Measuring Time Preferences and Anticipation: A Lab Experiment*

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Abstract

Several biases related to time preferences, in particular present and future biases, have important consequences on economic decisions. Present bias concerns individuals' self-control problem. Future bias can be defined as the anticipatory emotions individuals feel in the period preceding the consequences of their decision. Individual's acumen for anticipating their bias also has economics consequences. The individual aware of his bias seeks to constrain his action to overcome the consequences of his bias. Whereas a naive individual does not anticipate his bias and might choose the wrong commitment or the wrong action plan. Though extensive literature exists on the measurement of time preferences and related biases, scant attention has been given to the elicitation of the anticipation of these biases. This paper introduces a methodology for eliciting anticipation of time preferences using a lab experiment in two rounds with the same subjects. The second round elicits their time preferences regarding the temporal allocation of monetary rewards, whereas the first round elicits their anticipation of their allocation choices. I find that even though a majority of the participants can not be considered as biased and accurately anticipate their time preferences, when they are biased, both present- or future-biased participants tend to be naive about their bias, i.e., they underestimate their bias.

Keywords: Time inconsistencies; naiveté; anticipation; Convex Time Budget

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1 Introduction

Why do people enroll at gym and then never go to the gym? Two behavioral biases are responsible. First, people are present-biased if they have a self-control problem. They tend to postpone immediate costly activity, even if doing so will be more costly in the future or acting now could yield future benefits. So, for example, when present-biased people are deciding whether to go to the gym, they always postpone. Second, people can be naive about their present bias if they underestimate it. When they sign up for an annual membership, they are convinced they will go to the gym regularly. In other words, they do not anticipate their self-control problem. Only the combination of these two biases can explain this behavior. Indeed, if people were sophisticated, i.e., if they perfectly anticipated their self-control problem, they would not sign up for this subscription. To give another example, the combination of these two biases also explains two contradictory facts: high credit-card borrowing and illiquid wealth accumulation (Laibson *et al.*, 2007). By choosing their illiquid assets, present-biased and naive people do not accurately anticipate their inability to resist the temptation of immediate consumption and thus, they contract costly short-term loans. Up till now, the experimental literature has focused mostly on eliciting present bias and, little has been done to elicit naiveté bias. To fill this gap, this paper aims to elicit, through a lab experiment, the accuracy of participants' ability to anticipate their own potential bias.

Economists, through the standard model, have long considered that time preferences are stationary and time-consistent. In other words, the decision maker's relative preference for a reward sooner than a one later is the same provided that interval between the two rewards' dates remains constant and his preference is the same at different points of time. A representation of such preference implies constant discount rate as in the exponential discount function of Samuelson (1937). However, this specification of time preferences is known to be at stake with experimental datas. In Thaler (1981) experimental study, participants exhibit decreasing impatience over time. In Loewenstein (1987) study, respondents to a survey are willing to pay relatively more to be kissed by their favorite movie star (or to avoid an electric shock) in the future rather than immediately. This behavior can't be explained by an exponential model unless negative discount rates are considered. Instead, in line with Bentham (1879) and Jevons (1905), Loewenstein explains these results by utility of anticipation: "anticipal pleasure" or "anticipal pain". The time preferences of participants in Thaler and Loewenstein violate the stationary axioms. The fact that participants do not make the same decision if the immediate present is involved suggest that if they were asked to revise their future choices, their preference were re-

versed. In other words, the participants are considered to be time-inconsistent.[1] In Thaler, they are present-biased; that is, they give stronger relative weight to the early utility. In Loewenstein, they are future-biased; that is, they value waiting and are more patient in the immediate present. Present-biased preferences are often meant to capture self-control problems, so empirical evidence for present bias is easy to find[2] and can have important consequences for some industries (casinos, gym clubs, credit-card companies) and for welfare.

It is important to distinguish whether people are able to anticipate their bias. In this paper, we adopt the terminology of O'Donoghue and Rabin (2001): when people are time-inconsistent, they are either *sophisticated* if they are perfectly aware of their bias (i.e., they can anticipate their bias when making a decision that involves the immediate present) or *naive* if they wrongly believe they will make this decision as if they were time-consistent. We can also consider that people can be *partially naive* (i.e., they can anticipate their bias but are mistaken about its importance). Naiveté bias can have as important consequences as time-inconsistency bias. When sophisticated decision-makers look for commitments to have their hands tied, the naive ones fail to choose the right commitment. Moreover, through a wrong anticipation of future decisions, the naiveté bias can affect economic interactions. In a theoretical paper, DellaVigna and Malmendier (2004) show that as long as consumers are sophisticated, their present bias will have no effect on consumption levels, firms' profit, or social welfare. Firms have incentives to provide a perfect commitment to present-biased but sophisticated consumers (i.e., firms set their prices such that they consume as often as if they were time-consistent). However naive consumers are not able to accurately anticipate their consumption decisions. Thus the degree of naiveté not only implies allocation inefficiencies but also can be exploited by a monopoly, which take advantage of a fictive surplus, which are wrongly anticipated by naive consumers.

While time preferences and time-inconsistency biases are covered in a large number of empirical or experimental studies (for example Andersen *et al.*, 2008; Andreoni and Sprenger, 2012a; Ausubel, 1999; Benhabib *et al.*, 2010; DellaVigna and Malmendier, 2006; Thaler, 1981),[3] relatively few papers have empirically or experimentally investigated the naiveté bias. Few empirical papers measure the degree of naiveté (Acland and Levy, 2015; DellaVigna and Malmendier, 2006; Skiba and Tobacman, 2008). However, in real world situations, other factors

[1] Non stationary time preferences directly imply time inconsistency but only on condition that the preferences are also invariant (see Halevy, 2015). Time-inconsistencies can also be explained by other sources. such as time-variant preferences.

[2] Overconsumption of addictive goods (e.g., gambling, drugs, alcohol, cigarettes) or procrastination to avoid immediate costs, even if the costs will be much higher in the future (e.g., writing a paper, doing administrative duties, going to the gym), are good examples of the effects of lake of self-control.

[3] Technically, the cited experimental studies investigates whether the preferences of the participants are stationary. The direct elicitation of time inconsistencies requires longitudinal studies (see Halevy, 2015; Sayman and Öncüler, 2009).

might explain what seems to be a wrong anticipation of the future decision. For example, DellaVigna and Malmendier (2006) find that 80% of the people who buy an annual gym membership pay more than they would have paid per visit. They attribute this to the naiveté of consumers. Yet, other factors could, in part, explain this behavior. For example, one can imagine that people also derive utility by belonging to a sport club. Thus they are willing to pay more to be member of the club than they would pay for simply "dropping in" from time to time. One advantage of experimental studies is that they can be designed to capture only the part of the decision driven by naiveté bias. However, existing experimental studies mostly only investigate the existence of the naiveté bias through commitment choices (Ariely and Wertenbroch, 2002). They show that naiveté exists because participants can't choose the right commitment for themselves. To the best of my knowledge, only a single current working paper, by Augenblick and Rabin (2015), investigates and quantifies the degree of naiveté bias using anticipation choices.

Thereby this paper aims to elicit whether participants are able to accurately anticipate their future decisions without providing them any commitment device. Eliciting naiveté of biased individuals allows to determine whether these individuals will be able to undertake the right commitment device, if available, that will helps them to get over their bias for their future decisions.

This paper aims to measure naiveté bias through a lab experiment which is conducted in two rounds. During the second round, following the method of Andreoni and Sprenger (2012a), participants are given the opportunity to allocate a monetary budget between two dates to elicit their time preferences, different timings for the allocations are implemented. Comparing allocations choices when the immediate present is involved with those arising when only future dates are involved highlights the relative weight participants attribute to immediate utility. What is new is that, in the first round, the same participants are simply asked to anticipate what their future allocations will be. The participants lose nothing by wrongly anticipating their future decisions. In other words, they can't commit themselves. Thus, the simple comparison between what they anticipate choosing and their actual decisions allows to elicit their degree of naiveté.

I, first, investigate, the intertemporal utility function at the aggregate level by pooling together all the allocation decisions of all participants. It emerges that participants are present-biased. However, this results hides heterogeneity. Indeed, utility functions seem to be affected by two characteristics of the allocation decision: whether the value of the sooner token is smaller than

the one of the latter tokens and the delay lengths between the two allocation dates. By investigating the behavior of participants towards these characteristics, I find that participants are present-biased but only if the value of the sooner tokens is equal to or higher than the one of the latter token. In that case, they are also naive about their bias. However, when the value of the sooner token is lower (the most frequent allocation decision), then participants do not exhibit bias anymore the utility function parameters are estimated by delay lengths between the allocation dates. An other interesting result for this type of allocation is that participants, although unbiased, tend to underestimate more their sooner demand for tokens when the sooner date will be "Today" rather than in the future for shorter delays. This last result is puzzling as far as the traditional theory on time-inconsistency bias is concerned. One interpretation is that these participants do not consider the money itself as tempting but rather as a means for buying temptation goods: delaying monetary rewards when the immediate present is involved might be used as a commitment device. Then, these participants wrongly anticipate they are going to commit when in fact they fail to do so. This raises interesting questions about time-preferences elicitation using monetary rewards, which I discuss at the end of the paper.

The second step of the analysis focuses on the utility function parameters at the individual-level. The aggregate-level estimation may not be relevant in determining whether participants accurately anticipate their bias if there is heterogeneous behavior among participants. I find that a majority of participants exhibit no bias and accurately anticipate their time preferences. Additionally, a non-null percentage of unbiased or future-biased participants underestimate their sooner demand when immediate present will be involved. However, one main result emerges from the estimation of the individual time preferences: when the participants are biased, they also tend to be naive about their bias.

This paper proceeds as follows. Section 2 introduces the experiment design. Section 3 reviews the theoretical model. The analysis of the participants' decisions follows in Section 4 and Section 5. The paper ends with discussions and concluding remarks in Section 6.

2 Experimental design and procedures

2.1 Design of the experiment

The experiment proceeds over two rounds, with the same participants. The second round elicits participants' time preferences, whereas the first round elicits the anticipation of these preferences. The measure of participants' time-preferences is built on Andreoni and Sprenger (2012a)'s Convex Time Budget (CTB) method, which is extended to provide measurement of

their anticipation.

Elicitation of participants' time preferences and time-inconsistency biases During the second round, participants have to distribute several budgets of 20 tokens between two dates. A token has different values in euros depending on whether it is allocated to the sooner date or to the later date. Let a_t be the value of one token allocated to the earlier date t and a_{t+k} be the value of one token allocated to the later date with k representing the number of periods after the earlier date. P is defined as the gross rate between the values of the sooner token and the later one. Thus, for each allocation, participants have a monetary budget constraint m such that

$$Px_t + x_{t+k} = m$$

with $x_t = a_t n_t$ the total amount of monetary reward allocated to the sooner date (n_t, the number of sooner tokens) and $x_{t+k} = a_{t+k} n_{t+k}$ the monetary reward allocated to the later date (n_{t+k}, the number of later tokens).[4] While the later date ($t + k$) is always by definition in the future, the sooner date (t) can be in the present or in the future. The comparison between the allocations involving the immediate present ($t = 0$) and the other ones identifies preferences reversals. Participants exhibit present bias if they allocate more tokens to the sooner date when the decision involves the immediate present compared to the decision with the same characteristics involving two dates in the future. Conversely, participants are future-biased if they allocate more tokens to the sooner date when the decision involves only future dates.

The CTB method of Andreoni and Sprenger (2012a) is now well-established to elicit time preferences (Andreoni *et al.*, 2015; Ashton, 2014; Augenblick *et al.*, 2015; Giné *et al.*, 2012; Kuhn *et al.*, 2014). The main advantage of this method is the possibility of interior allocations. In line with Thaler (1981)'s study, time preferences were traditionnaly elicited using binary choices. Instead of distributing their budget between two dates, participants had to choose between a monetary reward at the sooner date or one at the later date. This method forced to consider a linear intertemporal utility function and so, does not take into consideration the participant willingness to smooth his earnings over time. Consequently, the elicited discount rates were very high and the present bias was overestimated (cf. literature review on the elicitation of time preferences of Frederick *et al.*, 2002). Another alternative method is introduced by Andersen *et al.* (2008). They first elicit the participants' degrees of risk aversion to measure the curvature of their utility function. Then, they incorporate this parameter to the intertemporal utility function of the participants to elicit their discount rates and their time-inconsistency bias.[5] Thus, by using this

[4] Therefore $m = 20a_{t+k} = 20Pa_t$ with $P = \frac{a_{t+k}}{a_t}$.

[5] They use the method of Harrison *et al.* (2005b). Each individual has to make binary choices for both Holt and

method, they assert that the curvature of the intertemporal utility function is explained only by risk preferences. However, the interpretation of the curvature of the intertemporal utility function is a matter of debate in the literature (Cheung, 2015b). Hence, the CTB method enable us to consider the curvature of the intertemporal utility function without making assumption about its interpretation.

Elicitation of participants' anticipation During the first round, the same participants are asked to anticipate how they believe they will choose to divide their budget at a projection date. The projection date is the second round one. For example, the instructions stated: "Imagine you are on the day June 10, if one token worth 0.98€ the same day and 1€ three weeks after this day, please indicate how you think you will distribute the 20 tokens on this day." The anticipated budget repartitions have the same characteristics as those in the second round. The comparison between the anticipated repartition and the one with the same characteristics made during the second round reveals whether participants accurately anticipate their time preferences.

2.2 Implementation of the experiment

This experiment has been conducted at the LEEP.[6] The first round occured in May 2014, and the second two weeks later, on June 2014. This delay between the two rounds is long enough for participants to forget their answer but short enough not to lose too many participants. In order to compare decisions, the two rounds have been scheduled on the same day of the week (Tuesdays) at the same hour of the day. For the first round, 95 participants showed up but only 75 (79%) came back for the second round. The sample of participants is composed of 80% students between 18 and 26 years old.[7]

CTB Parameters In each round, participants have to make 40 allocations. During the first round, participants anticipate what their choice will be for 40 allocations, and during the second round they choose the same 40 allocations.[8] This experiment follows a (2 x 5) design with two sooner dates $t = (0, 35)$ (in days) and for each, five delays $k = (21, 35, 49, 70, 105)$ (in days) to determine the later date. The value of the later token (a_{t+k}) is always 1 €, whereas the value of the sooner tokens a_t is between 0.7 € and 1.02 €.[9] Four values for the sooner tokens are proposed for each combinaison of sooner date and delay length. The value of the token allo-

Laury (2002) lotteries and Coller and Williams (1999) temporal decisions.

[6]Paris Experimental Economics Laboratory (LEEP), Maison des Sciences Economiques, 106-112 boulevard de l'hôpital, 75013 Paris. http://leep.univ-paris1.fr/accueil.htm

[7]The other participants are unemployed (5%) or employees (10%) who are between 26 and 37 years old.

[8]Screenshots of decisions participants have to make in both rounds can be found in Figure A.4 in the appendix.

[9]$P \in [0.98, 1.42]$ and recall that $P = \frac{a_{t+k}}{a_t}$.

cated to the sooner date can be smaller, equal to or higher than the one allocated to the later one. I denote *smaller-sooner allocations* as the allocations for which the value of the token allocated to the sooner date is smaller, *larger-sooner allocations* as the ones for which the value of the sooner token is higher, and *equal-sooner allocations* as the ones for which the value of the token is the same whether the token is allocated to the sooner date or to the later one. Among the 40 allocations, there are three larger-sooner allocations, two equal ones, and 35 smaller-sooner allocations. The entire set of decisions can be found in appendix in Table A.2 .

Four allocation decisions are presented by page. Each page displays a sooner date, a delay, and four different gross interests P between the value of the sooner token and the later one.[10] The order of the allocation decisions was not randomized. If this decision has obvious drawbacks by inducing order effect in the data, it also has advantages. Choosing the best allocation regarding their preferences can be difficult for participants, particularly when mentally computing the discount rates. I choose not to provide information about the associated annual effective rate (AER) because I believe participants do not have this information when they make everyday decisions. However, proposing the decisions in a certain order (increasing AER by pages and increasing delays over pages) gives participants a frame of references and helps them avoid too many inconsistencies (monotonicity violation) in the allocation choices. Given the purpose of this experiment, it is not a major issue that participants make relative decisions. The most important is that the comparability of the decisions remains consistent, in order to elicit time inconsistency and the accuracy of the anticipation. One important drawback of not randomizing the allocation decisions is that participants may get bored and pay less attention to the last decisions. Two elements about this issue, however, are reassuring. First, if the participants were bored for the last decisions, then they would have been in hurry to respond. Although the response time of participants rapidly decreases after the first allocation decisions, it remains constant afterwards (see Figure A.1 in the appendix). Second, if the participants are bored, one might consider that participants will be more likely to choose corner allocations over interior solutions. If we consider as references the two allocations of the middle of the experimental session, then no evidence exists that the choice of interior solutions is less likely for the last allocations or more likely for the first ones (see Table A.3 in the appendix).

Questionnaire and Cognitive Reflection Test Finally, besides the allocation choices, participants have to answer to the Cognitive Reflection Test (CRT),[11] which was administered both at

[10]Since for each combination of sooner date and delays the values of P are not necessarily the same, I present in the Appendix (Table A.1) the average values of the sooner tokens and the annual effective rates (AER) by delays and sooner date.

[11]This test is composed of three questions (see Figure A.5 in the appendix).

the end of the first round and in the second round after they choose all the allocations. Frederick (2005) designs the CRT to measure cognitive abilities of participants. It assesses the ability of participants to choose a reflective, deliberative correct answer rather than a spontaneous wrong answer. In his book, Kahneman (2011) sums up how the main behavioral biases can be explained by the use of "system 1" (spontaneous and intuitive thinking) rather than "system 2" (more reflective thinking). Frederick (2005) finds that participants in a lab experiment who score differently on this test also give different answers to elicitation tasks for time and risk preferences. The participants of the lab experiment of Kuhn *et al.* (2014) who have the highest CRT score are also less likely to exhibit present bias. At the end of the second round, participants filled in a questionnaire on their sociodemographic characteristics as well as on some of their attitudes (towards sports, alcohol, smoking, and saving) that can be explained by time-inconsistency bias and naiveté.

Payment Two types of payment are implemented: a participation fee and a compensation scheme aimed to incentivize participants decision. One decision is drawn among all the allocations participants have to make – both the ones chosen at the second round and the ones anticipated at the first round. The draw is made at the end of the second round but the payment procedure is known by participants from the beginning of the first round.

