of frequency. These two findings provide important implications for policy makers. Given that frequency is not crucial for eliciting behavioural changes, policy makers should leverage negative aspects, such as losses and costs, to promote efficient and aware consumption choices by means of informative devices.

Our third finding regards normative effects. We find that providing individuals with feedback embedding suboptimal information about peers is detrimental for eliciting changes toward optimal consumption behavior. In particular, we find that providing information about an efficient best performer has no effect on consumption behavior. On the other hand, providing information about an inefficient best performer significantly worsens individuals' willingness to engage in search for better consumption options. In this latter scenario, individuals anchor their behavior to the benchmark suggested by feedback. Providing information about subotpimal peers leads individuals to satisficing consumption behavior by lowering their aspiration levels. This result is also of practical relevance for policy making. It is better to avoid providing individuals with information about what others do unless these are virtuous examples to imitate.

Fourth, across all treatments we find women to be less willing to change their consumption choices toward the optimal ones. This is in line with the widely documented gender difference in economic preferences (Croson and Gneezy, 2009). In particular, the evidence that women are less willing to take risky choices than men (Byrnes et al., 1999) can provide a potential explanation behind women's aversion to search for better consumption options to increase their utility. One potential fruitful direction for future research would be to exploit the external validity of field settings to address gender difference in effort exertion to search for better consumption alternatives. As an example, we could vary the variance associated to each choice consequence by providing household women and men with tailored information leaflets about each appliance energy usage (i.e., using the washing machine in the afternoon makes a cost of x). This way, we can test whether varying perceptions of risk cancels out gender difference in effort exertion to search for alternative consumption strategies.

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