For this experiment, the method of payment is very important. The participants must not perceive different transaction costs and different risks between the different payment dates, in particular when the sooner allocation date is "Today".[12] Moreover, it is not desirable for the purpose of this experiment that the subjects decide to allocate all the tokens in one date in order to avoid several payment dates. For these purposes, I use a range of measures adapted from Andreoni and Sprenger (2012a)'s study. First, part are paid using Paypal. This method is similar to wire transfers used in other studies (Andersen *et al.*, 2008; Kuhn *et al.*, 2014) but there are several advantages.[13] The Paypal transfer is almost immediate rather than one day lag. Moreover, participants need to provide only an email address in order to receive the transfer rather than a bank account identity. In addition to being easier, Paypal increases confidence in the payment and reassures people who are skeptical about giving out bank details. Next, the participation payment is split in two. At each payment date determined by the allocation drawn, participants receive 5 € in addition to the amount they decided to allocate to each date. This measure discourages participants from allocating all the tokens to one date. Finally, when

[12] Usually, authors of studies about time preferences used front-end delay in order to avoid this problem (cf. discussion in Harrison and Lau, 2005). However, this method is not relevant to the purpose of this experiment, i.e., eliciting time-inconsistency and naiveté biases.

[13] Ashton (2014) also uses Paypal transfers.

the payment allocation is drawn, participants receive an acknowledgment of debt, whereby the experimenter pledge to them to pay the corresponding amounts they chose at the corresponding dates of the payment allocation drawn. This paper is also a reminder of the amounts and dates of payment, and it contains the contact information of the experimenter. The payment procedure also encourages them to come back for the second session. They only receive 5 € in cash at the first round for their participation, and they are told in the "welcome instruction" that they will receive at least 24 € if they come back for the second round (10 € more for their participation and 14 € minimum from their decision). The average payment received by people who participated to the two rounds is 34.32 € : 15 € of participation and 19.32 € from the allocation decision.

3 Model

In order to formalize the participants' time-preferences and to take into consideration their potential temporal bias, I use the (β, δ) model (Akerlof, 1991; Laibson, 1997; O'Donoghue and Rabin, 1999; Phelps and Pollak, 1968). The general utility at one period is the sum of the utility at this period and the discounted utilities of the other periods. However, at the traditional long-term discount rate δ, which depends on the delay between the reference period and the utility period, a short-term discount rate β is added. The utility function at period 0 follows as:

$$U_0 = u_0 + \sum_t \beta\delta^t u_t \,.$$

By giving a different relative weight to the immediate utility, the short-term discount rate captures their temporal bias. In this experiment, this rate is involved only if the sooner date of allocation is "Today". If β is equal to 1, participants value utilities in the same way whether or not immediate present is involved. If $\beta < 1$, participants attribute higher relative weight to immediate utility rather future ones: they are present-biased. Conversely, if $\beta > 1$, participants attribute lower relative weight to immediate utility: they are future-biased.

Following O'Donoghue and Rabin (2001), individuals may have faulty belief about their time-inconsistency problem. In other words, they anticipate their future utility using their belief on the short-term discount rate rather than the real one. In period 0, they anticipate that their utility at period 1 is

$$U_1 = u_1 + \sum_t \hat{\beta}\delta^t u_t \,.$$

If $\hat{\beta}$ is different from β, individuals' prediction of their future decisions is relatively worse when the immediate present is involved. If $\hat{\beta} = 1 (\neq \beta)$, individuals are totally naive. On the contrary,

they are totally aware of their bias, i.e., sophisticated, if $\hat{\beta} = \beta$. Thus if $\hat{\beta} \in [\beta; 1]$ for participants who are present-biased or if $\hat{\beta} \in [1; \beta]$ for those who are future-biased, agents underestimate their bias: they are naive.

Under the assumption that participants to this experiment have (β, δ) preferences, their utility from choosing the allocation (x_t, x_{t+k}) during the second round is

$$U_t(x_t, x_{t+k}) = u(x_t + \omega_t) + \beta^{t_0}\delta^k u(x_{t+k} + \omega_{t+k}) \tag{1}$$

with t_0, an indicator of whether $t = 0$ (i.e., the sooner date is "Today"). ω_t represents the Stone-Geary parameters for background consumption at the period t. The rewards of this experiment are monetary, and the utility function is not considered linear. Thus, in order to account for the real change in utility the participants derive from the monetary rewards of the experiment, it might be necessary to take into account the level of consumption outside the experiment. $u(x)$ is the utility function for each period. The utility function is not necessarily linear. I assume u is a Constant Relative Risk Aversion (CRRA) function: $u(x) = \frac{x^\alpha}{\alpha}$ where α represents the concavity degree of the utility function. If $\alpha = 1$ the function is linear, and if $\alpha < 1$ it is concave. Several interpretations can be given to the degree of concavity of the utility function. It can be explained by either or both the degree of risk aversion and the decreasing in marginal utility derived from wealth. Moreover for time preferences, α captures the participants willingness to smooth their earning over time. It is directly related to the intertemporal substitution elasticity, since this elasticity is equal to $\frac{1}{1-\alpha}$. In this experiment the intertemporal substitution elasticity captures how much the relative demand of later tokens compared to the one of sooner tokens (x_{t+k}/x_t) varies after a change in relative price P.

During the first round, subjects have to project themselves to a future date λ and declare the allocation $(x_{t,\lambda}, x_{t+k,\lambda})$ they think they will choose. Their predicted utility function at λ depends on their belief on their short-term discount rate,

$$U_{t,\lambda}(x_{t,\lambda}, x_{t+k,\lambda}) = u(x_{t,\lambda} + \omega_t) + \hat{\beta}^{t_0}\delta^k u(x_{t+k,\lambda} + \omega_{t+k}) \tag{2}$$

Equations (1) and (2) are the same if the immediate present is not involved ($t \neq 0$), since the short-term discount rate plays no role in the decision. For simplification, if (x_t, x_{t+k}) denote the chosen allocations during the second round and the anticipated ones during the first round,

the general formula of the utility function is

$$U(x_t, x_{t+k}) = \begin{cases} u(x_t + \omega_t) + \hat{\beta}\delta^k u(x_{t+k} + \omega_{t+k}) & \text{if } R_1 = 1 \text{ and } t = 0 \\ u(x_t + \omega_t) + \beta\delta^k u(x_{t+k} + \omega_{t+k}) & \text{if } R_2 = 1 \text{ and } t = 0 \\ u(x_t + \omega_t) + \delta^k u(x_{t+k} + \omega_{t+k}) & \text{if } t \neq 0 \end{cases} . \tag{3}$$

$R_1 = 1$ if the allocations are anticipated during the first round, and 0 otherwise. $R_2 = 1$ if the allocations are chosen during the second round, and 0 otherwise. The purpose of this experiment is to elicit whether time-inconsistent participants are aware of their inconsistencies. Thus, I will focus on estimating the short-run discount rate β and the anticipated one $\hat{\beta}$, but to that end, I will also need to elicit the long-term discount rate δ and the degree of curvature of the utility function α. Participants of the experiment choose their allocations by maximizing their utility function (3) subject to the budget constraint,

$$Px_t + x_{t+k} = M .$$

The tangency condition is given by

$$\frac{x_t + \omega_t}{x_{t+k} + \omega_{t+k}} = \left[\hat{\beta}^{R_1 t_0} \beta^{R_2 t_0} \delta^k P\right]^{1/\alpha - 1} . \tag{4}$$

Moreover, the demand function for the monetary amount allocated to the sooner date (the sooner demand) is

$$\begin{aligned} x_t \quad = \quad & \Big[\frac{(\hat{\beta}\delta^k P)^{(\frac{1}{\alpha-1})}(M + \omega_{t+k}) - \omega_t}{1 + P(\hat{\beta}\delta^k P)^{(\frac{1}{\alpha-1})}}\Big] R_1 t^0 + \Big[\frac{(\beta\delta^k P)^{(\frac{1}{\alpha-1})}(M + \omega_{t+k}) - \omega_t}{1 + P(\beta\delta^k P)^{(\frac{1}{\alpha-1})}}\Big] R_2 t^0 \\ & + \Big[\frac{(\delta^k P)^{(\frac{1}{\alpha-1})}(M + \omega_{t+k}) - \omega_t}{1 + P(\delta^k P)^{(\frac{1}{\alpha-1})}}\Big](1 - t^0) . \end{aligned} \tag{5}$$

Data from the experiment are analyzed under the assumption that participants anticipate and choose the allocations by maximizing their utility function specified as above, subject to the token budget constraint. Then the differences between the anticipated allocations during the first round and the chosen allocations during the second round are only due to a mistaken belief about the short-term discount rate. In other words, the empirical strategy rests on the assumption that the characteristics of the utility function, both the temporal components of the utility function δ and β and the shape of the period utility function α, are constant between the

two rounds.[14] One can argue that preferences may be unstable across time due for instance to exogenous shocks (changes in life expectancy, age, incomes, psychological shocks, etc.) and so the differences between the anticipated and real allocation decisions could be also explained by these shocks. However, with the design of this experiment and the small period between the two rounds, it is reasonable to consider that such shocks are unlikely or have insignificant effect on preferences. Moreover, the literature remains unclear on whether preferences are unstable across time. There is neither evidence that the temporal components of the preferences (δ and β) vary across time or are influenced by income shocks nor evidence for the instability of the risk preferences if we consider that α captures the risk preferences. First, Meier and Sprenger (2015), using a longitudinal study, find that the elicited distributions of the discount rates and the present-bias degrees are similar across the two years of their study. Balakrishnan *et al.* (2015) also found no evidence of a link between present bias and liquidity constraint that can explain the willingness to have immediate monetary rewards. Second, while risk preferences are not necessarily stable across different designs,[15] no evidence exits that they are unstable across time with the same design and the same participants (see longitudinal studies of Andersen *et al.*, 2008b; Baucells and Villasís, 2010, and Harrison *et al.*, 2005a).

4 Descriptive statistics

This section investigates participants' behavior through their allocation choices. This overall behavior foreshadows their time preferences, the shape of their utility function, and the anticipation of these preferences. First, I study the possibility that participants do not discount the future but rather try to maximize their monetary rewards. If these participants also accurately anticipate this decision strategy, they are not interesting for the purpose of this study. Second, participants' choice of corner or interior solutions are studied to glean information about the shape of their utility function. Third, the comparison between the demand for sooner tokens when the immediate present is involved with the demand when it is not enables to highlight potential time-inconsistency bias. Last, the difference between the anticipated allocations and the ones chosen during the second round documents the anticipation accuracy.

4.1 Choice criterion: only the biggest reward?

The value of the token allocated to the sooner date can be lower than, higher than or equal to the one of the token allocated to the later date. I use this choice to verify that none of the

[14] Assumption on the short-term discount rate is that it may be wrongly anticipated by the participants but not that it varies across time.

[15] For example, risk preferences can change due to a framing effect (Tversky, 1969) or changes in elicitation procedures (Bostic *et al.*, 1990).

participants has negative discount rates or only maximizes their payment without considering the delay length, in other words, whether they discount their future utility. If participants choose to allocate all their tokens to the later date for all decisions, then they exhibit negative discount rates. If they allocate all their tokens to the date for which the value of the tokens is the highest and are indifferent to the repartition of the tokens between the two dates when the value of the tokens is the same, then they maximize their payment without considering time. They do not discount the future. Participants who are identified as both maximizing their payoffs and anticipating it are beyond the scope of this study and will be withdrawn from the sample.

While none of the 75 participants allocate all their tokens to the later date for all the decisions, during the second round a third (25 participants) allocate their tokens in order to maximize their payment. They choose an impatient solution for the larger-sooner allocations (i.e., they allocate all their tokens to the early date) and a patient solution for the smaller-sooner allocations (i.e., they allocate all their tokens to the later date), and they are indifferent to the tokens repartition between the early date and the later one for the equal allocations. More interestingly, only almost half of those 25 participants (12 participants) perfectly anticipate their allocations. In other words, they know that they will not discount their future utility.[16]

Two results emerge. First, a third of the participants do not discount and choose to maximize their payment. This number is surprisingly high. Beside the maximization strategy, these participants may have an Annual Effective Rate (AER) lower than the proposed minimum, 7%. Second, only almost half of them anticipate it. The fact that some of them fail to anticipate such behavior might be evidence of a learning effect. By maximizing their payoffs instead of allocating tokens randomly, participants have a strategy they can better understand. But also this may be evidence for present bias and naiveté. Whereas their long-term discount rate is equal to 0, their short-term discount rate is lower than 1, and they are totally naive about it.

For the rest of the analysis, unless stated otherwise, the 12 participants who did not discount and anticipate it perfectly are removed as they provide no information for the deviation this experiment looks to identify.

Table 1: Overview of the participant allocations by categories

	Interior All.	**Impatient All.**	**Patient All.**
Median	16	11	24
Mean	28	23	29
Percentage of individuals with			
- None	19.05%	9.52%	23.81%
- All	7.94%	1.59%	0%

4.2 Corner and interior allocations

The participants' choice to always allocate all their tokens to one date or to distribute their budget between the two dates determines whether their utility function is linear. If they have linear utility function, the only criterion for allocating tokens is their discount rates. They allocate all their tokens to the date on which the weighted value of the tokens is higher. However, if they have a concave utility function, the decreasing marginal utility of monetary rewards for one period may lead them to distribute tokens on the two dates.

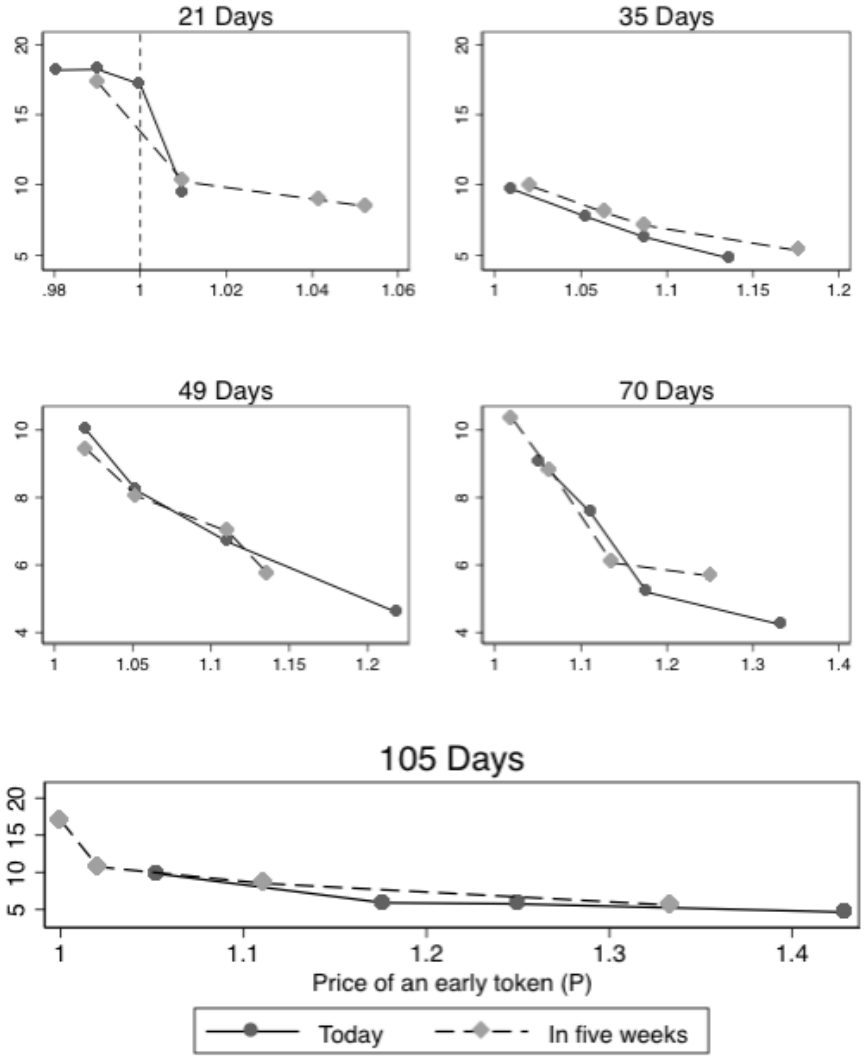
I label corner allocations as the ones for which the participants allocate all their tokens in one date. These allocations can be classified as either *impatient*, if all the tokens are allocated to the sooner date, or *patient*, if all the tokens are allocated to the later date. The allocation is *interior* if the participant allocates tokens on both dates. At the aggregate level, 36% of the allocations are patient, 29% are impatient, and 35% are interior. The repartition of the allocations at the individual level is summarized in Table 1. Only 19% of the participants choose any interior allocation. In other words, these participants have a linear utility function. Conversely, 81% of participants among those who discount choose at least one interior allocation. Thus, it is important to introduce a parameter to measure the curvature of this function to avoid overstating the long-term discount rate or the present bias. Also, only one participant always chooses the same allocation. He always allocates his tokens to the sooner date and anticipate this behavior. Given that the choice of this participant does not vary, he is drop for the rest of the analysis.

4.3 Demand functions for the sooner tokens

Comparing the sooner demand whether the immediate present belongs to the choice set highlights the existence of present or future bias. If the participants are present-biased, the demand for sooner tokens (and thus the number of tokens allocated to the sooner date) is higher when the early date is in the immediate present (i.e., the payment date is "Today") than when it is a future date. Conversely, if the participants are future-biased, the number of sooner tokens is

[16] If we consider that they are indifferent for the equal allocations, then five more participants anticipate their decisions well. However, this can also be interpreted as a wrong anticipation. All these participants follow the same pattern: they do not anticipate they will allocate all the tokens to the early date for the equal allocations.

Figure 1: Comparison of early payments (round 2)



lower when the early payment date is in the immediate present.

Figure 1 plots the number of tokens allocated to the earlier payoff date during the second round as a function of interest rates by delay lengths. The solid line represents the sooner demand when it is in the immediate present whereas the dashed one represents the sooner demand when only future dates are involved in the token repartition. The graph suggests that no obvious evidence exists for present or future bias. Only for the small delay of 35 days between the two payment dates, the demand for sooner tokens is slightly higher when the early date is in the future (i.e., "In five weeks"). This suggests evidence of a low future bias for this delay. Furthermore, the shape of the demand functions varies across delays and with the value of P. For $P < 1$, the shape of the demand function appears to be more concave than convex.

4.4 Anticipation of the sooner demand

4.4.1 Overall anticipation accuracy of the sooner demand

I focus on the anticipation of the sooner demand. To see how well participants anticipate their future allocation choices the anticipated allocations relies on the following classification from observed decisions. The allocation is underestimated (respectively overestimated) by the participant if the number of tokens he anticipates allocating to the sooner date is lower (respectively higher) than the number of sooner tokens he chooses during the second round for the allocation with the same characteristics. The allocation is perfectly estimated by the participant if he anticipates allocating the same number of tokens that he chooses during the second round for this allocation. The lightest bar on Figure 2 displays the average percentage of underestimated, overestimated, or perfectly estimated allocations. The allocations are mostly perfectly-anticipated. On average, a participant underestimates eight allocations and overestimates nine (out of 40). However only the estimation of the utility function parameters will allow to determine whether these observed mistaken in anticipation is due to one's own bias or simply to anticipation errors.

Furthermore, from Figure 2, we see that the proportion of allocations for which the sooner demand is underestimated, perfectly anticipated or overestimated is different whether or not the value of the sooner token is lower than the one of the later token. Whereas for 24% of the smaller-sooner allocations (SSA), the sooner demand is overestimated, it is only the case for 7% of the other allocations (ELSA) – equal-sooner ones and larger-sooner ones. Conversely, a slightly lower proportion of the smaller-sooner allocations are perfectly anticipated or underestimated. This suggests an heterogeneity of behaviors depending on the characteristics of the decision.

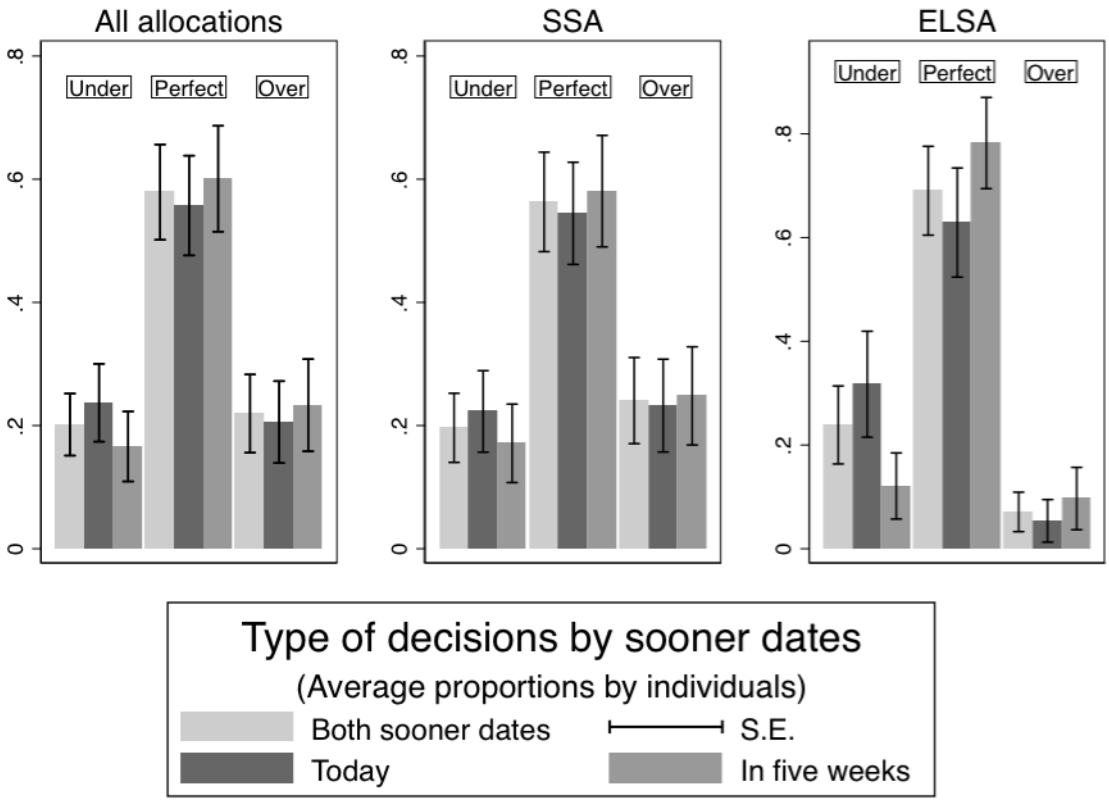
4.4.2 Anticipation when the sooner date is "Today" versus when it is "In five weeks"

If participants exhibit a temporal bias whether the immediate present is a characteristic of the decision, and are ignorant of their bias, then the number of underestimated or overestimated allocations should differ based on whether the earlier date involves the immediate present. Figure 2 presents the average proportion of each type of allocation by participant, by sooner date.

The proportion of underestimated allocations is significantly higher when the sooner date is "Today" (One side mean-comparison t-test:[17] p-value < 0.05) whereas the average propor-

[17]The null hypothesis of the Student test is that the mean of two independent samples (the sample on which

Figure 2: Anticipation of early payments, by sooner dates and by types of allocations

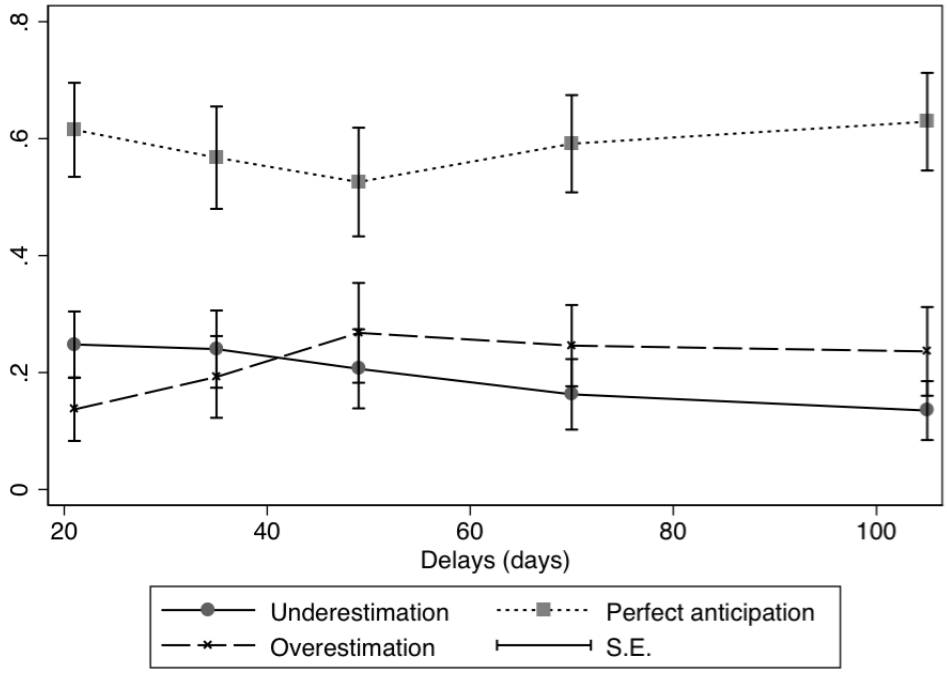


tion of perfectly anticipated or overestimated allocations is not significantly different. However, this difference is explained by the equal-sooner and larger sooner allocations (ELSA). The proportion of underestimated ELSA is 20% higher when the sooner date is "Today" and this difference is significant (One side mean-comparison t-test: p-value < 0.01) whereas the difference between the proportion of underestimated sooner-smaller allocation (SSA) when the sooner date is in the immediate present or in the future is not significantly different. Moreover the proportion of perfectly anticipated ELSA is also significantly lower when the sooner date is "Today" (One side mean-comparison t-test: p-value < 0.05) while it is not the case for the SSA. Figure 2 depicts the different proportions of SSA and ELSA which are underestimated, perfectly anticipated and overestimated.

This result suggests that participants tend to underestimate their willingness to obtain immediate gratification but only when postponing this gratification is costly. The intuition behind this result is that participants anticipate to smooth the gratification over time, even if it is costly but end up not resisting the temptation of the immediate (and higher) gratification. For a deeper analysis, the parameter estimation of the utility function will be necessary.

allocations are between "Today" and in a future date and the one on which the allocations are between two future dates) are equal. This test requires that the variances of the two samples are equal. For the one side test, the null hypothesis is tested against the strict inferiority or superiority of one mean on the other one.

Figure 3: Anticipation of early payments, by delay lengths (Average proportion of allocations by participants)



4.4.3 Accuracy of the anticipation by delays between payment dates

Figure 3 represents the average proportion of each type of anticipated allocations by participants for each length of the delay (for both sooner dates). The average proportion of perfectly anticipated allocation is constant for each delay length between the two payment dates (ANOVA:[18] p-value $= 0.45$). However, the average proportion of underestimated allocation decreases when the length of the delay increases (Page's trend test:[19] p-value < 0.05) whereas the average proportion of overestimated increases (Page's trend test: p-value < 0.1). These results are robust when only the SSA are considered.[20]

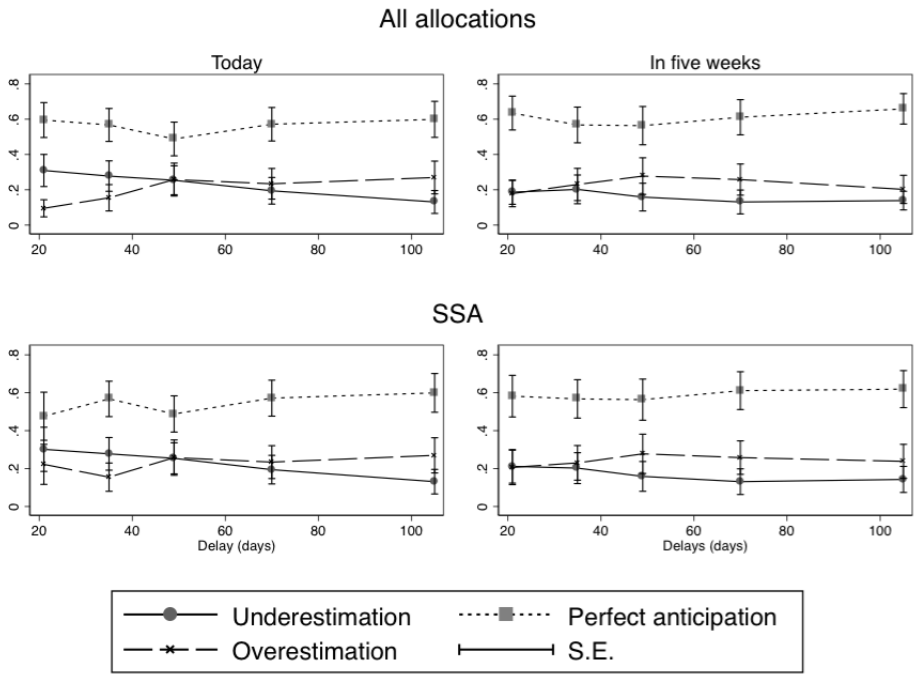
Figure 4 displays the same data on the average proportions of each type of anticipated allocations for each delay length, but now the average proportions are also computed by sooner dates ("Today" or "In five weeks") and depending on the relative value of the sooner token (all allocations are considered or only the smaller-sooner ones). The proportion of

[18]The ANOVA allows a generalization of the Student test to test whether the means on multiple samples are simultaneously equal. The ANOVA indicates whether all the samples are drawn from the sample population. Its null hypothesis is that all the average proportions of perfectly anticipated allocations are the same across delay lengths against the alternative that, at least for two different delay lengths, the average proportions of perfectly anticipated allocations are different.

[19]The Page (1963) trend test tests for the orderings of variables across treatments. Its null hypothesis is that all orderings of the proportion of underestimated allocations across delay length are equally likely against the alternative that the longer the delay is, the lower the proportion of underestimated allocation is.

[20]The analysis of the proportion of ELSA by delays is not relevant given that ELSA were not proposed for each combination of delay lengths and sooner dates. Recall that the set of allocations is represented by Table A.2 in the appendix.

Figure 4: Anticipation of early payments, by delay lengths, sooner dates and types of allocation (Average proportion of allocations by participants)



underestimated allocations is higher than the one of overestimated allocations for short delays between the two payment dates only if the sooner date is in the immediate present. This result is mitigated if only SSA are considered. Moreover, the proportion of overestimated allocations is greater for longer delays but the difference is not significant.

In a nutshell, participants are more likely to underestimate their sooner demand than overestimate it when the sooner date involves the immediate present and when the length between the two dates is short. However, the proportion of underestimated (overestimated) allocations tend to decrease (increase) with the delay lengths between the dates. Thus for longer delays the proportion of overestimated allocation is higher than the one of underestimated allocation even if this difference is not significant. These result are mitigated by considering only the smaller-sooner allocations. Two possible effects can explain this findings. First, participants do not expect their willingness of immediate gratification to be so high for small delays. For small delays they might believe they will be able to wait and increase their payment. Second, on the contrary, for larger delays they underestimate their capacity to be patient.

Two main results emerge from the analysis of the descriptive statistics. First, it is not clear that the sooner demand of the participants is higher or lower whether the immediate present is involved. Thus no clear evidence appear for present or future bias. Second, the analysis of

the anticipation of the sooner demand highlights that the anticipation accuracy of the sooner demand seems to be heterogeneous given the characteristics of the decision. It depends on whether the immediate present is involved, but also on the lengths of the delay and on whether the value of the sooner token is smaller that the one of the later token. But there might be noise in the anticipation, and analyzing the descriptive statistics is not enough to disentangle the noise from an actual wrong anticipation of the sooner demand. To go further, the estimation of the utility function parameters is necessary.

5 Parameter Estimation

5.1 Estimation strategy

The estimation of the utility function parameters must account for the fact that observations are censored for corner solutions. Such observations only provide thresholds for the parameters.

Andreoni and Sprenger (2012a) introduce two strategies for identifying the parameters of the utility function. The first one relies on the log of the tangency condition (4):

$$ln(\frac{x_t + \omega_t}{x_{t+k} + \omega_{t+k}}) = \frac{ln(\hat{\beta})}{\alpha - 1} R_1 t^0 + \frac{ln(\beta)}{\alpha - 1} R_2 t^0 + \frac{ln(\delta)}{\alpha - 1} k + \frac{1}{\alpha - 1} ln(P)\,. \tag{6}$$

The parameter α is estimated through the variation of the gross rate interest P, δ is identified by the variation of the delay length between the two payment dates k. In addition, the timing of the sooner date allows us to elicit β for the allocations of the second round and $\hat{\beta}$ for the allocations anticipated during the first round. This empirical model has two advantages. First, the equation is linear and can thus be easily estimated. Second a two-limit Tobit maximum likelihood regression can be implemented to consider the censoring observations. Its main weaknesses, however, are that the background consumption ω_t and ω_{t+1} must be known, since they cannot be estimated, and that the consumption must be strictly positive such that the log is well defined.

The second technique is to estimate the sooner demand function (5)

$$\begin{aligned} x_t \quad = \quad & \Big[\frac{(\hat{\beta}\delta^k P)^{(\frac{1}{\alpha-1})}(M + \omega_{t+k}) - \omega_t}{1 + P(\hat{\beta}\delta^k P)^{(\frac{1}{\alpha-1})}}\Big] R_1 t^0 + \Big[\frac{(\beta\delta^k P)^{(\frac{1}{\alpha-1})}(M + \omega_{t+k}) - \omega_t}{1 + P(\beta\delta^k P)^{(\frac{1}{\alpha-1})}}\Big] R_2 t^0 \\ & + \Big[\frac{(\delta^k P)^{(\frac{1}{\alpha-1})}(M + \omega_{t+k}) - \omega_t}{1 + P(\delta^k P)^{(\frac{1}{\alpha-1})}}\Big](1 - t^0) \end{aligned}$$

using non-least squares (NLS). This method allows to estimate the values of the background consumption parameters, at the cost of being unable to account for the censored data. The

parameters are estimated using an iteration process to find the values of the parameters that minimize the difference between the observed value of x_t and the estimated demand function.

Moreover, to ensure the robustness of the estimation, several values for the background consumption parameters ω_t and ω_{t+k} will be used to estimate the utility function parameters. Each based on different behavioral assumption. First, we can consider that the individuals engage in narrow bracketing (Rabin and Weizsacker, 2009), i.e., they make independent decisions without considering anything else. In that case, the background consumption parameters are set to be equal to 0 for both periods. They can also engage in narrow bracketing by being only focus on the lab experiment. Since they receive monetary rewards associated with the decisions in addition to the participation fees for each date, it might be correct to consider that the background consumption parameters are equal to the participation fees (5 €). Then, in order to account for potential heterogeneity among participants, the background parameters are set to be equal, at both periods, to the daily expenditure self-reported by participants. Finally, when using the NLS method on the sooner demand, the background consumption parameters are estimated by considering first that they vary across periods and second that they are constant across periods.

5.2 Aggregate-level estimation

To formally test whether participants exhibit present or future bias and accurately anticipate these biases, I estimate equation (5) with NLS or equation (6) with two-limits tobit, pooling all the allocation decisions from all subjects.[21]

In columns 1 through 5 of table 2, the parameters of the utility function are estimated using the NLS method on the sooner demand. In column 1, the background consumption parameters are assumed to be equal to 0. The estimated daily discount factor δ is 0.9993 (and significantly different from 1: p-value < 0.01) and the annual rate[22] is estimated at 29% (significantly different from 0: p-value < 0.01). Moreover, I estimate a short-term discount rate β, representative of the time-inconsistency bias, of 0.983. It differs significantly from 1 at 95% confidence, which is evidence for present bias. However, on average, the participants anticipate their short-term discount rate well, since $\hat{\beta}$ is not significantly different from β (p-value $= 0.28$). Finally, the degree of curvature of the utility function α is significantly different from 1 (p-value < 0.01) and estimated at 0.911. On average, the participants don't have a linear utility function.

In column 2, the background consumption parameters are set equal to the participation fees.

[21] In all specifications, standard errors are clustered at the subject level.
[22] $AR = \delta^{-365} - 1$

The estimated parameters are very close to the ones in column 1, though α decreases to 0.83. β is significantly different and lower than 1 at 95% confidence, and $\hat{\beta}$ is not significantly different from β (p-value $= 0.31$).

In column 3, the background consumption parameters are set to consider the heterogeneity of the participants. At both periods, they are equal to the self-reported daily expenditure. For this specification, again, β is significantly different and lower than 1 (p-value < 0.05) as $\hat{\beta}$ is not different from β (p-value $= 0.324$). The estimated value of α, 0.622, is lower and the estimated annual rate higher, 38.55%.

In column 4, the background consumption parameters are considered different at the two periods and are estimated. The estimated value of β is not significantly different from 1 anymore (p-value $= 0.937$). However, $\hat{\beta}$ is significantly different and higher than β (p-value < 0.05). α jumps to 0.976 and the annual rate decreases to 3.57%. Thus no further evidence exists for present bias, but it suggests that the participants overestimate their short-term discount rate and anticipate to be future-biased while they can be considered as time-consistent. Also, the estimated values of the background consumption are not the same across periods. The estimated value of the background consumption for the second payment date is significantly different and higher than the one for the first payment date (p-value < 0.001). Furthermore, the value of the first background consumption is negative.

In column 5, the values of the background consumption parameters are estimated but are restricted to be the same across periods. I estimate more similar parameters as in column 1, 2 and 3, though the estimated α is 0.975. The estimated β, 0.987, is significantly different from 1 (p-value < 0.01) and again $\hat{\beta}$ is not significantly different from β (p-value $= 0.246$).

In columns 6 through 8, the parameters of the utility function are estimated using the two-limits tobit method on the tangency condition. Column 6 depicts the estimated parameters of the utility function when the background consumption parameters are set to be equal to 0.01.[23] In column 7, the background consumption parameters are considered to be equal to the participation fees received at each date and in column 8, to be equal to the self-reported daily expenditure. Compared to the estimated parameters with the NLS method, the values of α and the one of the annual discount rate estimated with the two-limits tobit method are higher. The estimated utility function of participants is closer to be linear. Yet, the estimated values of β remain significantly lower than and different from 1, and $\hat{\beta}$ is estimated not significantly

[23] If the background consumption parameters were set to be equal to 0, the log ratio of the demand will not have been defined for corner allocations. Thus, as Andreoni and Sprenger (2012a), I set the background consumption parameters equal to 0.01 to overcome this problem.

different from β. This suggests that the existence of present bias when all the decisions from all the subject are pooled together is robust to the estimation methods.

The existence of present bias at the aggregate level is inconsistent with the findings of Andreoni and Sprenger (2012a) and also Ashton (2014), who studies the impact of hunger or cognitive-fatigue on intertemporal preferences using the CTB method. As in Andreoni and Sprenger, Ashton finds no evidence for present-bias for the control group and for the cognitive-fatigue treatment group. Yet, this findings is in line with the study of Kuhn *et al.* (2014) who find small but significant evidence for present bias. One novelty of this paper, is that participants are proposed allocation decisions in which the value of the sooner token is higher than the one of the later token. We have seen in the previous section that the behavior of participants might be different when the relative value of the sooner token is higher. Thereby, the intent of the next subsection is to determine the influence of the decision characteristics on the participants behavior at the aggregate level.

5.3 Influence of the decision characteristics

The aggregate level analyses pooled the data based on all the allocation decisions from all subjects and all delay lengths, constraining the preferences to be homogeneous. This assumption may raise issues if heterogeneity is present. Two dimensions of heterogeneity stand out more specifically from the preliminary outcomes of the descriptive statistics and lend themselves to analysis: the influence of the relative value of the sooner token – whether it is smaller or not than the value of the later token, and the influence of the delay lengths between the two payment dates.

5.3.1 Influence of the relative value of the sooner token

Table 3 displays the parameters of the utility function estimated first by pooling together only the SSA of all the individuals (columns 1 through 8) and second by pooling together only the ELSA (columns 9 through 11). When only the SSA are considered, the same estimation methods are used as when all the allocations where pooled together. Yet, because a very high proportion of the ELSA are corner allocations, the NLS estimation method might not be accurate.[24] Thus only the two-limits tobit method is used to estimate the parameters of the utility function. In this case, the values of the background consumption parameters are set to be equal to the same values as in the previous subsection: 0.01, 5 and the self-reported daily expenditure by participants.

[24]Only, 31.29% of these allocations are interior.

Table 2: Estimation of the aggregate parameters (All allocations)

	NLS					2LTob		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
α	0.9109***	0.8303***	0.6216***	0.9757***	0.9750***	0.9852***	0.9329***	0.9211***
	(0.0100)	(0.0149)	(0.0631)	(0.0035)	(0.0024)	(0.0031)	(0.0130)	(0.0164)
δ	0.9993***	0.9993***	0.9991***	0.9999***	0.9994***	0.9991***	0.9991***	0.9991***
	(0.0002)	(0.0002)	(0.0003)	(0.0000)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
AR	0.2910***	0.3119***	0.3855***	0.0357***	0.2273***	0.3860***	0.3722***	0.3912***
	(0.0953)	(0.1116)	(0.1485)	(0.0123)	(0.0699)	(0.1486)	(0.1431)	(0.1433)
β	0.9825 **	0.9827 **	0.9808 **	1.0002	0.9874 ***	0.9828**	0.9842*	0.9850*
	(0.0062)	(0.0071)	(0.0089)	(0.0022)	(0.0046)	(0.0082)	(0.0082)	(0.0084)
$\hat{\beta}$	0.9918	0.9928	0.9939	1.0070 **	0.9942	0.9904	0.9922	0.9934
	(0.0064)	(0.0075)	(0.0099)	(0.0034)	(0.0047)	(0.0097)	(0.0092)	(0.0090)
$\omega_t (= \omega_{t+k})$	0	5	ω_i[a]	-5.1318	-4.5400	0.01	5	ω_i[a]
				(0.6026)	(0.6196)			
ω_{t+k}				2.8249				
				(0.9625)				
H_0: $\beta = 1$	0.0480	0.0154	0.0315	0.9373	0.0065	0.0364	0.0540	0.0724
H_0: $\beta = \hat{\beta}$	0.2768	0.3110	0.3241	0.0351	0.2464	0.5679	0.5287	0.4956
N	4960	4960	4960	4960	4960	4960	4960	4960

The seven first rows displays the estimated values of the utility function. The parameter α corresponds to the curvature degree of the utility function; δ to the long-term discount rate; AR to the annual rate obtained from δ; β to the relative weight given to the immediate utility (i.e., the short-term discount rate); $\hat{\beta}$ to the belief on the short-term discount rate; ω_t to the background consumption at period t. The two last rows reports the p-values of the following hypothesis tests: H_0: $\beta = 1$ for the second last row and H_0: $\beta = \hat{\beta}$ for the last one.

In columns 1 through 5, the utility function parameters are estimated using the Non-Least Square (NLS) method on the sooner demand function (equation (5)) whereas in columns 6 through 8, these parameters are estimated using the two-limits tobit (2LTob) method on the tangency condition (equation (6)). Each column corresponds to a different assumption on the parameters ω_t and ω_{t+k}. Robust standard errors are clustered at the subject level.

The symbols ***, ** and * indicates the significance levels (respectively 1%, 5% and 10%) for the test of the following hypothesis: H_0: $\alpha = 1$, H_0: $\delta = 1$, H_0: $AR = 0$, H_0: $\beta = 1$ and H_0: $\hat{\beta} = \beta$.

[a] ω_i indicates self-reported average daily expenditure, which varies across subjects.

By differentiating the type of allocations when estimating the utility function parameters, we observe that the aggregate behavior of participants towards immediate gratification is different when the value of the sooner tokens is higher than the one of the later tokens. When pooling together only the SSA, the estimated value of β is significantly different and higher than 1. Moreover, participants accurately anticipate their future value of β since $\hat{\beta}$ is estimated not to be different from β. These results are robust for almost all the specifications considered. The only specification in which β is estimated not to be significantly different from 1 is when the background consumption parameters are estimated and considered different at each period. This suggests that participants are future-biased and accurately anticipate that they will be future-biased. Conversely, when only the ELSA are considered, β is estimated significantly lower than 1 and $\hat{\beta}$ is significantly higher and different from β. This suggests that participant

are present-biased and unaware of this bias – they underestimate it. The overestimation of β for ELSA is consistent with what we have seen in the previous section: the proportion of ELSA for which the sooner demand is underestimated is higher when the sooner date is "Today" than "In five weeks" (Figure 2). Furthermore, the estimated values of α are different for the two types of allocations. For ELSA, the estimated utility function is very close to be linear since α is very close to 1 although significantly different from 1. When the values of the sooner token is lower (for SSA), the estimated utility function is estimated more concave (estimated values of α are lower). This difference in the degree of curvature of the utility function for the two types of allocations might explain why present bias predominates when all the allocations are pooled together, despite the relative small number of ELSA.

To sum up, participants tend to have different behaviors whether the value of the sooner token is smaller than the one of the later token or not. First, they are more willing to smooth their earnings over time since α is estimate to be smaller for the SSA than for the ELSA. Second, for the SSA, participants tend to be future-biased, i.e, their sooner demand is relatively smaller when the sooner date involves the immediate present and they perfectly anticipate it. One way to explain future bias is that participants may experience anticipation emotions by expecting their future rewards. In that case, they are more willing to delay their rewards when the sooner date is "Today" as compare to when it is in the future. The other way to explain it is the ambiguous role of money. Using money to elicit time-inconsistency biases has limitations. Money may be considered not as tempting but merely as a means for buying temptation goods. Thus, participants can use it as a commitment device. In that case, participants may appear to be future-biased while they only delay the monetary rewards when the sooner date is "Today" to tie their hands not to buy temptation goods.

Finally, on the contrary, for the ELSA, participants tend to be present-biased and naive about it. Thus, one way to explain this different behavior goes as follows: participant are willing to delay the monetary rewards to commit themselves when the decision involves the immediate present at a constant long-term discount rate for the SSA. However, they are not willing to pay for this commitment. It is the case for the ELSA since the value of the sooner token is higher than the one of the later token. This is consistent with previous studies where participants are not willing to pay for a commitment device even if they take it when it is free (Augenblick *et al.*, 2015). On the contrary, for ELSA, if the sooner date is "Today", rather than in the future, participants do not avoid the temptation to allocate more money on the sooner date. Moreover, they do not accurately anticipate this behavior.

Table 3: Estimation of the aggregate parameters, for SSA and for ELSA

	SSA								ELSA		
			NLS				2LTob			2LTob	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
α	0.8627***	0.7530***	0.4570***	0.9379***	0.9375***	0.9785***	0.9031***	0.8860***	0.9979***	0.9904***	0.9895***
	(0.0178)	(0.0291)	(0.0960)	(0.0105)	(0.0094)	(0.0050)	(0.0211)	(0.0269)	(0.0004)	(0.0015)	(0.0019)
δ	0.9994*	0.9994	0.9993	0.9991***	0.9994**	0.9993	0.9994	0.9993	0.9997***	0.9997***	0.9997***
	(0.0003)	(0.0004)	(0.0005)	(0.0001)	(0.0002)	(0.0005)	(0.0005)	(0.0005)	(0.0000)	(0.0000)	(0.0000)
AR	0.2347	0.2236	0.3016	0.4001***	0.2354**	0.2706	0.2595	0.2886	0.1038***	0.0973***	0.0998***
	(0.1485)	(0.1739)	(0.2260)	(0.0714)	(0.1116)	(0.2236)	(0.2141)	(0.2149)	(0.0154)	(0.0139)	(0.0143)
β	1.0268**	1.0333**	1.0340**	1.0141	1.0162*	1.0350**	1.0368**	1.0379**	0.9859***	0.9865***	0.9864***
	(0.0128)	(0.0147)	(0.0166)	(0.0097)	(0.0097)	(0.0176)	(0.0173)	(0.0176)	(0.0021)	(0.0020)	(0.0019)
$\hat{\beta}$	1.0304	1.0365	1.0402	1.0177	1.0202	1.0305	1.0337	1.0352	0.9963***	0.9964***	0.9966***
	(0.0125)	(0.0138)	(0.0173)	(0.0122)	(0.0105)	(0.0167)	(0.0158)	(0.0155)	(0.0017)	(0.0016)	(0.0017)
$\omega_t (= \omega_{t+k})$	0	5	ω_i[a]	-3.3556	-3.4984	0.01	5	ω_i[a]	0.01	5	ω_i[a]
				(0.5480)	(0.5064)						
ω_{t+k}				-5.4493							
				(1.5754)							
$H_0 : \beta = 1$	0.036	0.0236	0.0398	0.1473	0.0931	0.0476	0.0330	0.0313	0,0000	0,0000	0,0000
$H_0 : \beta = \hat{\beta}$	0.8312	0.8636	0.7820	0.8104	0.7757	0.8549	0.8916	0.9019	0,0001	0,0000	0,0000
N	4340	4340	4340	4340	4340	4340	4340	4340	620	620	620

The seven first rows displays the estimated values of the utility function. The parameter α corresponds to the curvature degree of the utility function; δ to the long-term discount rate; AR to the annual rate obtained from δ; β to the relative weight given to the immediate utility (i.e., the short-term discount rate); $\hat{\beta}$ to the belief on the short-term discount rate; ω_t to the background consumption at period t. The two last rows reports the p-values of the following hypothesis tests: H_0: $\beta = 1$ for the second last row and H_0: $\beta = \hat{\beta}$ for the last one.

In columns 1 through 8, the utility function parameters are estimated by pooling together the choices of the smaller-sooner allocations (SSA), first, by using the Non-Least Square (NLS) method on the sooner demand function (5) (columns 1 through 5) and then by using the two-limits tobit (2LTob) method on the tangency condition (6) (columns 6 through 8). In columns 9 through 11, these parameters are estimated by pooling together the choices of the equally- and larger-sooner allocations (ELSA) and by using the two-limits tobit method. Each column corresponds to a different assumption on the parameters ω_t and ω_{t+k}. Robust standard errors are clustered at the subject level.

The symbols ***, ** and * indicates the significance levels (respectively 1%, 5% and 10%) for the test of the following hypothesis: H_0: $\alpha = 1$, H_0: $\delta = 1$, H_0: $AR = 0$, H_0: $\beta = 1$ and H_0: $\hat{\beta} = \beta$.

[a] ω_i indicates self-reported average daily expenditure, which varies across subjects.

5.3.2 Influence of the delay length between the two payment dates

It has been shown, comparing the demand for sooner tokens when the early payment is "Today" with when it is "In five weeks" (see Figure 1), that only for the second delay length (of 35days) do participants seem to exhibit a bias. Moreover, in Figure 3, the proportions of underestimated and overestimated allocations vary across delay lengths, particularly for the first three delay lengths. Thus, three classes of delays can be distinguished to consider heterogeneity: the short-delay class, when the delay between the two payment dates is 21 days (*SD*); the medium-delay class, with a delay of 35 days (*MD*); and the long-delay class, with delays of 49, 70, and 105 days (*LD*).

For identification matters, I assume the long-term discount rate δ is constant across delays and consider that both the short-term discount rate β (as well as its anticipation $\hat{\beta}$) and the degree of curvature of the utility function α may vary. This implies that only the NLS method can be used to estimate the parameters of the utility function. Indeed, given that the value of δ depends on the estimated value of α with the two-limits method (see equation 6), so that δ cannot be assumed constant without also assuming that α is constant across delays. Another issue is that the number of ELSA is too small by delay lengths and the proportion of corner solutions is too high to perform a NLS estimator. As a result, these parameters are estimated only by pooling together all the allocations and by pooling together only the SSA. However, the parameters are not estimated when considering only the ELSA. The NLS estimations of the utility function parameters for varying hypothesis on the background consumption are presented in Table 4.

The estimated value of the curvature degree of the utility function α decreases when the delay length increases. This result is robust for all the estimation strategies. Table 5 represents the p-values associated to the pairwise equality tests of α by delay lengths. To determine whether the values of α are significantly different, the threshold probability of the null hypothesis rejection needs to be adjusted using the Bonferroni correction. To avoid underestimating the probability of making a type-I error because of multiple tests, the significance level is divided by the number of tests (for three tests, the two variables are significantly different at 5% for a p-value lower than $0.05/3 = 0.0167$). By considering all the allocations, the value of α for the shortest delay length is always larger and significantly different from the value of α for larger delays. For the medium delay length, the value of α is larger than the one for larger delay length and the difference is insignificant only when the estimated value of the background consumption is constrained to be the same at the two payment dates (column 5). When only the SSA are con-

Table 4: Parameters estimation across delay-length class

	All allocations					SSA				
			NLS					NLS		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
δ	0.9990***	0.9989***	0.9987***	0.9997***	0.9994***	0.9993*	0.9993	0.9991*	0.9991***	0.9993**
	(0.0002)	(0.0002)	(0.0003)	(0.0001)	(0.0001)	(0.0004)	(0.0004)	(0.0005)	(0.0002)	(0.0003)
AR	0.4585***	0.4919***	0.5982***	0.1314***	0.2519***	0.2797*	0.2752	0.3898	0.3944***	0.2754**
	(0.1315)	(0.1347)	(0.1848)	(0.0381)	(0.0617)	(0.1680)	(0.1894)	(0.2630)	(0.0851)	(0.1371)
α										
- *SD*	0.9736***	0.9583***	0.9136***	0.9833***	0.9963***	0.9188***	0.8763***	0.7471***	0.9418***	0.9446***
	(0.0029)	(0.0043)	(0.0177)	(0.0037)	(0.0006)	(0.0202)	(0.0294)	(0.0751)	(0.0166)	(0.0150)
- *MD*	0.9054***	0.8407***	0.6379***	0.9605***	0.9593***	0.9017***	0.8338***	0.6239***	0.9478***	0.9459***
	(0.0131)	(0.0196)	(0.0773)	(0.0064)	(0.0068)	(0.0140)	(0.0212)	(0.0793)	(0.0105)	(0.0098)
- *LD*	0.8693***	0.7707***	0.5049***	0.9463***	0.9508***	0.8448***	0.7270***	0.4165***	0.9223***	0.9184***
	(0.0152)	(0.0227)	(0.0824)	(0.0081)	(0.0057)	(0.0205)	(0.0342)	(0.1001)	(0.0154)	(0.0144)
β										
- *SD*	0.9924**	0.9937*	0.9961	0.9967	1.0028	1.0008	1.0005	0.9995	0.9940	1.0009
	(0.0035)	(0.0033)	(0.0041)	(0.0024)	(0.0021)	(0.0109)	(0.0107)	(0.0118)	(0.0129)	(0.0114)
- *MD*	1.0243*	1.0290*	1.0309	1.0182**	1.0060	1.0134	1.0161	1.0194	1.0057	1.0086
	(0.0141)	(0.0157)	(0.0187)	(0.0087)	(0.0112)	(0.0137)	(0.0147)	(0.0187)	(0.0122)	(0.0116)
- *LD*	1.0432***	1.0507***	1.0553***	1.0220**	1.0093	1.0371*	1.0440*	1.0507*	1.0265	1.0270
	(0.0156)	(0.0176)	(0.0202)	(0.0096)	(0.0118)	(0.0200)	(0.0223)	(0.0265)	(0.0178)	(0.0170)
$\hat{\beta}$										
- *SD*	1.0045***	1.0051***	1.0077***	1.0047***	1.0054**	1.0324*	1.0325*	1.0293	1.0276*	1.0320*
	(0.0045)	(0.0044)	(0.0062)	(0.0031)	(0.0026)	(0.0156)	(0.0156)	(0.0181)	(0.0189)	(0.0158)
- *MD*	1.0630***	1.0704***	1.0787**	1.0418**	1.0350**	1.0529***	1.0585***	1.0683**	1.0399**	1.0415**
	(0.0142)	(0.0149)	(0.0219)	(0.0111)	(0.0120)	(0.0145)	(0.0149)	(0.0237)	(0.0138)	(0.0132)
- *LD*	1.0347	1.0422	1.0487	1.0163	1.0016	1.0206	1.0266	1.0359	1.0108	1.0118
	(0.0134)	(0.0149)	(0.0185)	(0.0091)	(0.0102)	(0.0153)	(0.0166)	(0.0221)	(0.0145)	(0.0133)
$\omega_t = \omega_{t+k}$	0	5	ω_i[a]		-4.0886	0	5	ω_i[a]		-3.0341
					(0.4655)					(0.5686)
ω_t				-4.1076					-3.0340	
				(0.5186)					(0.5828)	
ω_{t+k}				0.6370					-4.4882	
				(1.3331)					(1.8270)	
N	4960	4960	4960	4960	4960	4340	4340	4340	4340	4340

The parameter δ corresponds to the long-term discount rate; AR to the annual rate obtained from δ; α to the curvature degree of the utility function; β to the relative weight given to the immediate utility (i.e., the short-term discount rate); $\hat{\beta}$ to the belief on the short-term discount rate; ω_t to the background consumption at period t. The parameters α, β and $\hat{\beta}$ are estimated for different length of delays between the allocation dates. SD corresponds to delays of 21 days; MD to delays of 35 days and LD to delays of 49, 70, and 105 days.

The utility function parameters are estimated using the Non-Least Square (NLS) method on the sooner demand function (5). In columns 1 through 5, these parameters are estimated by pooling together all the allocation decisions whereas in columns 6 through 10, only the smaller-sooner allocations (SSA) are pooled together to estimate the parameters. Each column corresponds to a different assumption on the parameters ω_t and ω_{t+k}. Robust standard errors are clustered at the subject level.

The symbols ***, ** and * indicates the significance levels (respectively 1%, 5% and 10%) for the test of the following hypothesis: H_0: $\alpha = 1$, H_0: $\delta = 1$, H_0: $AR = 0$, H_0: $\beta = 1$ and H_0: $\hat{\beta} = \beta$.

[a] ω_i indicates self-reported average daily expenditure, which varies across subjects.

sidered, the significance of the difference between the value of α for the shortest delay length and the larger ones is not stable. However, for the shortest delay length (21 days between the two payment dates), half of the allocation decisions are dropped, since they involve a higher

Table 5: P-value associated to the test H_0: $\alpha_i = \alpha_j$

All allocations

	(1) $\omega = 0$		(2) $\omega = 5$		(3) ω_i		(4) $\hat{\omega}_t \neq \hat{\omega_{t+k}}$		(5) $\hat{\omega}_t = \hat{\omega_{t+k}}$	
	α_{SD}	α_{MD}	α_{SD}	α_{MD}	α_{SD}	α_{MD}	α_{SD}	α_{MD}	α_{SD}	α_{MD}
α_{MD}	0***		0***		0.0001***		0***		0***	
α_{LD}	0 ***	0.0001***	0***	0***	0***	0***	0***	0.0195*	0 ***	0.1553
$\alpha_{SD} = \alpha_{MD} = \alpha_{LD}$	0		0		0		0		0	

SSA

	(6) $\omega = 0$		(7) $\omega = 5$		(8) ω_i		(9) $\hat{\omega}_t \neq \hat{\omega_{t+k}}$		(10) $\hat{\omega}_t = \hat{\omega_{t+k}}$	
	α_{SD}	α_{MD}	α_{SD}	α_{MD}	α_{SD}	α_{MD}	α_{SD}	α_{MD}	α_{SD}	α_{MD}
α_{MD}	0.3632		0.1552		0.0798		0.6207		0.9071	
α_{LD}	0.0031***	0***	0.0006***	0***	0.0002***	0***	0.1634	0.0058**	0.0757	0.0038**
$\alpha_{SD} = \alpha_{MD} = \alpha_{LD}$	0.0001		0		0		0.0215		0.0147	

Bonferroni adjustment: the probability threshold of H_0 rejection is divided by the number of multiple tests (3).
*** : $p < 0.0033$ (significance at 1%); **: $p < 0.0167$ (significance at 5%); *: $p < 0.0333$ (significance at 10%).

value of the token at the sooner payment date. Then, the estimation of the parameters for this delay is less precise. Yet, by comparing the value of α for the medium delay length and the one for the larger delay lengths, these values are always significantly different. The utility function of participants is less concave for shorter delay (i.e., α is higher). The interpretation of this result is of no concern to the main purpose of this article, I will discuss it in the last section. However, it shows that allowing the utility function parameters to change across delay lengths might increase the accuracy of the estimated parameters.

Let us now focus on the analysis of the short-term discount rate and its anticipation. If only the SSA are considered, β is estimated not significantly different from 1 for almost all specifications and for all delay lengths. The estimated value of β is weakly-significantly higher than 1 only for the longer delays and when the background consumption is not estimated. However, what is interesting is that for medium delays (and weakly for shorter delays) $\hat{\beta}$ is estimated significantly higher than β. In other words, for these allocations and these delays, participants tend to underestimate relatively more their sooner demand when the sooner date involves the immediate present, although they cannot be considered as biased. A possible interpretation relies on the idea that money can be considered by participants as a commitment device. They may anticipate to delay their rewards when the sooner date is "Today" but do not succeed in doing it. In this case, they are naive about their ability to commit.

By comparison, the parameters estimation of the utility function when all the allocations are pooled together may gives us some indications about how participants behave for the ELSA. However, it has to be taken with cautiousness. First, participants were proposed ELSA not for all delays and the number of ELSA is relatively low. Second we previously saw that considering all the allocations leads to an inaccurate estimation of the parameter α which influences

the estimation of the other parameters. The fact that participants tend to underestimate their sooner demand when the sooner date involves immediate present for short and medium delays ($\hat{\beta}$ significantly than β) holds and is even more robust. The main difference when all the allocations are considered is that estimated values of β for longer delays are significantly higher than 1 (expect when the background consumption parameters are supposed to be equal at each period and estimated) although β is well-anticipated. Thus, it suggests that participants might behave with future bias the longer is the delay.

To sum up, taking into consideration that parameters of the utility function may differ with delay lengths leads us to question the existence of bias when the sooner date is in the immediate present. Participants might be more likely to be future-biased for longer delays but this result is not robust across specifications. However, there is heterogeneity across delays for the ability of participants to accurately anticipate the weight they will attribute to immediate utility. They tend to overestimate it for shorter delays. Yet, this result does not suggest naiveté on bias but naiveté on their ability to commit themselves by delaying immediate monetary rewards.

Thereby, utility functions seem to be affected by two characteristics of the allocation decision: whether the value of the sonner token is smaller than the one of the later token and the delay lengths between the two payment dates. In a nutshell, participants tend to underestimate relatively more their sooner demand when the sooner date will be "Today" rather than "In five weeks" for shorter delays. When the allocations is equal- or larger-sooner, participants tend to have a less concave utility function but, interestingly, they are more likely to be present-biased and naive about this bias. However, this results might not be holding for larger delay lengths between payment dates. Conversely, for smaller-sooner allocations, participants exhibit no bias if we take into consideration that the curvature of the utility function increases with delays.

Furthermore, at the aggregate-level, in most of the cases, we see that participants seem to accurately anticipate their short-term discount β. However, the relevance of the aggregate-level estimation can be questioned for determining whether participants are biased and whether they accurately anticipate their bias. Indeed, the model presented account for the heterogeneity of the decision's characteristics but do not allow for heterogeneous preferences among participants. Some participants can be present-biased and others future-biased. In addition, if both of them underestimate their bias, i.e., future-biased participants underestimate their short-term

discount rate and present-biased ones overestimate it, on average the difference between $\hat{\beta}$ and β might not be significantly different from 0. Thus, only the comparison between the individual parameter for temporal bias and the one for anticipation makes sense. This is the intent of the next section.

5.4 Individual-level estimation

A first attempt to better consider the heterogeneity of the participant is to assume that both their bias and their ability to anticipe it are driven by the cognitive abilities, then, the parameters of the utility function can be estimated at the individual level.

5.4.1 Estimation by cognitive abilities class

At the end of each round, participants answer Frederick (2005)'s three-question Cognitive Reflection Test (CRT). Following their answers, I construct five classes of cognitive abilities regarding their score during both rounds. The first class is composed of participants who give no correct answer to either CRT (LCRT).[25] The second class is composed of participants who have no correct answer to the first CRT but improve their score by responding well to one or more questions on the second CRT (LLCRT). The third class consists of participants who accurately answer to one or two questions on the first CRT and on the second CRT, and those who answer to one question correctly of the first CRT well then do better on the second CRT (MCRT). The fourth class is composed of participants who accurately answer two questions on the first CRT and three on the second CRT (HLCRT). Finally, the fifth class is composed of those who correctly answer all the questions on both CRTs (PCRT).[26]

Table 6 presents the different values of the parameters β and $\hat{\beta}$ by cognitive classes estimated using the NLS method according to the same assumption on background consumption and by, first pooling together all the allocation decisions (columns 1 trough 5) and then only the SSA (columns 1 trough 5). The estimated values of the other parameters of the utility function can be found in the appendix in Table A.5 .

Evidence for heterogeneity among participants emerges from the parameters estimation by cognitive class. The participants in the lowest class tend to be future-biased and to be naive about their bias, but only when the SSA are considered. For the participants who belong to the two next classes, the parameter estimation is not stable but they seem to accurately anticipate

[25] I also group in this class the one participant who gives one right answer to the first CRT but none to the second CRT.

[26] In appendix, table A.4 summarizes the cognitive classes are constructed and how many participants comprise each class.

Table 6: Estimated values of β and $\hat{\beta}$ by cognitive abilities class

	All allocations					SSA				
			NLS					NLS		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
β										
LCRT	0.9978	1.0032	1.0085	0.9995	0.9991	1.0995***	1.1259***	1.1387***	1.0714**	1.0486***
	(0.0084)	(0.0115)	(0.0129)	(0.0014)	(0.0014)	(0.0287)	(0.0373)	(0.0434)	(0.0346)	(0.0211)
LLCRT	0.9734**	0.9698**	0.9798	0.9937	0.9812	0.9957	0.9980	1.0192	0.9965	0.9942
	(0.0130)	(0.0149)	(0.0213)	(0.0051)	(0.0122)	(0.0196)	(0.0224)	(0.0295)	(0.0177)	(0.0172)
MCRT	0.9830	0.9810	0.9692*	1.0040*	0.9919	1.0133	1.0141	0.9992	1.0254	1.0111
	(0.0152)	(0.0164)	(0.0180)	(0.0104)	(0.0132)	(0.0238)	(0.0252)	(0.0228)	(0.0241)	(0.0206)
HLCRT	0.9661*	0.9614	0.9281**	0.9999*	0.9692	0.9930	0.9934	0.9626	1.0139	0.9929
	(0.0188)	(0.0256)	(0.0449)	(0.0026)	(0.0171)	(0.0266)	(0.0313)	(0.0450)	(0.0093)	(0.0230)
PCRT	0.9775**	0.9740***	0.9730**	0.9963***	0.9838**	1.0013	1.0148	1.0146	0.9921	0.9949
	(0.0101)	(0.0094)	(0.0114)	(0.0020)	(0.0077)	(0.0157)	(0.0218)	(0.0279)	(0.0164)	(0.0133)
$\hat{\beta}$										
LCRT	0.9833	0.9807	0.9745	1.0013	0.9994	1.0150*	1.0258*	1.0194**	0.9688*	1.0042*
	(0.0113)	(0.0155)	(0.0160)	(0.0022)	(0.0018)	(0.0316)	(0.0389)	(0.0382)	(0.0410)	(0.0141)
LLCRT	1.0037*	1.0065**	1.0180**	1.0128	1.0071*	1.0369	1.0453	1.0596	1.0468	1.0286
	(0.0077)	(0.0093)	(0.0181)	(0.0079)	(0.0066)	(0.0158)	(0.0186)	(0.0256)	(0.0217)	(0.0133)
MCRT	1.0017	1.0003	1.0067	1.0184*	1.0061	1.0320	1.0331	1.0422	1.0443	1.0274
	(0.0140)	(0.0147)	(0.0210)	(0.0121)	(0.0127)	(0.0227)	(0.0235)	(0.0339)	(0.0260)	(0.0207)
HLCRT	1.0135***	1.0078***	0.9757***	1.0335***	1.0162***	1.0562***	1.0527***	1.0211***	1.0694***	1.0573**
	(0.0229)	(0.0283)	(0.0498)	(0.0147)	(0.0197)	(0.0353)	(0.0375)	(0.0540)	(0.0191)	(0.0335)
PCRT	0.9874	0.9867	0.9892	0.9995	0.9900	1.0212	1.0369	1.0431	1.0143	1.0115
	(0.0077)	(0.0104)	(0.0118)	(0.0029)	(0.0062)	(0.0241)	(0.0277)	(0.0339)	(0.0301)	(0.0209)
ω	0	5	ω_i	$\hat{\omega}_t \neq \hat{\omega}_{t+k}$	$\hat{\omega}_t = \hat{\omega}_{t+k}$	0	5	ω_i	$\hat{\omega}_t \neq \hat{\omega}_{t+k}$	$\hat{\omega}_t = \hat{\omega}_{t+k}$

The parameter β corresponds to the relative weight given to the immediate utility (i.e., the short-term discount rate); $\hat{\beta}$ to the belief on the short-term discount rate; ω_t to the background consumption at period t. The parameters β and $\hat{\beta}$ (and the other parameters of the utility function) are estimated for different cognitive abilities classes.

The utility function parameters are estimated using the Non-Least Square (NLS) method on the sooner demand function (5). In columns 1 through 5, these parameters are estimated by pooling together all the allocation decisions whereas in columns 6 through 10, only the smaller-sooner allocations (SSA) are pooled together to estimate the parameters. Each column corresponds to a different assumption on the parameters ω_t and ω_{t+k}. Robust standard errors are clustered at the subject level.

The symbols ***, ** and * indicates the significance levels (respectively 1%, 5% and 10%) for the test of the following hypothesis: H_0: $\beta = 1$ and H_0: $\hat{\beta} = \beta$.

[a] ω_i indicates self-reported average daily expenditure, which varies across subjects.

their short-term discount rate and not to exhibit bias. For the HLCRT class, while they are not biased, they systematically overestimate their short-term discount rate. Thus, they anticipate they will be more likely to delay monetary rewards when the allocation involves the immediate present. While it is not possible to assume that they overestimate their short-term discount because they are naive about their present bias, they may want to commit themselves in order to overcome the consequences of their bias, but then finally fail to commit. The participants who belong to highest cognitive class accurately anticipate their short-term discount rate but they are also present-biased when all the allocations are considered.

To sum up, participants with low level cognitive abilities tend to be naive when they exhibit present bias or future bias, whereas participants with the highest cognitive abilities may be present-biased but they accurately anticipate it.

Table 7: Individual estimated parameter statistics (self-reported average daily consumption)

All allocations								
Param.	N	Mean	S.D.	Median	5th Percentile	95th Percentile	Min	Max
δ	59	0.9998	0.0082	0.9994	0.9912	1.0032	0.9803	1.0550
AR	59	26.3682	183.1246	0.2581	-0.6863	23.7390	-1.0000	1418.6964
α	59	0.4844	1.0480	0.8066	-3.0952	0.9888	-4.2634	.9943
β	59	1.0591	0.6397	0.9928	0.6968	1.1367	0.5943	5.8811
$\hat{\beta}$	59	1.0350	0.2518	0.9991	0.8562	1.1643	0.7265	2.4573
ω	59	11.9879	11.6922	8.5714	2.1429	42.8571	0.1429	71.4286

SSA								
Param.	N	Mean	S.D.	Median	5th Percentile	95th Percentile	Min	Max
δ	51	1.0017	0.0108	0.9992	0.9937	1.0190	0.9804	1.0575
AR	51	34.2680	194.7927	0.3403	-0.9989	8.8939	-1.0000	1372.4276
α	51	0.2700	1.0879	0.7400	-1.8852	0.9683	-4.0039	0.9856
β	51	1.1371	0.4841	1.0193	0.7438	1.5581	0.6185	3.6914
$\hat{\beta}$	51	1.0603	0.2871	1.0363	0.7805	1.2500	0.5233	2.8432
ω	51	11.7395	11.7240	7.1429	2.1429	28.5714	0.1429	71.4286

5.4.2 Individual-level estimation

The utility function parameters are estimated for each participant. For the sake of clarity, I estimate α, δ, β, and $\hat{\beta}$ by controlling only for self-reported background consumption ($\omega_t = \omega_{t+k} = \omega_i$). These parameters are estimated both by pooling together all the allocations and by pooling together only the smaller-sooner allocations for each participant. However, given the small number of ELSA and the small number of allocation decisions by delays it will not be accurate to estimate the utility function parameters by pooling together only the ELSA nor by delay lengths.

When considering all the allocations decisions, I remove four participants because their estimated values of parameters are outliers (AR > 5000 and $\alpha < -20$). Thus, when all the allocations are pooled together, the utility function parameters are estimated for 59 participants. And 12 participants were removed when considering only the sooner-smaller allocations: for seven subjects the estimation was not possible because of the absence of variation in their decisions or the estimation method did not converge and the estimated values of the parameters for five subjects are outliers. Thus, when only the SSA are pooled together, the utility function parameters are estimated for 51 participants.

Table 7 summarizes the estimated values of the parameters of the subjects' time preferences.[27] For both specifications, the average values of the short-term discount rate is above 1, and the average anticipated short-term discount rate is lower than the real one. Figure A.2 represents

[27] The detailed values of the parameters estimated by considering all the allocations are presented in Table A.6 in the appendix; the values estimated by considering only the sooner-smaller allocations are presented in Table A.7 in the appendix.

Table 8: Proportion of individuals with temporal bias and linear utility (self-reported average daily consumption)

	All allocations	SSA
Present Bias	0.26	0.08
Futurs Bias	0.03	0.20
No bias	0.71	0.72
Underestimation of β	0.12	0.14
Overestimation of β	0.27	0.29
Insignificant difference	0.61	0.57
Concave utility	0.93	0.78
Linear utility	0.07	0.22
N participants	59	51

the distribution of the estimated short-term discount rate β and the accuracy of the anticipation $\hat{\beta} - \beta$.

The same differences emerge whether only the SSA are considered or all the allocations. First, the estimated value of α is lower, i.e., the utility function of the participants is more concave in the first case. Second, for the first specification, more participants have a short-term discount rate lower than 1, while for the second specification, most of them have a short-term discount rate higher than 1. Yet in both cases the estimated values of β are highly concentrated around 1. In Figure A.2 , we also see that the estimated anticipation accuracy ($\hat{\beta}-\beta$) is highly concentrated around 0. Thus, to decide whether the individuals are time-inconsistent and do not accurately anticipate their short-term discount rate, it is necessary to test whether β is statistically different from 1 and $\hat{\beta}$ is statically different from β for each individual.

Table 8 displays the proportion of individuals who can be considered as present-biased (if $\beta < 1$ and the p-value of the null hypothesis: $\beta = 1$ is lower than 0.1), future-biased (if $\beta > 1$ and the p-value of the null hypothesis: $\beta = 1$ is lower than 0.1), and unbiased (if the p-value of the null hypothesis: $\beta = 1$ is higher than 0.1). A majority of the participants are time-consistent in both cases. The value of β is not significantly different from 1 for 71% (72%) of the remaining participants if we consider all the decisions (only the SSA). Thus in both cases, the same proportion of individuals can be considered as time-inconsistent. However, the proportions of present- and future-biased subjects are not the same, whether all the decisions are considered or only the SSA. The proportion of participants who can be considered future-biased is much higher in the latter case (20% vs 3%) as opposed to those who can be considered as present-biased (8% vs 26%). Table A.8 in the appendix reports the proportion of participants who exhibit bias when all the decisions are considered compared to when only the SSA are. It is even clearer that some participants tend to be less future-biased when the value of the token at the sooner date is equal to or higher than the value of the token at the later date.

Table 9: Anticipation accuracy of the short-term discount rate by biases (self-reported average daily consumption)

	All allocations			
	Underestimation $\hat{\beta} < \beta$	Insignificant difference $\hat{\beta} = \beta$	Overestimation $\hat{\beta} > \beta$	Total
Future bias ($\beta > 1$)	50%	50%	0%	3%
No bias ($\beta = 1$)	14%	71%	14%	71%
Present bias ($\beta < 1$)	0%	33%	67%	26%
Total	12%	61%	27%	100% (59 part.)

	SSA			
	Underestimation $\hat{\beta} < \beta$	Insignificant difference $\hat{\beta} = \beta$	Overestimation $\hat{\beta} > \beta$	Total
Future bias ($\beta > 1$)	40%	50%	10%	20%
No bias ($\beta = 1$)	8%	59%	32%	72%
Present bias ($\beta < 1$)	0%	50%	50%	8%
Total	14%	57%	29%	100% (51 part.)

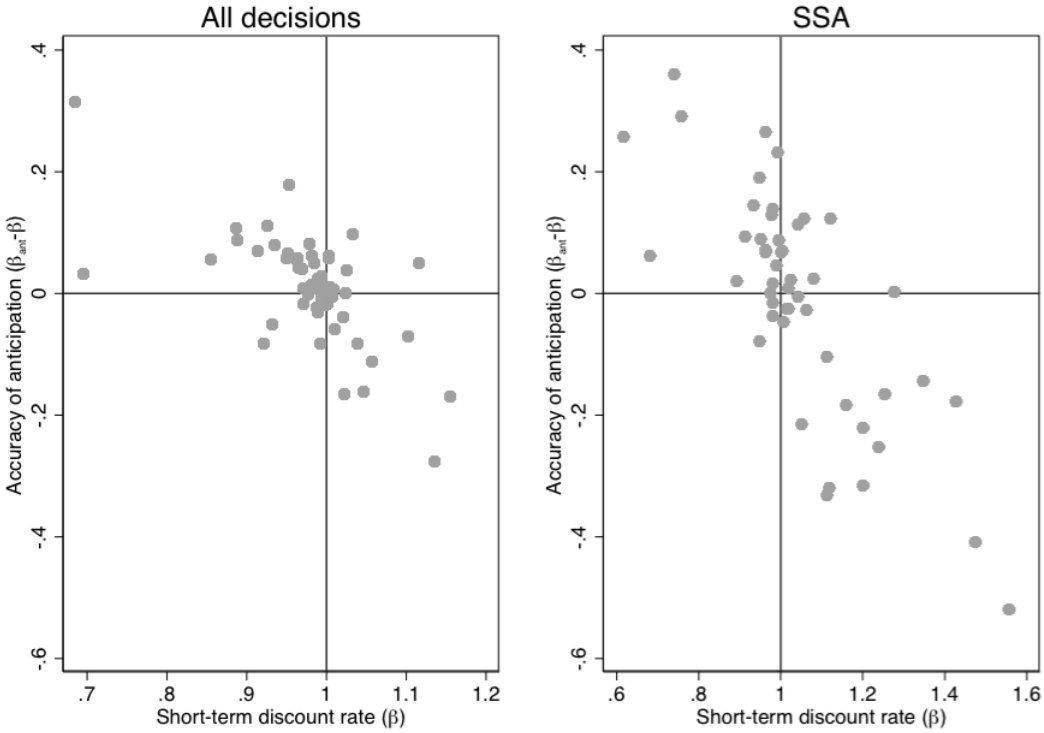
Again, this result is consistent with participants delaying immediate monetary rewards in an attempt to implement a commitment device. Moreover, as we already discussed, it also has been shown that individuals are not willing to pay to commit themselves. This may explain the different proportions of participants that can be considered as future-biased between whether the ELSA are removed to estimate the utility function parameters of participants. Indeed, for the ELSA, they have to renounce to some monetary rewards to commit since the value of the token at the later date is lower than the one at the sooner date.

Table 8 also summarizes the proportion of individuals who underestimate, overestimate, or accurately anticipate their short-term discount rate. A majority of the participants anticipates their short-term discount rate well, and among those who do not accurately anticipate their β, a higher proportion overestimate it. However, the anticipation accuracy of the short-term discount rate can only be interpreted by considering the temporal bias of the participant.

Table 9 represents the proportion of unbiased or biased participants who underestimate, accurately anticipate, or overestimate their short-term discount rate.[28] None of the present-biased participants overestimate their bias. On the contrary, they tend to underestimate it by overestimating their short-term discount rate: 67% of them if all the decisions are considered, and 50%

[28]Figure A.3 in the appendix represents the proportion of participants by bias and anticipation accuracy of the short-term discount rate.

Figure 5: Accuracy of the anticipation ($\hat{\beta} - \beta$) by values of the short-term discount rate (β) (self-reported average daily consumption)



For clarity, some estimated values are not represented. When all the allocations are considered, two pairs (β,$\hat{\beta} - \beta$) are not represented: (0.59,1.59) and (5.88,-3.42). When only the SSA are considered, two pairs are not represented: (3.69,-0.85) and (3.01,-2.48).

if only the SSA are considered. By comparison, this pourcentage is only 27% of all participants (for all allocations) and 29% (for SSA). Moreover, among the future-biased participants, 50% (all decisions) or 40% (SSA) tend to underestimate their bias (by underestimating their short-term discount rate). Whereas this pourcentage is only12% of all participants (for all decisions) and 14% (for SSA). These two last categories of participants are naive about their biases. Thus, if participants are biased, they are also more likely not to be fully aware of their bias.

Furthermore, when only the SSA are considered, 10% of the future-biased participants overestimate their short-term discount rate (and 0 future-biased participants when all the decisions are pooled together). Together with those who are unbiased and overestimate their short-term discount rate – 14% (all decisions) or 32% (SSA) of the unbiased participants – these participants anticipate committing by delaying the monetary rewards when the immediate present is involved but fail to commit when facing the decision. Finally, it can be noted that among the unbiased participants 14% (for all the allocations) or 8% (for SSA) wrongly anticipated to be present-biased. This behavior is surprising and cannot be explained by existing theories.

Figure 5 represents the values of the anticipation accuracy ($\hat{\beta} - \beta$) regarding the values of the

short-term discount rate (β). The accuracy of the anticipation decreases when the short-term discount rate increases. The superior corner at the left of the graph and the inferior one at the right represent naive participants. The first one represents naive present-biased subjects, whereas the last one represents the naive future-biased participants. Most of the observations are located in the naive zone.

To sum up, even though a majority of the participants are time-consistent and accurately anticipate their time preferences, when they are time-inconsistent, both present- and future-biased participants tend to be naive about their bias, i.e., they underestimate their bias.

6 Conclusion and discussions

Up to now, the experimental literature has mostly focused on eliciting the present bias and little has been done to elicit individual belief about this bias. This paper aims to elicit the accuracy of the participants' anticipation of their potential biases. The experiment proceeds in two rounds, with the same participants. The second round elicits the participants' time preferences, whereas the first round elicits the anticipation of these preferences. To measure participants' time-preferences, I use Andreoni and Sprenger (2012a)'s Convex Time Budget method, and adapt this method to measure participants' anticipation.

First, I estimate the parameters of the intertemporal utility function at the aggregate level by pooling together all the allocation decisions of all participants. It emerges that participants are present-biased. However, this results hide heterogeneity. Indeed, utility functions seem to be affected by two characteristics of the allocation decision: whether the value of the sooner token is smaller than the one of the later tokens or not and the delay lengths between the two payment dates. By investigating the behavior of participants towards these characteristics, I find that participants are present-biased but only if the value of the sooner tokens is equal to or higher than the one of the latter token. In that case, they are also naive about their bias. However, this results might not be holding for larger delay lengths between payment dates. Moreover, when the value of the sooner token is lower, the most frequent allocation decisions, then participants does not exhibit bias anymore if we estimate the utility function parameters by delays. This is because we better take into consideration that the curvature of the utility function increases with delays. An other interesting result for this type of allocation is that participants, although unbiased, tend to underestimate relatively more their sooner demand when the sooner date will be "Today" rather than in the future for shorter delays. The last result is surprising and I will discuss it at the end of this section.

Second, I estimate the utility function parameters of each participant. The aggregate-level estimation may not be relevant in determining whether participants accurately anticipate their bias if there is heterogeneous behavior among participants. I find that a majority of participants exhibit no bias and accurately anticipate their time preferences. Additionally, a non-null percentage of unbiased or future-biased participants underestimate their sooner demand when immediate present will be involved. However, one main result emerges from the estimation of the individual time preferences: when the participants are biased, they also tend to be naive about their bias.

This paper helps us to better understand both individuals' time-inconsistency bias and their ability to anticipate it. For monetary allocations, behaviors are subsequently heterogeneous across individuals. The sample for this experiment is quite homogeneous: the majority of the subjects are students in their twenties and yet I observe heterogeneity. Next, it seems that even the characteristics of the allocation decisions may influence whether participants are more likely to exhibit bias or to accurately anticipate it.[29]

Several results tangential to the purpose of this paper appear during the analysis and deserve some discussion. First, the parameter α decreases when the delay length increases. Explaining this depends on how one interprets the parameter α. While it represents the curvature degree of the utility function, the economics meaning of α in this setting is a matter of debate. This parameter can be interpreted as a measure of either risk aversion, elasticity of the intertemporal substitution, or reduction of the wealth marginal utility. The intuition to explain lower α for longer delay goes as follows: the longer the delay is, the riskier the future is perceived. However, the relation between time and risk preferences is a core issue in the design of experimental studies that elicit time preferences. An important question is whether the utility under risk is interchangeable with the utility over time. Andersen *et al.* (2008) make this assumption and estimate the degree of curvature of the utility function using risk-elicitation tasks. However, Andreoni and Sprenger (2012b) assert that "risks preferences are not time preferences". Indeed, by adapting their CTB design to include uncertainty about payment, they elicit a more concave utility function compared to the one with certain payment. Although their method was criticized (Cheung, 2015a; Epper and Fehr-Duda, 2015; Miao *et al.*, 2015), other studies confirm their results with different methods (Abdellaoui *et al.*, 2011; Cheung, 2015b). In relation to this question, the finding that α decreases with the delay length suggests an approach where α will be dependent on delay lengths. Nevertheless, this experiment is not designed to answer this

[29]Given the small number of allocation decisions and participants in this experiment, it would not have been reasonable to estimate, at the individual level, different parameters for different characteristics of the decision.

question, and the small number of observations doesn't allow to make more precise tests to check this hypothesis.

Second, the use of monetary rewards in eliciting time-inconsistency bias comes with limitation. A substantial proportion of participants overestimate their future bias or anticipate they will be future-biased while they are not. This behavior is puzzling, given theories on time-inconsistency biases. It cannot be considered that those people are naive about their bias. One interpretation is that these participants anticipate committing themselves by delaying the monetary rewards when it involves the immediate present, but then, end up failing to commit. This result raises an interesting question that deserve to be better examined in future research: whether the potential naiveté of individuals about their ability to commit can explain that they tend to choose the wrong commitment or action plan for them; particularly when commitment is costly. In the same spirit, if monetary rewards are used to elicit time-inconsistency bias, then it is necessary to find a way to disentangle participant understanding of the money role – whether it is tempting, or a way to commit, or something in between. The study of the anticipation is a first step in that direction. But, the use of unambiguous tempting goods such as ice-cream (Olea and Strzalecki, 2014) or immediate costly activities (Augenblick *et al.*, 2015; Augenblick and Rabin, 2015) may be more relevant.

Finally, behavior seems to be volatile on the different characteristics of the decision, then the subjects' time-inconsistency bias might depend on the object of their decision. It will be interesting to test whether one person may exhibit a time-inconsistency bias for one good and not for another one and wether this bias changes with the temporal characteristics of the decisions.

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Appendix

A Additional materials

Table A.1 : Average values of early tokens and AER, by sooner dates and delays

	Today		In Five Weeks		Total	
Delay	a_t	**AER**	a_t	**AER**	a_t	**AER**
21	1.0050	-6.3794	0.9775	64.7186	0.9912	29.1696
35	0.9350	136.2406	0.9225	198.1238	0.9288	167.1822
49	0.9125	151.0291	0.9275	92.1818	0.9200	121.6054
70	0.8625	181.7410	0.9000	105.3885	0.8813	143.5647
105	0.8250	146.2869	0.9075	68.1175	0.8663	107.2022
Total	0.9080	121.7836	0.9270	105.7060	0.9175	113.7448

a_t*:* Values of sooner tokens *AER:* Annual Effective Rate

Table A.2 : Set of Allocation Decisions

N Alloc	t	k	N	a(t+k)	a(t)	P ou (1+r)	Annual Rate	AER
1	0	21	20	1	1.02	0.98	-34.08	-28.89
2	0	21	20	1	1.01	0.99	-17.21	-15.81
3	0	21	20	1	1.00	1.00	0.00	0.00
4	0	21	20	1	0.99	1.01	17.56	19.19
5	0	35	20	1	0.99	1.01	10.53	11.11
6	0	35	20	1	0.95	1.05	54.89	73.06
7	0	35	20	1	0.92	1.09	90.68	147.37
8	0	35	20	1	0.88	1.14	142.21	313.43
9	0	49	20	1	0.98	1.02	15.20	16.41
10	0	49	20	1	0.95	1.05	39.21	47.97
11	0	49	20	1	0.90	1.11	82.77	128.58
12	0	49	20	1	0.82	1.22	163.51	411.15
13	0	70	20	1	0.95	1.05	27.44	31.57
14	0	70	20	1	0.90	1.11	57.94	78.41
15	0	70	20	1	0.85	1.18	92.02	150.68
16	0	70	20	1	0.75	1.33	173.81	466.31
17	0	105	20	1	0.95	1.05	18.30	20.07
18	0	105	20	1	0.85	1.18	61.34	84.58
19	0	105	20	1	0.80	1.25	86.90	138.22
20	0	105	20	1	0.70	1.43	148.98	342.28
21	35	21	20	1	1.01	0.99	-17.21	-15.81
22	35	21	20	1	0.99	1.01	17.56	19.19
23	35	21	20	1	0.96	1.04	72.42	106.16
24	35	21	20	1	0.95	1.05	91.48	149.34
25	35	35	20	1	0.98	1.02	21.28	23.71
26	35	35	20	1	0.94	1.06	66.57	94.46
27	35	35	20	1	0.92	1.09	90.68	147.37
28	35	35	20	1	0.85	1.18	184.03	526.96
29	35	49	20	1	0.98	1.02	15.20	16.41
30	35	49	20	1	0.95	1.05	39.21	47.97
31	35	49	20	1	0.90	1.11	82.77	128.58
32	35	49	20	1	0.88	1.14	101.58	175.76
33	35	70	20	1	0.98	1.02	10.64	11.23
34	35	70	20	1	0.94	1.06	33.28	39.47
35	35	70	20	1	0.88	1.14	71.10	103.47
36	35	70	20	1	0.80	1.25	130.36	267.39
37	35	105	20	1	1.00	1.00	0.00	0.00
38	35	105	20	1	0.98	1.02	7.09	7.35
39	35	105	20	1	0.90	1.11	38.62	47.11
40	35	105	20	1	0.75	1.33	115.87	218.00

Figure A.1 : Average response time, by decision page order

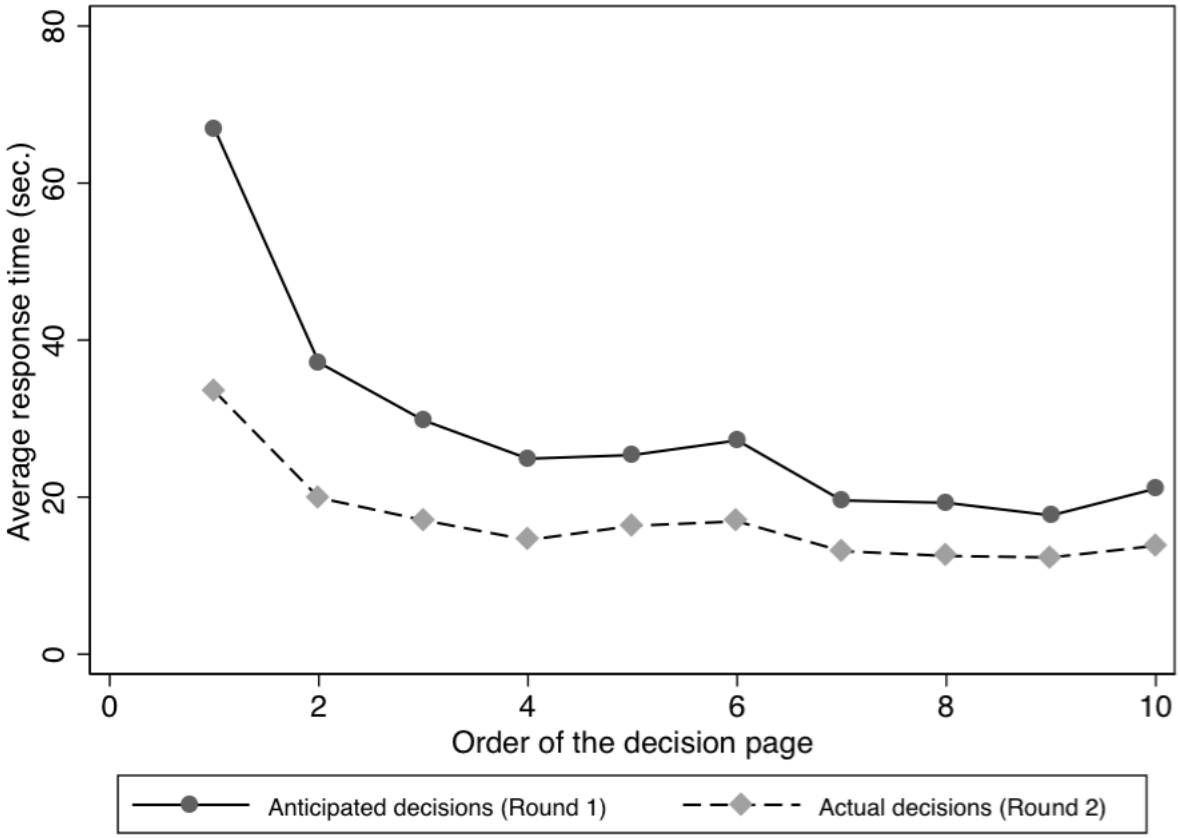


Table A.3 : Estimation results : logit interior allocations

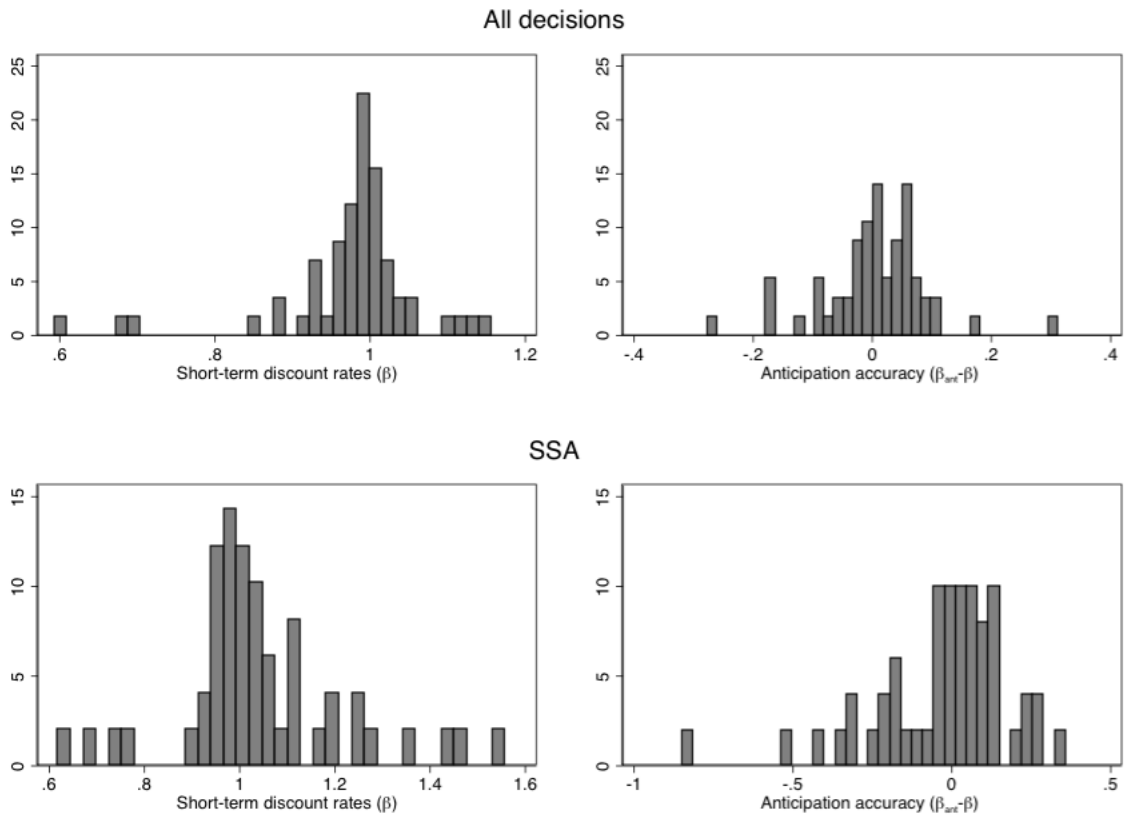
Interior allocations	b	se	z	p-values
delay1T0	.1034256	.1117026	.9259008	.3544975
delay2T0	.0848621	.1089784	.7787064	.4361527
delay3T0	.1453592	.1084625	1.3401800	.1801868
delay4T0	.1046830	.1098782	.9527181	.3407329
delay2T35	-.0070258	.1121132	-.0626674	.9500313
delay3T35	-.0561443	.1109537	-.5060160	.6128454
delay4T35	-.1760550	.1130019	-1.5579830	.1192372
delay5T35	-.1214718	.1123907	-1.0808000	.2797861
AER	.0000755	.0002315	.3261926	.7442786
_cons	-.8952832	.0680744	-13.1515300	0

Table A.4 : Classes of cognitive abilities

		CRT2			
		0	1	2	3
CRT1	0	25	7	1	0
	1	1	7	6	0
	2	0	0	3	4
	3	0	0	0	8

CRT Class	No. of Participants
LowCRT	26
LowLearningCRT	8
MediumCRT	16
HighLearningCRT	4
PerfectCRT	8

Figure A.2 : Estimated short-term discount rates (β) and anticipation accuracy ($\hat{\beta} - \beta$) (self-reported average daily consumption)



For clarity, some estimated values are not represented. When we consider all the allocations, two pairs (β,$\hat{\beta}$) are not represented: (5.88,2.45) and (0.59,2.18). When we consider only the sooner-smaller allocations, two pairs are not represented: (3.01,0.52) and (3.69,2.84).

Figure A.3 : Accuracy of the anticipation over temporal bias (self-reported average daily consumption)

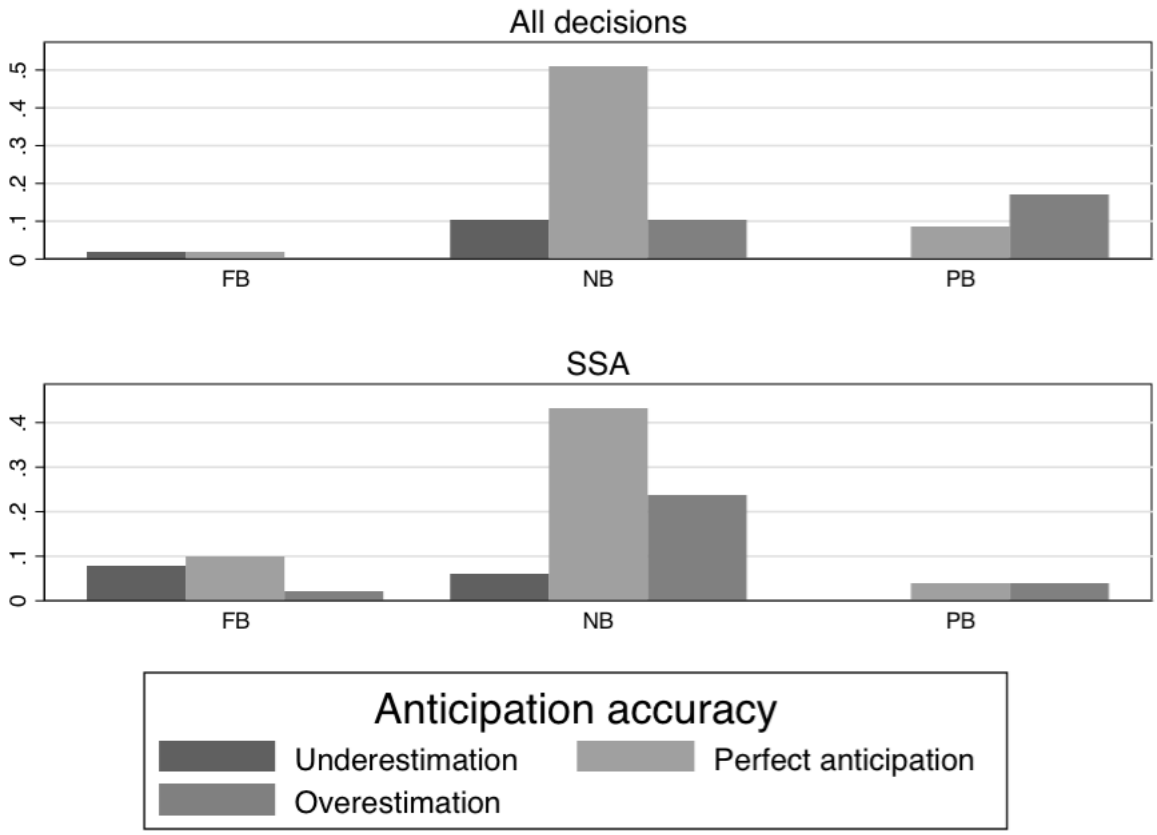


Table A.5 : Parameters estimation by cognitive abilities class

	All allocations					SSA				
			NLS					NLS		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
δ										
LCRT	1.0000	1.0002	1.0003	0.9999	0.9998***	1.0012*	1.0018	1.0021	0.9987***	1.0002
	(0.0002)	(0.0004)	(0.0005)	(0.0002)	(0.0000)	(0.0007)	(0.0011)	(0.0015)	(0.0002)	(0.0002)
LLCRT	0.9991**	0.9990**	0.9985***	0.9998**	0.9990***	0.9990*	0.9990*	0.9984***	0.9988***	0.9990*
	(0.0004)	(0.0004)	(0.0005)	(0.0001)	(0.0003)	(0.0005)	(0.0006)	(0.0006)	(0.0004)	(0.0005)
MCRT	0.9985***	0.9985***	0.9983***	0.9997**	0.9985***	0.9984***	0.9984***	0.9982**	0.9989***	0.9984***
	(0.0005)	(0.0004)	(0.0005)	(0.0001)	(0.0005)	(0.0006)	(0.0006)	(0.0007)	(0.0002)	(0.0013)
HLCRT	0.9977**	0.9978**	0.9968**	0.9994***	0.9977**	0.9975**	0.9975**	0.9962*	0.9985***	0.9975**
	(0.0011)	(0.0010)	(0.0015)	(0.0001)	(0.0011)	(0.0013)	(0.0012)	(0.0019)	(0.0005)	(0.0013)
PCRT	0.9996	0.9996	0.9997	0.9999**	0.9997*	0.9998	0.9999	1.0003	0.9984***	0.9998
	(0.0003)	(0.0005)	(0.0004)	(0.0000)	(0.0002)	(0.0005)	(0.0010)	(0.0010)	(0.0004)	(0.0004)
AR										
LCRT	0.0060	-0.0680	-0.1126	0.0358	0.0618***	-0.3569**	-0.4809**	-0.5302**	0.5795***	-0.00761**
	(0.0864)	(0.1307)	(0.1669)	(0.0083)	(0.0085)	(0.1641)	(0.2080)	(0.2554)	(0.1331)	(0.0533)
LLCRT	0.4079*	0.4386*	0.7313**	0.0897**	0.4203**	0.4381	0.4553	0.8268**	0.5616**	0.4237
	(0.2097)	(0.2309)	(0.3033)	(0.0623)	(0.1796)	(0.2842)	(0.3193)	(0.4071)	(0.2200)	(0.2526)
MCRT	0.7308**	0.7476***	0.8335***	0.1358**	0.7284**	0.8092**	0.8227**	0.9227*	0.5141***	0.7858**
	(0.2983)	(0.2853)	(0.3665)	(0.0541)	(0.2845)	(0.3874)	(0.3812)	(0.5082)	(0.1355)	(0.3992)
HLCRT	1.2896	1.2563	2.1795	0.2291***	1.2937	1.5169	1.5217	2.9536	0.7261**	1.5112
	(0.8952)	(0.8151)	(1.7362)	(0.0440)	(0.9381)	(1.1611)	(1.1094)	(2.7863)	(0.3280)	(1.1899)
PCRT	0.1463	0.1672	0.1004	0.0426*	0.1072*	0.0766	0.0257	-0.1055	0.8173***	0.0867
	(0.1165)	(0.1983)	(0.1704)	(0.0138)	(0.0607)	(0.2139)	(0.3564)	(0.3105)	(0.2744)	(0.1438)
α										
LCRT	0.9010***	0.7754***	0.5935***	0.9940***	0.9965***	0.7879***	0.5524***	0.2084***	1.0456***	0.9658***
	(0.0192)	(0.0288)	(0.0463)	(0.0009)	(0.0006)	(0.0382)	(0.0665)	(0.1311)	(0.0139)	(0.0073)
LLCRT	0.9362***	0.8722***	0.4778**	0.9596***	0.9748***	0.9130***	0.8376***	0.3623**	41.9059***	0.9514***
	(0.0180)	(0.0294)	(0.2299)	(0.0129)	(0.0066)	(0.0281)	(0.0464)	(0.2860)	(11.8110)	(0.0185)
MCRT	0.9111***	0.8460***	0.6697***	0.9434***	0.9717***	0.8840***	0.8073***	0.5901***	17.5526***	0.9490***
	(0.0168)	(0.0254)	(0.0989)	(0.0161)	(0.0047)	(0.0259)	(0.0397)	(0.1313)	(3.3588)	(0.0143)
HLCRT	0.9202***	0.8604***	0.6381*	0.9570***	0.9389***	0.8963***	0.8273***	0.5615*	45.8024***	0.9082***
	(0.0156)	(0.0357)	(0.2095)	(0.0200)	(0.0124)	(0.0254)	(0.0476)	(0.2633)	(13.3864)	(0.0547)
PCRT	0.9595***	0.8899***	0.8410***	0.9884***	0.9864***	0.9239***	0.8215***	0.7449***	26.3017***	0.9602***
	(0.0125)	(0.0163)	(0.0211)	(0.0042)	(0.0032)	(0.0241)	(0.0373)	(0.0632)	(7.7490)	(0.0147)
ω	0	5	ω_i	$\hat{\omega}_t \neq \hat{\omega}_{t+k}$	$\hat{\omega}_t = \hat{\omega}_{t+k}$	0	5	ω_i	$\hat{\omega}_t \neq \hat{\omega}_{t+k}$	$\hat{\omega}_t = \hat{\omega}_{t+k}$
ω_t										
LCRT				-5.0812		-5.0146			-7.8299	-4.4500
				(1.6965)		(0.8583)			(1.2269)	(0.7987)
LLCRT				-3.5118		-3.6247			-3228.0460	-2.7305
				(1.1574))		(1.2090)			(.)	(1.3236)
MCRT				-4.4624		-4.5430			-1201.3396	-4.0667
				(1.2042)		(0.8053)			(.)	(1.1023)
HLCRT				-6.8829		-1.5486			-3590.9841	-0.8418
				(3.3410)		(0.8523)			(.)	(3.7624)
PCRT				-3.9065		-3.1664			-1556.6314	-2.4009
				(1.7308)		(1.7431)			(.)	(1.2705)
ω_{t+k}										
LCRT				-2.5422					-15.4315	
				(0.8361)					(1.0752)	
LLCRT				4.8562					-3229.1538	
				(2.4459)					(4.7782)	
MCRT				5.0117					-1198.2871	
				(2.3475)					(3.3950)	
HLCRT				6.0635					-3584.5167	
				(3.0983)					(7.6351)	
PCRT				2.8213					-1565.3419	
				(1.9358)					(3.9178)	

The parameter δ corresponds to the long-term discount rate; AR to the annual rate obtained from δ; α to the curvature degree of the utility function; ω_t to the background consumption at period t. All the parameters are estimated for different cognitive abilities classes.

The utility function parameters are estimated using the Non-Least Square (NLS) method on the sooner demand function (5). In columns 1 through 5, these parameters are estimated by pooling together all the allocation decisions whereas in columns 6 through 10, only the smaller-sooner allocations (SSA) are pooled together to estimate the parameters. Each column corresponds to a different assumption on the parameters ω_t and ω_{t+k}. Robust standard errors are clustered at the subject level.

The symbols ***, ** and * indicates the significance levels (respectively 1%, 5% and 10%) for the test of the following hypothesis: H_0: $\alpha = 1$, H_0: $\delta = 1$ and H_0: $AR = 0$.

The values of the estimated background consumption as well as the estimated values of α in column 9. However, Augenblick *et al.* (2015) suggest that though the value of the background consumption may affect the value of the curvature of the utility function, the discounting parameters may not be affected (for a detailed discussion of the use of different background parameters, see Andreoni and Sprenger, 2012a). β and $\hat{\beta}$ are the most interesting variables, and in this case, even with outliners of background consumption and of α, the range of the estimated values of β and $\hat{\beta}$ is reasonable enough to be considered.

[a] ω_i indicates self-reported average daily expenditure, which varies across subjects.

Table A.6 : Individual estimated parameters (all allocations, self-reported average daily consumption)

N	AR	(s.e.)	α	(s.e.)	[p-val] ($\alpha = 1$)	β	(s.e.)	[p-val] ($\beta = 1$)	$\hat{\beta}$	(s.e.)	[p-val] ($\beta = \hat{\beta}$)	ω
1	.2622	(.002)	.9787	(0)	[0]	1.0052	(.0001)	[.5519]	1.0134	(.0001)	[.437]	2.9
4	.0422	(.0035)	.933	(.0001)	[0]	.9719	(.0002)	[.0442]	1.0111	(.0002)	[.0417]	5.7
5	1418.6964	(93926312)	-3.0952	(16.9264)	[.3227]	.5943	(.1008)	[.2052]	2.1843	(3.1962)	[.4476]	42.9
7	-.0321	(.0178)	.8431	(.0012)	[0]	1.0244	(.0011)	[.4706]	.8562	(.0013)	[.0008]	10.7
10	.0686	(.0066)	.9176	(.0002)	[0]	.9722	(.0004)	[.1463]	.954	(.0004)	[.4449]	7.1
12	-.2061	(.0202)	.8066	(.002)	[0]	1.0054	(.0011)	[.8705]	1.0054	(.0011)	[1]	12.9
13	.1798	(.0077)	.8712	(.0004)	[0]	1.0087	(.0004)	[.6756]	1.0022	(.0004)	[.8008]	11.4
14	1.302	(.0414)	.7981	(.0009)	[0]	.9543	(.0005)	[.0463]	1.1309	(.0011)	[0]	7.1
15	2.0539	(.0123)	.9825	(0)	[0]	1.0044	(.0001)	[.7094]	1.0599	(0)	[0]	2.1
16	2.5354	(.1177)	.9453	(.0001)	[0]	1.0102	(.0004)	[.6173]	1.0154	(.0004)	[.8289]	2.9
17	.3346	(.1631)	.4184	(.0943)	[.062]	1.1168	(.0153)	[.3476]	1.1643	(.0214)	[.7123]	14.3
18	.4978	(.0066)	.9378	(.0001)	[0]	.9835	(.0002)	[.267]	1.0432	(.0003)	[.0038]	7.1
21	-.5792	(.0299)	.6436	(.0106)	[.0009]	1.0121	(.0021)	[.7918]	.9522	(.0018)	[.2935]	14.3
23	.0386	(.0056)	.9353	(.0002)	[0]	1.023	(.0004)	[.2631]	.9828	(.0003)	[.1129]	2.1
25	3.9168	(.7555)	.8838	(.0005)	[0]	1.0345	(.0007)	[.1898]	1.1296	(.0011)	[.0072]	3.6
26	.0656	(.004)	.9413	(.0001)	[0]	.9907	(.0002)	[.5386]	1.0142	(.0003)	[.2581]	4.3
27	1.1726	(.0451)	.6302	(.0035)	[0]	.978	(.0007)	[.4001]	.9752	(.0007)	[.933]	21.4
29	-.22	(.0111)	.9035	(.0004)	[0]	.9871	(.0004)	[.5326]	.9975	(.0005)	[.6995]	7.1
30	1.0033	(.0134)	.9655	(0)	[0]	.9829	(.0002)	[.258]	.9958	(.0002)	[.4451]	2.9
31	1.087	(.1009)	.6101	(.0099)	[.0002]	1.059	(.0024)	[.2325]	.9455	(.0017)	[.0647]	28.6
32	-.2989	(.0217)	.8288	(.0018)	[.0001]	.9953	(.001)	[.8841]	1.0226	(.0012)	[.5194]	10
33	-.337	(.0238)	.7988	(.0025)	[.0001]	.9947	(.0012)	[.8774]	1.0086	(.0012)	[.753]	11.4
34	.2581	(.0078)	.8778	(.0003)	[0]	.9512	(.0004)	[.0142]	1.0074	(.0004)	[.0303]	.1
36	.0371	(.0002)	.9916	(0)	[0]	.9993	(0)	[.8143]	1.0027	(0)	[.4375]	5.7
37	.2726	(.0061)	.9065	(.0002)	[0]	.9906	(.0003)	[.5879]	.9579	(.0003)	[.1324]	11.4
38	1.5156	(.2786)	.4578	(.0268)	[.0014]	1.1043	(.0045)	[.1252]	1.0328	(.0029)	[.312]	14.3
39	23.739	(1141.3963)	.3774	(.0977)	[.05]	.8888	(.0072)	[.1923]	.9933	(.0053)	[.3039]	7.1
40	.4607	(.0532)	.543	(.0176)	[.0009]	1.156	(.006)	[.0476]	.9854	(.0022)	[.0441]	5.7
41	2.042	(.0481)	.9374	(.0001)	[0]	.9658	(.0004)	[.0789]	1.0223	(.0003)	[.0103]	5.7
42	-.685	(.2039)	-4.2634	(19.156)	[.2329]	.6866	(.051)	[.1691]	.9991	(.0193)	[.2412]	14.3
43	-.105	(.0494)	-.9331	(.3613)	[.0019]	1.0475	(.0033)	[.4141]	.8842	(.0029)	[.0442]	8.6
44	-1	(0)	-3.8558	(278.3734)	[.7718]	5.8811	(1306.6393)	[.8929]	2.4573	(60.6343)	[.9047]	11.4
45	-.4685	(.026)	.7451	(.0044)	[.0003]	.9275	(.0013)	[.0519]	1.0369	(.0018)	[.0455]	7.1
46	1.9416	(.0627)	.8992	(.0002)	[0]	.9866	(.0004)	[.5021]	1.0355	(.0004)	[.0436]	8.6
47	.0327	(.0001)	.9943	(0)	[0]	.9928	(0)	[.0008]	.9984	(0)	[.0515]	3.6
48	-.3735	(.0189)	.7703	(.0025)	[0]	1.0412	(.0013)	[.249]	.9579	(.0009)	[.0586]	7.1
49	.4745	(.0083)	.586	(.0021)	[0]	1.0023	(.0004)	[.9038]	.984	(.0003)	[.4298]	42.9
50	-.3791	(.0261)	.7548	(.0038)	[.0002]	.99	(.0014)	[.7872]	.9643	(.0013)	[.5757]	14.3
51	75.5525	(40062.304)	-.7672	(1.4127)	[.1412]	.6968	(.0322)	[.0953]	.7265	(.0284)	[.7618]	28.6
53	8.1793	(29.2921)	.5225	(.0257)	[.0039]	.8564	(.0039)	[.0241]	.9109	(.0029)	[.3729]	14.3
54	-.6863	(.0269)	.2776	(.0473)	[.0014]	.8891	(.0026)	[.0343]	.9744	(.0023)	[.1736]	21.4
55	1.7596	(.0384)	.9328	(.0001)	[0]	.9654	(.0004)	[.0774]	1.018	(.0003)	[.0191]	5
56	4.574	(2.8596)	.829	(.0021)	[.0004]	.9335	(.0016)	[.0972]	.8801	(.0024)	[.2799]	5.7
57	.576	(.0253)	.7799	(.0017)	[0]	.9151	(.001)	[.0074]	.9829	(.0009)	[.0785]	21.4
58	.0247	(.0033)	.9549	(.0001)	[0]	.9948	(.0002)	[.7155]	.9789	(.0002)	[.3837]	2.9
59	.2921	(.0049)	.929	(.0001)	[0]	.973	(.0002)	[.0769]	.9802	(.0002)	[.7034]	8.6
60	1.5815	(.0503)	-.072	(.0171)	[0]	1.0275	(.0005)	[.211]	1.0638	(.0006)	[.1823]	71.4
61	.0933	(.0138)	.5256	(.006)	[0]	1.0046	(.0007)	[.8656]	1.0648	(.001)	[.1]	7.1
62	.797	(.009)	.88	(.0002)	[0]	1.0003	(.0002)	[.9837]	.9796	(.0002)	[.2648]	14.3
63	.3951	(.0009)	.9888	(0)	[.0001]	1.025	(0)	[0]	1.023	(0)	[.7753]	1.4
66	-.6445	(.033)	.7292	(.0079)	[.0033]	.9667	(.0019)	[.4458]	1.0062	(.0021)	[.4889]	10
67	-.4857	(.0307)	.5847	(.0128)	[.0004]	.995	(.0019)	[.9075]	.991	(.0019)	[.942]	21.4
68	-.3352	(.0653)	.6599	(.0171)	[.0113]	1.1367	(.009)	[.154]	.8594	(.0044)	[.0377]	7.1
69	-.3234	(.0246)	.7373	(.0039)	[.0001]	.9932	(.0013)	[.852]	.9092	(.0013)	[.0772]	17.1
70	.4407	(.0046)	.9581	(0)	[0]	.9535	(.0002)	[.0012]	1.0172	(.0002)	[.0002]	5
71	5.6468	(1.3949)	.9238	(.0002)	[0]	.9799	(.0007)	[.4456]	1.0596	(.0004)	[.0066]	4.3
72	-.2332	(.0117)	.8977	(.0005)	[0]	.9987	(.0005)	[.9516]	.9987	(.0005)	[1]	7.1
74	-.9504	(.0118)	.2457	(.2155)	[.1083]	.9231	(.0092)	[.4253]	.8388	(.0134)	[.4513]	14.3
75	.1236	(.0149)	.7972	(.0013)	[0]	.9367	(.0007)	[.0226]	1.0151	(.0008)	[.0351]	17.9

Table A.7 : Individual estimated parameters (SSA, self-reported average daily consumption)

N	AR	(s.e.)	α	(s.e.)	[p-val] ($\alpha = 1$)	β	(s.e.)	[p-val] ($\beta = 1$)	$\hat{\beta}$	(s.e.)	[p-val] ($\beta = \hat{\beta}$)	ω
1	.3403	(.0036)	.9683	(.0001)	[0]	1.027	(.0002)	[.0758]	1.0468	(.0004)	[.3457]	2.9
4	-.2969	(.0162)	.8449	(.0011)	[0]	.9835	(.0006)	[.5162]	1.1208	(.0023)	[.0091]	5.7
7	-.3617	(.0529)	.7468	(.0075)	[.0047]	1.1147	(.0066)	[.1613]	.7805	(.005)	[.0092]	10.7
10	-.1537	(.026)	.8585	(.0014)	[.0003]	.9823	(.0013)	[.6214]	.9428	(.0012)	[.36]	7.1
12	-.9494	(.0186)	.141	(.4226)	[.1909]	1.279	(.0902)	[.3562]	1.279	(.0902)	[1]	12.9
13	.0441	(.0174)	.8092	(.0015)	[0]	1.0647	(.0014)	[.0879]	1.0358	(.0011)	[.4795]	11.4
14	1.6697	(.099)	.74	(.002)	[0]	.9964	(.0008)	[.9005]	1.2258	(.0033)	[.0002]	7.1
15	2.1613	(.0176)	.9808	(0)	[0]	1.008	(.0001)	[.5085]	1.0751	(.0001)	[0]	2.1
16	2.7194	(.2252)	.9365	(.0002)	[0]	1.0218	(.0007)	[.416]	1.0281	(.0007)	[.8333]	2.9
17	.7342	(.3208)	.3702	(.145)	[.1029]	1.3497	(.0887)	[.2445]	1.2048	(.0383)	[.4625]	14.3
18	.5687	(.0099)	.9286	(.0001)	[0]	.997	(.0003)	[.8703]	1.0829	(.0007)	[.0036]	7.1
21	-.9989	(.0001)	-.8389	(4.6965)	[.3992]	1.5581	(.8128)	[.538]	1.0363	(.0427)	[.539]	14.3
23	-.1796	(.025)	.87	(.0013)	[.0007]	1.2427	(.0148)	[.0503]	.9875	(.001)	[.0411]	2.1
25	6.8555	(6.774)	.8424	(.0014)	[.0001]	1.1251	(.0023)	[.0118]	1.2461	(.0053)	[.0258]	3.6
26	-.317	(.0321)	.8324	(.0025)	[.0013]	1.0613	(.0022)	[.1973]	1.1829	(.0077)	[.1328]	4.3
27	1.1663	(.0621)	.6031	(.0059)	[0]	.9846	(.0011)	[.639]	.9668	(.001)	[.6535]	21.4
30	1.0065	(.0172)	.9629	(.0001)	[0]	.9833	(.0003)	[.3418]	.9982	(.0003)	[.4566]	2.9
31	1.4495	(.3262)	.4999	(.032)	[.0068]	1.164	(.0102)	[.1094]	.9782	(.0036)	[.0875]	28.6
34	.0256	(.0054)	.7832	(.0006)	[0]	.9928	(.0003)	[.6679]	1.0377	(.0004)	[.0419]	.1
37	.2507	(.0113)	.886	(.0004)	[0]	1.0111	(.0006)	[.6627]	.9616	(.0005)	[.1039]	11.4
38	2.2276	(1.1697)	.2984	(.0783)	[.0146]	1.2575	(.0231)	[.0947]	1.0911	(.0077)	[.185]	14.3
39	332.6634	(3097609.9)	-.1714	(1.3647)	[.3197]	.9511	(.0231)	[.7488]	1.1394	(.0569)	[.5011]	7.1
40	.5068	(.0705)	.5204	(.0239)	[.0028]	1.2049	(.0108)	[.0533]	.9821	(.0028)	[.0424]	5.7
41	2.1215	(.0701)	.9335	(.0001)	[0]	.9651	(.0005)	[.1247]	1.0351	(.0004)	[.0084]	5.7
42	-.7652	(.1903)	-4.0039	(20.5723)	[.2739]	.6185	(.0755)	[.1696]	.8733	(.0264)	[.2513]	14.3
43	-.2464	(.0644)	-1.1642	(.5626)	[.0053]	1.0528	(.0046)	[.4383]	.8362	(.0045)	[.0329]	8.6
44	-1	(0)	-3.9454	(279.9229)	[.7685]	3.6914	(277.462)	[.8721]	2.8432	(106.8947)	[.8997]	11.4
45	-.7793	(.0382)	.5126	(.0429)	[.0216]	.9668	(.0039)	[.5963]	1.2301	(.0215)	[.0958]	7.1
46	2.1923	(.1096)	.8903	(.0003)	[0]	1.0027	(.0006)	[.9077]	1.0678	(.0006)	[.0268]	8.6
47	-.9979	(.0002)	.6081	(.1851)	[.3658]	.7613	(.0604)	[.3351]	1.0503	(.0232)	[.3592]	3.6
48	-.7426	(.0258)	.5933	(.0173)	[.0029]	1.205	(.0107)	[.0514]	.8884	(.0026)	[.0158]	7.1
49	.4289	(.0122)	.5202	(.0041)	[0]	1.0193	(.0006)	[.4276]	.9934	(.0005)	[.3608]	42.9
50	-.9999	(0)	-1.2057	(12.5156)	[.5351]	1.4774	(1.0825)	[.6478]	1.0674	(.0943)	[.6582]	14.3
51	1372.4276	(1.173e+08)	-1.8852	(11.4691)	[.3973]	.685	(.101)	[.3253]	.7447	(.0786)	[.7353]	28.6
53	8.8939	(43.5512)	.5248	(.0313)	[.0091]	.8968	(.0039)	[.1042]	.9148	(.0036)	[.79]	14.3
54	-.9669	(.0068)	-.5875	(.9833)	[.1142]	.7438	(.0225)	[.0925]	1.1026	(.0206)	[.1438]	21.4
55	1.8349	(.0569)	.926	(.0001)	[0]	.9671	(.0005)	[.1544]	1.0341	(.0004)	[.0147]	5
56	5.8702	(10.2841)	.7948	(.0052)	[.0058]	.9507	(.0025)	[.3273]	.871	(.0043)	[.2482]	5.7
57	.5884	(.0419)	.7529	(.0034)	[.0001]	.9148	(.0016)	[.0358]	1.0064	(.0017)	[.0764]	21.4
58	-.3845	(.0529)	.8418	(.0037)	[.0116]	1.1159	(.0069)	[.1691]	1.01	(.0023)	[.2166]	2.9
59	.2755	(.0079)	.9205	(.0002)	[0]	.9785	(.0004)	[.2785]	.9781	(.0004)	[.9852]	8.6
60	1.9486	(.1069)	-.241	(.0317)	[0]	1.0827	(.001)	[.0098]	1.1061	(.0011)	[.4793]	71.4
61	.0903	(.0208)	.4211	(.0123)	[0]	1.0439	(.0013)	[.2294]	1.1557	(.0028)	[.0275]	7.1
62	.8894	(.0123)	.8746	(.0002)	[0]	1.0221	(.0003)	[.2304]	.9955	(.0003)	[.2178]	14.3
63	.426	(.0013)	.9856	(0)	[.0002]	1.0447	(.0001)	[.0002]	1.0369	(.0001)	[.5438]	1.4
67	-.9978	(.0002)	-1.1961	(5.6548)	[.3591]	1.4292	(.409)	[.5045]	1.25	(.1596)	[.6493]	21.4
68	-.9646	(.0291)	-.2881	(2.5211)	[.4201]	3.0059	(17.7868)	[.6359]	.5233	(.1737)	[.5923]	7.1
69	-.9196	(.0234)	.2081	(.2349)	[.1071]	1.1216	(.0218)	[.4128]	.8012	(.016)	[.1601]	17.1
70	.4656	(.0061)	.9538	(.0001)	[0]	.9542	(.0002)	[.0046]	1.042	(.0003)	[.0001]	5
71	7.9078	(7.4759)	.9022	(.0005)	[0]	.9814	(.0013)	[.6127]	1.1083	(.0013)	[.0074]	4.3
75	-.0618	(.0357)	.7076	(.0059)	[.0003]	.9354	(.0017)	[.1207]	1.0778	(.003)	[.0319]	17.9

Table A.8 : Proportion of individuals who exhibit bias (all the decisions and Smaller-Sooner decisions only)

		SSA		
		FB	NB	PB
All decisions	FB	0.039	0	0
	NB	0.136	0.576	0
	PB	0	0.186	0.068

Figure A.4 : Examples of allocation decision pages during first round (top) and during the second round (bottom)

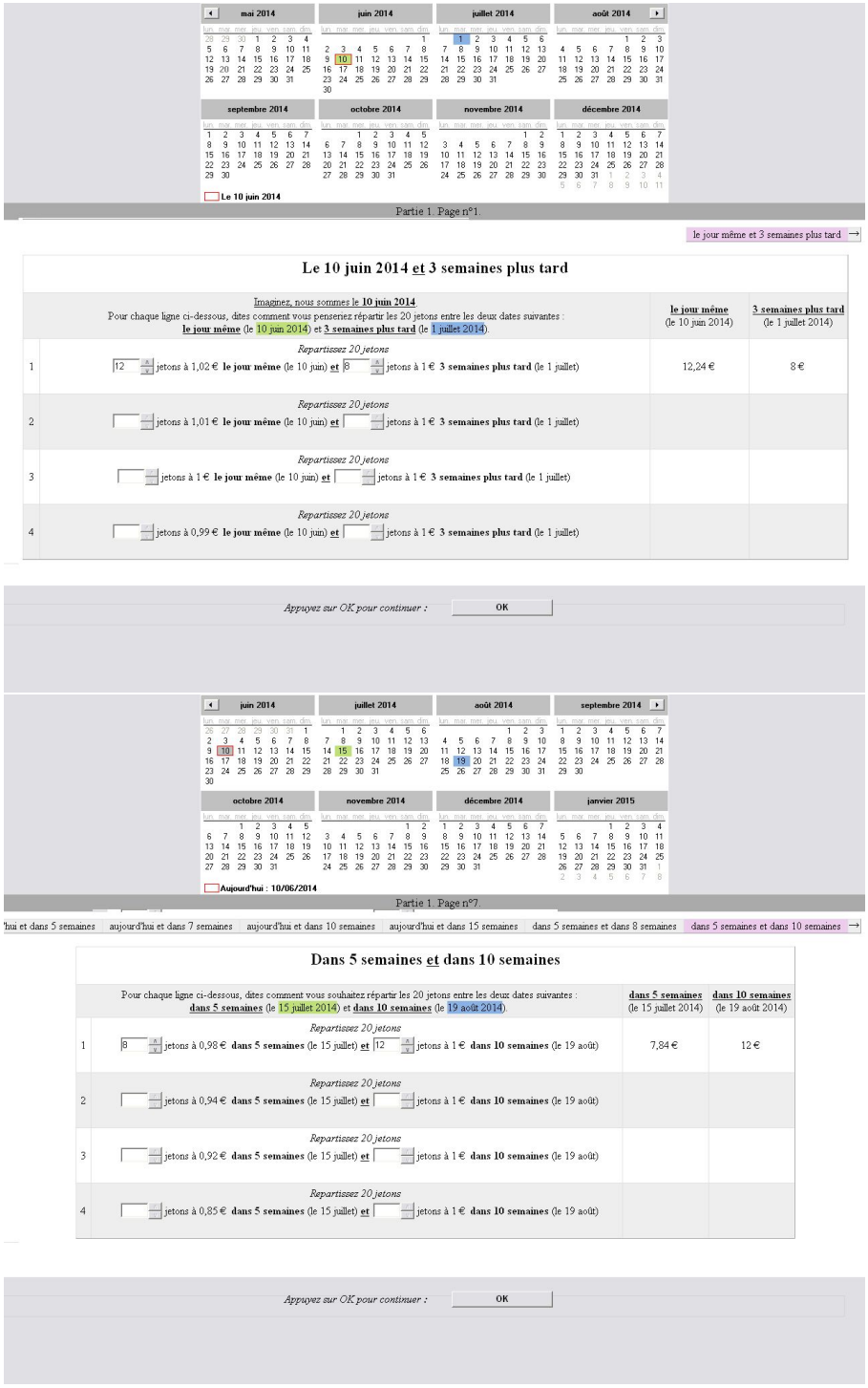


Figure A.5 : Questions used for the Cognitive Reflection Test (Frederick (2005))

1. A bat and a ball cost $1.10 in total. The bat costs $1.00 more than the ball. How much does the ball cost?
2. If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets?
3. In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake?