Hunger Games: Does Hunger Affect Time Preferences?

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Using a novel laboratory experiment I find that hunger increases monetary impatience. This effect is larger when monetary rewards are immediate, which shows that present bias is a visceral response and can help explain why the poor tend to make more shortsighted economic decisions. Given possible confounds between physical and mental resource depletion, I also manipulated cognitive fatigue. I find that cognitive fatigue also increases monetary impatience; nevertheless this effect is driven by an increase in corner solutions. I argue that this may reflect a decrease in attention and an increase in heuristic-based choices. However, more work is needed to confirm this hypothesis.

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Classic economic theory focuses on static preferences and relies on the Homo Economicus assumption. However, there is growing evidence that cognitive, emotional and visceral states can mediate behavioral biases and shape preferences (DellaVigna, 2009).

As Homo Sapiens, we know that our cognitive, emotional and visceral states fluctuate and that we tent to face and make many important economic decisions, with potential long term consequences, when we are fatigue, stress, hungry, etc. Therefore, better understanding the relationship between such factors and preferences could enlighten our understanding of the economic decision-making process. Particularly in the case of hunger (a visceral factor) since it may help us explain why the poor, who are more susceptible to food insecurity and as a result more likely to frequently experience hunger, tend to make more short-sighted economic decisions (Haushofer and Fehr, 2014).

A couple of decades ago Loewenstein's (1996) seminal work prompted a number of studies which demonstrated that *"the discrepancy between the actual and desired value placed on a particular good or activity increases with the intensity of the immediate good-relevant visceral factor."* However, less has been done to test whether visceral factors activate behavioral biases in general.[1]

This study extends on this notion by drawing parallel evidence from psychology, economics, and neuroscience and showing that hunger affects time preferences.

To date, only a single study has shed some light into the question, does hunger indirectly affect non-hunger related decisions? Danziger, Levav and Avnaim-Pesso (2011) find that the percentage of favorable parole decisions fluctuates in relation to the time in which judges take a food break. They argue that this is due to mental resource depletion. However, they are unable identify whether the fluctuation in judges' decisions is due to resources been replenished by eating (mitigating hunger or glucose depletion) or resting (mitigating cognitive fatigue

[1]For example, Loewenstein, Nagin and Paternoster (1997) find that when individuals are sexually aroused they are more likely to expect to be sexually aggressive. Read and van Leeuwen (1998) find that future food choices are significantly affected by an individual's current state of appetite. Also, Van Boven and Loewenstein (2003) show that subjects attitudes towards others thirst depend on their own thirst.

or ego depletion), or both.

The main goal of the present study is to test whether hunger affects time preferences. Nonetheless, it is also important to differentiate between physical and mental resource depletion effects. Therefore, I conducted a controlled laboratory experiment where I manipulated the state of hunger and cognitive fatigue of participants making intertemporal choices. These intertemporal choices were based on Andreoni and Sprenger's (2012) Convex Time Budget (CTB) methodology, in which participants have to decide how much of a monetary reward they want to cash on an earlier and/or a later date given that whatever is cashed on the later date *earns* interest. One of the main benefits of using CTB is that it also allows for the recovery of structural time preference parameters for each subject in the sample.

In summary, I find that both hunger and cognitive fatigue increase monetary impatience, but only hunger affects time preferences. Hunger activates present bias by disproportionately increasing monetary impatience when choices involve immediately available monetary rewards. In contrast, cognitive fatigue increases the number of all-sooner allocations. I argue that this may reflect a decrease in attention and an increase in heuristic-based choices. However, further works is needed to test this hypothesis. Interestingly, while the interaction of both treatments leads to an increase on present bias it also increase monetary patience; which I suspect is due to the parameters used in the experimental design. Also, consistent with Andreoni and Sprenger's (2012) results, individuals under the control condition (not hungry nor cognitively fatigued) display reasonable levels of discounting, present bias, and intertemporal elasticity of substitution.

To my knowledge this is the first study to prove that present bias is a visceral response. These results lay the groundwork for future research exploring whether hunger affects the individual's economic decision-making process. Moreover, they open the door to a new research agenda that could help explain why the poor tend to make more shortsighted economic decisions. These research is tightly interconnected with the behavioral poverty-trap literature. Banerjee and Mullainathan (2007) suggest that *"...the impatience that the poor often show is as much a result of their poverty as it is a cause".* Hunger may be another factor that feeds this vicious cycle.

Additionally, it highlights the importance parameter choice and conducting future work to identify the optimal methodology (e.g. choice consistency, patterns of behavior, CTB) to investigate how cognitive state-levels affect economics preferences.

The remainder of the paper is organized as follows: Section I motivates the research question and describes the related literature. Section II details the experimental design. Section III provides summary statistics. Section IV discusses the results. Section V concludes.

I. Motivation

In recent decades researchers have shown an increased interest in understanding how and which brain systems are associated with individual economic decisions (Camerer, Loewenstein and Prelec, 2005). For example, using functional magnetic resonance imaging (fMRI), McClure et al. (2004) demonstrate that parts of the limbic system are preferentially activated by economic decisions that involve immediate monetary rewards, i.e. Blood-oxygen-level dependent (BOLD) signal changes in the ventral striatum (VStr), medial orbitofrontal cortex (MOFC), medial prefrontal cortex (MPFC), posterior cingulate cortex (PCC), and left posterior hippocampus are greater when decisions involve money available today. The consensus among neuroscientists is that the role of the orbitofrontal cortex (OFC) is to determine just how rewarding a reward actually is (Wallis, 2007).[2] Not surprisingly the OFC is believed to be the best candidate as the network that assigns value, which underlines economic choice (Padoa-Schioppa and Assad, 2006).

[2]It has been documented that outputs of the inferior temporal visual cortex (i.e. visual stimuli) as well as outputs from other sensory systems (e.g. taste, touch, olfaction) are fed into the OFC to produce representations of the expected reward value, including monetary reward value (Rolls, 1999; Rolls and Grabenhorst, 2008).

Concurrently, neuroscientists have documented evidence that hunger and/or fasting is associated with significantly increased activity in the brain's limbic system. For example, Tataranni et al. (1999) used positron emission tomography (PET) studies to show that that hunger is associated with increased relative cerebral blood flow (rCBF) in limbic areas of the brain (e.g, OFC, and parahippocampal cortex); and Li et al. (2012) use fMRI to show that fasting increases BOLD signals of limbic areas of the brain (e.g, OFC, parahippocampal cortex, and caudate). Additional evidence shows that the OFC is sensitive to the level of hunger/satiety (Rolls, 1999; Hinton et al., 2004; Siep et al., 2009).[3]

Moreover, there is growing evidence that physiological and biological factors are linked to individual economic behavior. For example, stress, induced by mild physical pain Porcelli and Delgado (2009) or cortisone pills (Kandasamy et al., 2014), increases risk aversion. Similarly, stress and negative emotions increase impatience (Cornelisse et al., 2013; Lerner, Li and Weber, 2012). Also, Dickinson, McElroy and Stroh (2014) find that glucose increases individuals' response times affecting the likelihood of a Bayesian error, and Kuhn, Kuhn and Villeval (2014) find self-control depletion and sugar effects on time preferences—since the effects are mainly driven by increases in the intertemporal substitution elasticity they suspect that the primary mechanism is an increase in subjects' attention to the decision and not an inability to resits the temptation of an immediate monetary reward. Other relevant studies include Schofield (2013), who used a high intake treatment and and Ramadan to evaluate the impact of caloric intake on productivity. She finds that high-caloric intake led to improvements in physical and cognitive tasks, increased labor supply, and income (about 10%); while Ramadan (low-caloric intake) led to a 20% to 40% decrease in productivity per individual.

However, there is yet to be a study formally linking hunger and economic behav-

[3]For example, Hinton et al. (2004) use PET to scan participants after fasting or after food intake and find that brain activity changes when a person's state shifts from hunger to satiety. They find that during the intrinsic state of hunger, there is increased activation in the hypothalamus, amygdala, insula cortex, medulla, striatum, and anterior cingulate cortex; while satiety was associated with increased activation in the lateral OFC and temporal cortex.

ior. The most closely related study to this endeavor was conducted by Danziger, Levav and Avnaim-Pesso (2011) to test the age-old wisdom *"Law is what the judge ate for breakfast"*. In this study, they recorded judges' sequential parole decisions, over a period of 50 days, before and after two daily food breaks. They find that the percentage of favorable decisions drops steadily from about 65% at the beginning of a session to nearly zero before the break, and returns abruptly to about 65% after the break. Their findings suggest that judicial rulings can be swayed by variables that should have no weight on legal decisions. In this case they interpret such variable as *mental depletion*. However, they are unable identify whether the fluctuation in judges' decisions is due to resources been replenished by eating (mitigating hunger or glucose depletion) or resting (mitigating cognitive fatigue or ego depletion), or both.

In the present study, I use a novel laboratory experiment to explore *whether hunger affects economic decisions not directly associated with hunger* (in this case choices over monetary rewards). Also, in order to clarify if and how hunger and cognitive fatigue interact, I implemented a 2x2 factorial experiment. The two treatment conditions in this experiment were hunger and cognitive fatigue.[4]

More specifically, I manipulated the order in which 4 different activities or stages were administer to subjects. These included a decision task, an arithmetical task, a tasting activity and filler tasks, and a demographic questionnaire and auxiliary survey. This generated the control and treatment groups needed to estimate the effect of hunger and cognitive fatigue on time preferences (i.e. can hunger help explain why some individual display time-inconsistent preferences).

To provide some background, while standard economic model assumes time-consistent preferences, there is substantial evidence that individual preferences vary over time (i.e. preferences are time inconsistent). Thaler (1981), the first to empirically test this assumption, found discounting to be steeper in the immediate

[4]An abundance of evidence shows that cognitive costs play an important role in consumers' decisions (e.g. credit card market, Ausubel (1991); retirement investments, Hastings and Tejeda-Ashton (2008); and tax salience, Chetty, Looney and Kroft (2009)) for a more in-depth review of the literature, see DellaVigna (2009).

future than in the more distant future. A slight modification to the standard economic model—the implementation of a present bias parameter (β) that, in addition to the time-consistent discount factor (δ), weights all utility to be realized in the future (Laibson, 1997; O'Donoghue and Rabin, 1999)–helps explain why individuals sometimes end up consuming more/less leisure/investment goods than what they had initially planned to consume.

An individual is said to have time-inconsistent preferences, or being present bias, if $\beta < 1$. Since β weights all utility to be realized in the future, when evaluating a decision in which the outcome is realized in future, the individual weights the future outcome by β in addition to the standard discount factor δ. Therefore, with time-inconsistent preferences, individuals generate plans believing that their future-selves will be able to follow through with their plans. However, as the future becomes the present, they fail to do so. This leads to self-control problems.

More recently, researchers have focused on improving the methodology used to elicit time preferences. They argue that when transaction costs are equal across choices and subjects trust the payments will be received, there is no evidence of time-inconsistent preferences. Andreoni and Sprenger (2012) developed the CTB, which helps mitigate biases arising from assuming a linear consumption utility when measuring time preferences. CTB works by asking subjects to decide how many of a total allocation of m tokens (generally $m = 100$) they want cash at an earlier date and how many they wanted to cash at a later date, with the value of the token increasing in time. In fact, Andreoni and Sprenger (2012) conclude that this may suggest that present bias is a visceral response activated when earlier rewards are actually immediate.

In the following section, I detail the controlled laboratory experiment used to test whether hunger affects intertemporal preferences.[5]

[5]A future research goal is to identify the specific mechanism (e.g. brain activity) through which hunger affects time preferences.

II. Experimental Design

Each experimental session consisted of 4 different stages (explained in detail in the following section): a) a decision task, monetary choices used to elicit time preferences; b) an arithmetical task, timed-arithmetical problems used to induce cognitive fatigue; c) a tasting activity and filler tasks, the provision of a nutrition shake combine with filler tasks lasting approximately 15 minutes used to satiate appetite; and d) a demographic questionnaire and auxiliary survey, used to collect additional information on individual characteristics and dietary practices. Figure 1 illustrates how the ordering of these stages defines each of the cells/conditions resulting from the $2x2$-factorial design.

A. Procedures

The experiment took place in the Social Sciences Experimental Lab (Xlab) at the University of California, Berkeley. During the sign-up process, which took place between a week and 24 hours before each session, individuals were asked to fast for at least 3 hours before the session. I conducted sessions during weekdays and weekends, as well as on different times of the day (from 9:00 a.m. to 1:00 p.m.) to eliminate date and time-of-the-day effects. During the sign-up process individuals with glucose and food sensitivities were also informed that they were not qualified to participate in the study.

Upon arrival to the laboratory, subjects were assigned to a computer station. The nutritional drinks were set up in a table behind panels to the left of the room (see Figure 2). A server-based application was developed to implement the experiment.[6] Each subject was issued a user id and password. Through the application, subjects were given informed consent. They were guided and received instructions for each of the stages and learned about their experimental earnings. This included the payment amount and date(s) in which they would

[6]Appendix A provides screen-shots of the application, including the consent form and instructions scripts used.

receive them.[7] The responses and the time stamp for each of the responses were collected and stored on the server hosting the application.

Since the decisions task, arithmetical task, and demographic questionnaire and auxiliary survey were solely administered through the web-based application, I will refer to these three stages of the experiment as the computer-based experimental tasks (CETs), from this point forward.[8]

B. Compensation

At the beginning of the CETs, subjects were informed that they were going to face a total of 65 rounds, and that in each of these rounds they were going to have 45-seconds to either solve an arithmetical task or make an economic decision. Subjects were also informed that only one round was going to be selected to determine their experimental compensation, and they were reminded to make each decision and solve each problem carefully since any one of the 65 rounds had equal chances to be chosen at random.[9]

When implementing time discounting studies, the researcher must ensure that, except for their timing, choices are equivalent (i.e. all costs associated with receiving payments should be the same across periods). I used payment procedures similar to those implemented by other researchers (Andreoni and Sprenger, 2012) in addition to unique measurements design to make transaction costs across all periods equal. First, payments were made electronically (via Paypal) to eliminate disproportionate preference for present in-lab payments. Second, at the beginning of the experiment subjects were informed that they would receive a $10-participation fee in addition to their experimental compensation. Furthermore, the date on which they would receive this participation compensation would depend on whether the task randomly selected to determine their experimental compensation was an arithmetical task. Were that the case they would receive the

[7]The application also provided subjects with practice rounds for arithmetical and decision tasks.
[8]CETs are circled in gray in Figure 1.
[9]By selecting a random round to determine their compensation I avoid wealth effects.

$10-participation in a single payment (on the day of the experiment); or a decision tasks, in which case they would receive the $10-participation fee in two payments ($5 on the earlier date and $5 on the later date stated on the randomly selected decision round). Implementing a $10-participation fee serves several purposes: it allows to fulfill the Xlab minimum compensation requirements; it increased subjects' trust, since they would receive both an earlier and a later date payment independent of their allocation; and it reduces the bias towards concentrating payments in a single period, by eliminating multiple payment inconvenience since two payments were sent regardless. Third, at the end of the experiment subjects provided the email account to which they wanted to receive their compensation payment(s). Also, at the end of the experiment, I personally gave each subject my business card with my email and phone number shown and invited them to contact me if they had any inquiries about the study, including the payment procedures.[10] In the auxiliary survey I asked subjects if they trusted that they would receive their experimental payment on the promised date, and over 95% of subjects replied yes.[11]

C. Tasting Activity and Filler Tasks

All subjects participated in a tasting activity before/after the CETs; this allows for the manipulation of their hunger/satiation level.[12] Protein has been documented as the most satiating macro-nutrient (Rolls, Hetherington and Burley, 1988; Weigle et al., 2005; Astrup, 2005; Bertenshaw, Lluch and Yeomans, 2008). Therefore I used a high-protein (35 grams), low-calorie (160 calories), low-sugar (1 gram), and low-carbohydrate (2 grams) nutritional shake (12 fl. oz.).[13]

[10] The total amount and the date(s) in which they would receive their compensation were hand-written on the back each card.

[11] This is similar to the 97% positive replies Andreoni and Sprenger (2012) report for the same question in their sample.

[12] I flipped a coined to determine whether subjects participating in the first session would participate in the tasting activity before/after the computer based experimental sessions. Since I wanted to control for date and time-of-the-day effects, I used this initial allocation to allocate the before/after condition to the remaining sessions and keep a balance panel.

[13] This particular drink was chosen to because its nutritional content allow me to avoid sugar and caffeine interactions.

Subjects were instructed, via a message on their computer screen, to go to the left side of the room, take a can, consume all of its contents, then give the empty can to the researcher who would give them a paper-based survey (containing "filler tasks"), and return to their desk to complete it. Subjects had 15 minutes to complete the paper-based survey and were not able to proceed to following stages of the experiment prior completion of the survey.[14]

For subjects in the hunger and interaction condition who participated in the tasting activity after the CETs, the filler tasks included ratings of the drink flavor and presentation data as well as ratings on the feeling of satiation after drinking the nutritional shake, dietary practices, and perceptions on the drink nutritional content. This supplementary data allowed me to verify the satiating effectiveness of the nutritional shake, which is discussed in detail in the following section. For subjects in the control and cognitive-fatigue condition who participated in the tasting activity before the CETs, the filler tasks included ratings of the drink flavor and presentation but did not include any questions related to the feeling of satiation after drinking the nutritional shake, dietary practices, or perceptions on the drink nutritional content to avoid biasing their responses the results.

D. Decision Task

I used Andreoni and Sprenger's (2012) CTB methodology to elicit time preferences. In CTB, subjects choose a continuous combination of c_t and c_{t+k} along the convex budget set

$$(1+t)c_t + c_{t+k} = m, \tag{1}$$

where $(1+t)$ represents the price of earlier earnings; and c_t and c_{t+k} represent the experimental earnings at an earlier and a later date, respectively. The experimental earnings are determined by choosing how many tokens of a total allocation

[14]This was enforced by a timer, programmed on the application, that only allow subject to proceed to the following screen after 15 minutes.

of m tokens they want *cash* on an earlier and/or a later date. The value of each token depends on which date the token is cashed and tokens cashed on later dates generally have larger values, i.e. $(1+t) \geq 1$. The convex budgets used were chosen to resemble those used by Andreoni and Sprenger (2012). My unique application design allows for better control of order and anchoring effects, since it presents each convex budget as an independent round and facilitates the randomization of the order of all choices for each subject and well as randomly resetting the allocation starting point in each round.[15]

Table 1 summarizes the 55 convex budgets faced by each subject.[16] The total token allocation was fixed at 100 for all convex budgets ($m = 100$). Each convex budget is defined by a (t,k)-choice set and a (v_t, v_{t+k})-budget, where: t represents the earlier date measure in days from the date of the experiment; k represents the delay between the earlier and the later date measured in days; v_t represents the earlier token cash-value, i.e. the value of each token if cashed on the earlier date; and v_{t+k} represents the later token cash value, i.e. the value of each token if cashed on the later date. Table 1 also shows the price of earlier earnings or gross rate over k days, $(1+r) = \frac{v_{t+k}}{v_t}$, which ranges from 0 to 2; the standardized daily interest rate, $(1+r)^{1/k}$; and the annual interest rate compounded quarterly. The reason relatively high annual interest rates are used is because the monetary payments and delays were relatively small and using smaller annual interest rates could have biased results in favor of present bias.

E. Arithmetical Task

In order to induce cognitive fatigue, subjects were required to solve arithmetical problems consisting of four 3-digit addition problems for a total of 10 rounds.[17] The cognitive-fatigue treatment was assigned randomly to half of the subjects

[15]Figure A4 and Figure A3 provide a screenshot of the decision rounds before and after a choice is made.

[16]Each convex budget was presented as a separate round, and subjects had 45 seconds to make their decision.

[17]Figure A2 provides a screenshot of the arithmetical task round as it was presented to subjects.

within a session. As illustrated in Figure 1 the subjects in the control and hunger condition faced the arithmetical task rounds only after the decision task rounds, while the subjects in the cognitive-fatigue and interaction condition faced the arithmetical task rounds before the decision task rounds. If one of the arithmetical task rounds was selected at random to determine the experimental compensation subjects received $15, in addition to their $10-participation fee, only if they had correctly solved all four arithmetical problems in the selected round.

F. Demographic Questionnaire and Auxiliary Survey

The last part of the CETs consisted of a demographic questionnaire and auxiliary survey.[18]

III. Summary Statistics

A. Manipulation of hunger

First, subjects were required to fast for at least 3 hours before the experimental session as requested during the sign-up process. In the auxiliary survey I asked subjects to report the time at which they consumed their last meal before coming to the experiment.[19] Using this data, I was able to identify subjects that did not comply with the fasting requirements (17 out of 160 participants). Table 2 summarize subjects' characteristics for compliers and non-compliers. Non-compliers do not appear to be significantly different from compliers; except for the time since their last meal (measured in hours) and their self-reported levels of hunger, which is expected. Therefore, I will not include them when estimating treatment effects.[20]

Second, I collected 3 measures of self-reported hunger level. After the CETs subjects had to rank on a scale from 0 to 10, where 0 is "Not At All" and 10

[18] A list of these questions is provided in Appendix C of Ashton (2014).

[19] Demographic questionnaire and auxiliary survey questions are provided in Appendix D of Ashton (2014).

[20] In Appendix C I compare non-compliers to the control group and find that, as one would expect, these two groups behave in a similar way.

is "Extremely", how hungry they were both upon arrival to the lab and at that moment.[21] In addition, I asked subjects under the control and cognitive-fatigue conditions (i.e. those that completed the tasting activity after the CETs) to rank their hunger level using the same scale. In order to accept the fasting/nutritional-shake manipulation as a successful manipulation of hunger/satiation levels, the following about these measurements needs to be truth:[22]

- Self-reported hunger level upon arrival to the lab is the same for all subjects. Indeed, I do not find a significant difference on for the self-reported hunger level upon arrival to the lab between the subjects who completed the tasting activity before the CETs [$\mu = 5.86$, SD= 2.88], i.e. those under the control and cognitive-fatigue conditions; and the subjects who completed the tasting activity after the CETs [$\mu = 5.77$, SD= 2.02], e.g. those under the hunger and the interaction conditions: $t(141) = 0.21$, $p = 0.836$.

- Self-reported hunger level during auxiliary survey is greater for those who had not completed the tasting activity yet. This is confirmed by the significant difference in self-reported hunger level between subjects under the hunger and interaction conditions [$\mu = 6.85$, SD= 2.00], i.e. those who had not completed the tasting activity yet; and subjects under the control condition and cognitive-fatigue treatment [$\mu = 4.50$, SD= 2.80]: $t(141) = 5.76$, $p <= 0.001$.

- Nutritional shake reduces hunger. First, I find a significant difference between the self-reported hunger level upon arrival to the lab [$\mu = 5.86$, SD= 2.88] and during the auxiliary survey [$\mu = 4.50$, SD= 2.80] for those under the control and cognitive-fatigue conditions: $t(71) = 5.14$, $p < 0.001$. Second, I find a significant difference between the self-reported hunger during the auxiliary survey [$\mu = 6.80$, SD= 2.00] and after the tasting activity

[21]Note that subjects were asked to rank their hunger level upon arrival to the lab in retrospect to avoid "Hawthorne effects", i.e. biasing their experimental responses.

[22]While non-compliers are not included, and they display significantly different self-reported hunger levels, including them does not change the results.

[$\mu = 4.93$, SD$= 2.67$] for those under the hunger and interaction conditions: $t(68) = 5.95$, $p < 0.001$.[23]

The fasting requirement combined with the nutritional-shake tasting activity resulted in a successful manipulation of hunger. Therefore, hereafter, I will refer to subjects that complied with the fasting requirements and completed the tasting activity after the CETs as subjects that received the *hunger treatment*.

B. Sample

Table 2 summarizes subjects characteristics measured using the demographic questionnaire, auxiliary survey, filler tasks, and experimental questions. A total of 160 subjects participated in the experiments, out of which 143 complied with the fasting requirement. Column (1) shows that compliers, the group of interest, earned an average experimental compensation of $25.2. Overall, 46.2% are male, their average age is 20.7 years, 46.2% declared English as Second Language (ESL), 30.8% work, and 70.6% have a credit card. In average, subjects can correctly answer 4.5 [out of 5] numeracy questions, and 1.2 [out of 2] IQ questions. During the 10 arithmetical rounds, each in which they were given four 3-digit addition problems, they were able to solve in average 2.5 problems correctly in 40.2 seconds, and they spend an average of 10.1 seconds in each of the 55 decision rounds.

Table 3 summarizes the same characteristics as Table 2 for each of the cells resulting from the $2x2$-factorial design described in the previous section. Notice that I also implemented a low-dose condition by using a nutritional shake with 23g of protein, instead of 35g as in the control condition. The objective was to compare subject responses at different protein dose levels, i.e. dose-response. Out of the 143 compliers: 29 are under the control condition, 12 are under to the low-dose condition, 31 are under the cognitive-fatigue condition, 37 are under the hunger condition, and 34 are under the interaction condition.[24]

[23]Two out of the 79 subjects in hunger and interaction conditions did not report their hunger level after the tasting activity.

[24]Due to limited resources, I only collected data for 12 subjects under the low-protein control con-

IV. Results[25]

This section presents the results of the previously outlined $2x2$-factorial experiment, to assess the hunger (fasting or treatment 1 and cognitive fatigue (solving timed-arithmetical problems or treatment 2) and on time preferences (choices between earlier and/or later monetary rewards).

The results are presented using 2 different approaches. First, I take a non-parametrical approach, which provides a broad view of the treatment and interaction effects. Second, I use Andreoni and Sprenger (2012)'s CTB methodology to estimate both aggregate-level (by condition) and individual-level time preference parameters (discounting, present bias, and intertemporal elasticity of substitution).

A. Non-parametrical Analysis

In Figure 3 I plot the mean number of tokens cashed earlier against the gross interest rate, $(1 + r)$.[26] I plot separate points for each condition and separate graphs by both the immediacy of the earlier date in days, immediate ($t = 0$) and non-immediate ($t > 0$), and the delay between the earlier and the later date in days ($k = 35, 70, 98$). The number of tokens cashed earlier by subjects under the hunger condition, versus the number of tokens cashed earlier by subjects under the control condition, seems to be persistently higher; particularly when the earlier date is immediate. This can pose as potential evidence for present bias or hyperbolic discounting. Interestingly, the number of tokens cashed earlier by subjects under the cognitive-fatigue condition does not decline monotonically

dition. While this is not sufficient to precisely estimate dose-response effects it allows me to explore the relationship between the protein dose and subjects' experimental responses, which is discussed in Appendix C.

[25] As noted in the previous section, I will only include the 131 subjects under the four main conditions in this section. A brief analysis of the results for subjects under the low-dose condition and non-compliers is presented in Appendix C.

[26] When there is more than one (v_t, v_{t+k})-combination for a gross rate, e.g. $(1 + r) = 1.25$, I report the average.

with the interest rate.[27]

Figure 4 graphs the mean tokens cashed earlier for non-compliers and each of the conditions by the delay of the earlier date.[28] In order to have a comparable set of choices across immediacy of the earlier date (t) and delay between earlier and later date (k), I only included the balanced combination of convex budgets from Table 1 (i.e. $(1+r)$-budgets in all nine (t,k)-choice sets), however estimates do not significantly change if all choices are included. The means are also presented in Table 4.[29]

Monetary Impatience — Let's define monetary impatience as the desire to cash a monetary reward earlier even if waiting to cash the reward would result in a significant monetary gain (i.e. the monetary reward earns interests). At the aggregate level, i.e. independent of the immediacy of the earlier date ($t = 0, 7, 35$), we find that subjects under the control condition cashed 36.81 [SE = 5.057] earlier tokens in average. Consistent with predictions, subjects under the cognitive-fatigue [$\mu_F = 50.41$, SE = 5.560] and hunger [$\mu_H = 50.31$, SE = 3.956] conditions cash significantly more tokens earlier ($p = 0.073$ and $p = 0.038$, respectively). Subjects under the interaction condition [$\mu_I = 33.53$, SE= 4.241], i.e. those that received both the cognitive-fatigue and hunger treatment, seem to cash slightly less tokens earlier ($p = 0.620$).

Present Bias — As I discussed in Section I, an individual displays present-biased preferences if, relative to immediate outcomes, she/he disproportionately discounts non-immediate outcomes. In Figure 4 and Table 4, I contrast the effects including only choices with immediate earlier dates ($t = 0$) against the effects including only choices with non-immediate earlier dates ($t > 0$). This can

[27]Andreoni and Sprenger (2012) find that the number of tokens cashed earlier decline monotonically with the interest rate, increases with delay, and are not significantly higher when the earlier date is immediate, versus non-immediate.

[28]Means and standard errors were generated from regressions of the tokens cashed earlier on condition status, with standard errors clustered at the individual level.

[29]Standard errors are clustered at the individual level.

provide a non-parametric measure of present bias for each of the treatment and control conditions. In comparison, I find that the effect on tokens cashed earlier is significantly larger if the earlier date was immediate, than if the earlier date was non-immediate, only for subjects under the hunger [$\mu_{H_{t=0}} - \mu_{H_{t>0}} = 5.07$, $p < 0.05$] and interaction [$\mu_{I_{t=0}} - \mu_{I_{t>0}} = 5.68$, $p < 0.01$] condition.

Corner Effects — These non-parametrical aggregate results, by nature, lack individual heterogeneity details. Overall less than 26.0% of subjects (34 out of 131) have no interior choices in all of their chosen budgets, which is consistent with linear preferences. However, as seen in Figure 5, almost twice as many subjects (35.3%) have no interior choices under the cognitive-fatigue condition, compare to the control (17.7%). This is not the case under the hunger (14.7%) and the interaction condition (17.7%). Additionally, Figure 6 plots the overall percent of corner and interior solutions by condition, i.e. the percent of choices in which all tokens were cashed earlier (*impatient*), all tokens were cashed later (*patient*), and some tokens were cashed earlier and some tokens were cashed later (*interior*); and Table 5 estimates the respective "corner effects", i.e. the decrease/increase on patient and impatient choices by treatments and interaction. One can see that, in contrast with the average percentage of impatient (23.3%) and patient (47.0%) choices made by subjects under the control condition, subjects under the cognitive-fatigue condition make significantly more impatient choices (Coef = 16.9%, $p < 0.05$) but do not make significantly less patient choices, i.e. choose more corner solutions; while subjects under the hunger condition do not make significantly more impatient choices but do make significantly less patient choices (Coef = −19.0%, $p < 0.05$).

20-cent Heuristic — While insignificant, the most puzzling result is that subjects under the interaction condition, i.e. those that receive both the cognitive-fatigue and hunger treatment, seem to cash slightly less tokens earlier than those under the control condition. A potential explanation for this result, consistent with a priori expectations, is that while subjects under the cognitive-fatigue condition use a corner heuristic (i.e. choose either all-earlier or all-later tokens), subjects under the interaction condition may be using a 20-cent heuristic to simplify the decision problem even further and, since in 37 out of 55 convex budgets the value of tokens cashed on later dates is 20 cents, this could be making them seem more patient or sensitive the cost of early income. In fact, notice that while not significant, only the interaction of both treatments has a positive effect on patient choices (Table 5).

In summary, cognitive fatigue and hunger increase monetary impatience. While hunger has a significantly larger effect when choices involve immediate monetary rewards, cognitive-fatigue does not. Also, the cognitive-fatigue effect appears to be driven by an overall increase in corner solutions, i.e. the number of all-earlier allocations increases and the number of all-later allocations remains constant. While corner solutions can be decisions that any rational agent could make every time, they could also represent heuristics or rules-of-thumb use by individuals to simplify the decision problem. In fact, while insignificant, only subjects under the cognitive-fatigue condition seem to spend less time in average completing each decisions task than subjects under the control condition (see 3). Overall, these results suggest that hunger and cognitive fatigue may be affecting time preferences through different mechanisms, which we will further explore in the following section.

B. Parametrical Analysis

Following Andreoni and Sprenger's (2012) CTB methodology, I estimate the time preference parameters for subjects under control and each of the treatment (cognitive-fatigue and hunger) and interaction conditions. First, I provide a brief summary of CTB methodology and my estimation strategy. Then, I estimate the parameters jointly by condition, clustering the standard errors at the individual level, and report the p-values for the null hypothesis of equality between the control and each of the treatment and interaction conditions. Lastly, I estimate the parameters for each individual, report and plot the estimated parameters by conditions, and test for distributional differences between the control and each of the treatment and interaction conditions using a two-sample Wilcoxon-Mann-Whitney test.

Methodology

I assume individuals have a time separable CRRA utility function with (β-δ)-parameters (Laibson, 1997; O'Donoghue and Rabin, 1999):

$$U(c_t, c_{t+k}) = \frac{1}{\alpha} c_t^{\alpha} + \beta\delta^k \frac{1}{\alpha} c_{t+k}^{\alpha}, \tag{2}$$

where δ is the discount factor; β is the present bias parameter; c_t and c_{t+k} represent the experimental earnings at t and $t{+}k$, respectively; and α is the CRRA curvature parameter, which represents the intertemporal elasticity of substitution. This form captures the present-biased time preferences, when $\beta < 1$; but can also be reduced to exponential discounting, when $\beta = 1$. Maximizing Equation B2 subject to the future value Equation 1 yields to the tangency condition

$$\frac{c_t}{c_{t+k}} = \begin{cases} (\beta\delta^k(1+r))^{\left(\frac{1}{\alpha-1}\right)} & \text{if } t = 0 \\ (\delta^k(1+r))^{\left(\frac{1}{\alpha-1}\right)} & \text{if } t > 0 \end{cases}, \tag{3}$$

and the demand for tokens cashed earlier

$$c_t = \begin{cases} \dfrac{m(\beta\delta^k(1+r))^{\left(\frac{1}{\alpha-1}\right)}}{1+(1+r)(\beta\delta^k(1+r))^{\left(\frac{1}{\alpha-1}\right)}} & \text{if } t = 0 \\ \dfrac{m(\delta^k(1+r))^{\left(\frac{1}{\alpha-1}\right)}}{1+(1+r)(\delta^k(1+r))^{\left(\frac{1}{\alpha-1}\right)}} & \text{if } t > 0 \end{cases}. \tag{4}$$

Now, following Andreoni and Sprenger (2012)'s approach, I can use non-linear least squares (NLS) to estimate the time preference patameters by condition. Which yields to the structural regression equation

(5)

$$c_t = \left[\frac{m(\beta_C^{\tau}\delta_C^{k}(1+r))^{\left(\frac{1}{\alpha_C-1}\right)}}{1+(1+r)(\beta_C^{\tau}\delta_C^{k}(1+r))^{\left(\frac{1}{\alpha_C-1}\right)}}\right]\cdot\mathbb{C} + \left[\frac{m(\beta_F^{\tau}\delta_F^{k}(1+r))^{\left(\frac{1}{\alpha_F-1}\right)}}{1+(1+r)(\beta_F^{\tau}\delta_F^{k}(1+r))^{\left(\frac{1}{\alpha_F-1}\right)}}\right]\cdot\mathbb{F} + \left[\frac{m(\beta_H^{\tau}\delta_H^{k}(1+r))^{\left(\frac{1}{\alpha_H-1}\right)}}{1+(1+r)(\beta_H^{\tau}\delta_H^{k}(1+r))^{\left(\frac{1}{\alpha_H-1}\right)}}\right]\cdot\mathbb{H} + \left[\frac{m(\beta_I^{\tau}\delta_I^{k}(1+r))^{\left(\frac{1}{\alpha_I-1}\right)}}{1+(1+r)(\beta_I^{\tau}\delta_I^{k}(1+r))^{\left(\frac{1}{\alpha_I-1}\right)}}\right]\cdot\mathbb{I} + \epsilon,$$

where τ is an indicator for whether or not the earlier date is immediate, i.e. $\tau = 1$ if $t = 0$ and $\tau = 0$ otherwise; and $\mathbb{C}$, $\mathbb{F}$, $\mathbb{H}$, and $\mathbb{I}$ are indicators for the control, cognitive-fatigue, hunger, interaction conditions, respectively.

Aggregate Estimates

As mentioned before, the richness of the CTB methodology allows me to estimate time preference parameters (discounting, present bias, and intertemporal elasticity of substitution) since experimental allocations are identify as solutions to standard intertemporal optimization problems.

Table 6 presents the aggregate-level time preference parameters by condition and F-statistic and p-value corresponding to the null hypothesis of equality between the aggregate parameter estimated for subjects under the control condition and each of the treatment and interaction conditions.[30]

Present Bias — I do not find evidence of present bias for subjects under the control [$\hat{\beta_C} = 1.001$, SE $= 0.011$] and cognitive-fatigue [$\hat{\beta_F} = 0.993$, SE $= 0.025$] conditions, i.e. the hypothesis of no present bias or $\beta = 1$ cannot be rejected

[30]The analogous specification is presented in Andreoni and Sprenger (2012)'s column (3) of Table 2. The aggregate parameter estimates under all the model specifications used and functional forms assumed by Andreoni and Sprenger (2012) are reported in Appendix B.

for the control ($F_{1,28}$=0.01, $p = 0.921$) nor the cognitive-fatigue ($F_{1,30} = 0.08$, $p = 0.781$) conditions. Nevertheless, for subjects under the hunger [$\hat{\beta_H} = 0.952$, $SE = 0.025$] and interaction [$\hat{\beta}_I = 0.974$, $SE = 0.011$] conditions, β is estimated significantly below 1 and the hypothesis of no present bias is rejected ($F_{1,36} = 11.07$,$p < 0.001$ and $F_{1,33} = 5.48$,$p = 0.019$, respectively). Consistent with predictions, and the non-parametrical analysis presented in the previous subsection, hunger appears to disproportionately increase monetary impatience when monetary rewards are immediate; which is reflected on significantly lower estimates of β for subjects under the hunger ($F_{1,65} = 7.23$,$p = 0.007$) and interaction ($F_{1,62} = 2.95$, $p = 0.086$) conditions, relative to subjects under the control condition.

CRRA Curvature (or intertemporal elasticity of substitution) — While the aggregate curvature is estimated to be significantly different than 1 (in favor of non-linear utility) for all conditions [$\alpha_C = 0.867$ (SE = 0.021), $\alpha_F = 0.806$ (SE = 0.024), $\alpha_H = 0.$ (SE = 0.017), $\alpha_I =$, (SE = 0.013)], only subjects under the cognitive-fatigue condition display a marginally significant higher degree of curvature than those under the control condition ($F_{1,59} = 3.71$, $p = 0.054$). In other words, subjects under the cognitive-fatigue condition appear to be less responsive to the cost of early income. However, one must be careful when interpreting these results since one would expect more corner solutions to deliver a lower degree of curvature.

Annual Discount Rate — The annual interest rate for subjects under the cognitive-fatigue and hunger condition are estimated at 164.6 (SE = 0.589) and 148.0% (SE = 33.8%), respectively. Nevertheless, only the annual interest rate for subjects under the hunger condition is marginally significantly higher than the annual interest rate for subjects under the control condition. This which is estimated at 73.0% (SE = 29.9%): $F_{1,65} = 3.37$, $p = 0.067$. Interestingly the annual interest rate for subjects under the interaction condition is estimated at 60.7% (SE = 0.164), which is lower, but not significantly different than the annual interest rate for subjects under the control condition: $F_{1,59} = 0.19$, $p = 0.661$. The latter may be due to subjects under the interaction condition using a 20-cent heuristic, as mentioned in the non-parametrical analysis, which given the parameters used in the experiment makes them seem very sensitive the cost of early income. Overall, the annual interest rates seem to be less precisely estimated than the annual interest rate estimated by Andreoni and Sprenger (2012).[31] This may be due to noise added by the introduction of the randomization of both the ordering of the questions and the slider starting point in the application.

It is worth highlighting that the aggregate estimates for the present-bias and curvature parameters for subjects under the control condition are very close in magnitude to those obtained by Andreoni and Sprenger (2012); which was expected since subjects in their sample received neither the cognitive-fatigue nor the hunger treatment.[32] This provides additional evidence for the validity and consistency of the CTB methodology.

Individual Estimates

Table 7 summarizes the individual parameter estimates by condition. Due to lack of choice variation, it was not possible to estimate parameters for 3 subjects under the control condition, 2 subjects under the cognitive-fatigue condition, and 2 subjects under the interaction condition (in total 7 out of the 131 subjects under all four main conditions).[33] Also, parameter estimates for some subjects result in extreme outliers due to the limited number of observations per subject. Therefore, I trim the parameters at the 5th and 95th percentiles losing 12 more observations for each parameter. Comparing the aggregate estimates to the me-

[31] They estimate the annual interest rate at 37.1% [SE = 0.091].
[32] They estimate $\hat{\beta}$ at 1.007 [SE = 0.006] and $\hat{\alpha}$ at 0.897 [SE = 0.009].
[33] Andreoni and Sprenger (2012) are also unable to estimate parameters for 10 out of 97 subjects.

dian of the 114 remaining individual estimates by condition I find that: a) the annual interest rate is slightly higher for all conditions, but the relationship between conditions is sustained; b) the present bias parameter (β) is virtually the same for all conditions; and c) the CRRA curvature parameter (α) is estimated much closer to 1 for all conditions, and the difference between subjects under the control and the cognitive-fatigue fatigue condition is not as pronounced for the median individual estimates as it was for the aggregate estimates.

Figure 7, Figure 8, and Figure 9 plot the kernel density estimates for individual annual interest rate, present bias parameter, and CRRA curvature parameter, respectively. The two-sample Wilcoxon-Mann-Whitney test for equality of distribution between the control and each of the treatment and interaction conditions suggest that:

- First, consistent with the non-parametrical and aggregate results, only subjects under the hunger condition have a statistically significant different underlying distribution of the annual interest rate than subjects under the control condition ($z = -1.91$, $p = 0.057$), with the subjects under the hunger condition having the higher rank-sum.

- Second, also consistent with the non-parametrical and aggregate results, subjects under both the hunger and the interaction condition have statistically significant different underlying distributions of the present bias parameter than subjects under the control condition ($z = 2.37$, $p = 0.018$ and $z = 1.88$, $p = 0.061$, respectively), with subjects under the control condition having the higher rank-sum in both cases.

- Lastly, in contrast with the aggregate results, I do not find evidence of statistically significant differences between the underlying distribution of the CRRA curvature parameter for the subjects under the control condition and subjects under any of treatment and interaction conditions. This is not surprising since, as expected, individuals with less interior solutions have less utility function curvature.[34]

V. Conclusion

In summary, hunger and cognitive fatigue increase monetary impatience and affect time preferences. However, the results suggest that they affect time preferences through different mechanisms, which can help explain the conflicting results from the interaction condition.

On one hand, the hunger effect seems to be concentrated in the present bias parameter (β) and is driven by disproportionately exacerbating impatience on immediate versus non-immediate monetary rewards. In other words, hunger increases monetary impatience and the effect is larger when earlier rewards are immediate. This effect is statistically significant and consistent independent of the approach and/or aggregation level. Furthermore, this is consistent with the initial proposition that hunger may affect economic decisions because it is associated with activation of brain areas that are disproportionately activated when immediate rewards are available. However, more work needs to be done to understand the exact relationship between hunger, brain activity and economic decision-making.

On the other hand, the cognitive-fatigue effect seems to be concentrated on the utility curvature parameter (α) and is driven by an increase in all-earlier token allocations and overall corner solutions. Nevertheless, this effect seems to be only marginally statistically significant at the aggregate level and fades when looking at individual level parameters. The effect that cognitive fatigue has on time preferences may be caused by a decrease in individuals' attention, who then look to simplify choices by following heuristics or rules-of-thumb such as all-earlier or all-later allocations. However, these results are not conclusive and more is needed to test this and alternative hypotheses. Perhaps a better

[34]Tables D1 to D4 of Appendix D provide the parameter estimates for each individual. It is worth noting that for some individuals with only corner solutions the CRRA utility curvature parameter ($\hat{\alpha}$)is estimated bellow 0.999. When plotting the demand for tokens for each of these individuals one can see that those with $\hat{\alpha}$ <0.999 seem to display a certain level of choice inconsistency. This suggests that some issues may arise when using CTB to test cognitive-state level effects on time preferences.

approach to study the effects of cognitive fatigue on decision making would be to test for utility maximization consistency a la Choi et al. (2014). In fact, Castillo, Dickinson and Petrie (2014) use this methodology to study the effect of sleepiness on risk preferences.

Finally, this study contributes to the field of behavioral economics by proving that present bias is a visceral response. These results also open the door to a new research agenda that could help explain why the poor tend to make more short-sighted economic decisions. The goals of this research agenda should include exploring the relationship between hunger and risk preferences (e.g. risk/loss aversion, certainty effect) as well as hunger and social preferences (e.g. altruism, cooperation), addressed by Ashton and Nebout (2015) and Ashton (2015) respectively. Additionally, it is of interest to identify the mechanisms through which hunger and cognitive fatigue affect decisions. Particularly, mapping the link between hunger, brain activity, and economic decision-making.

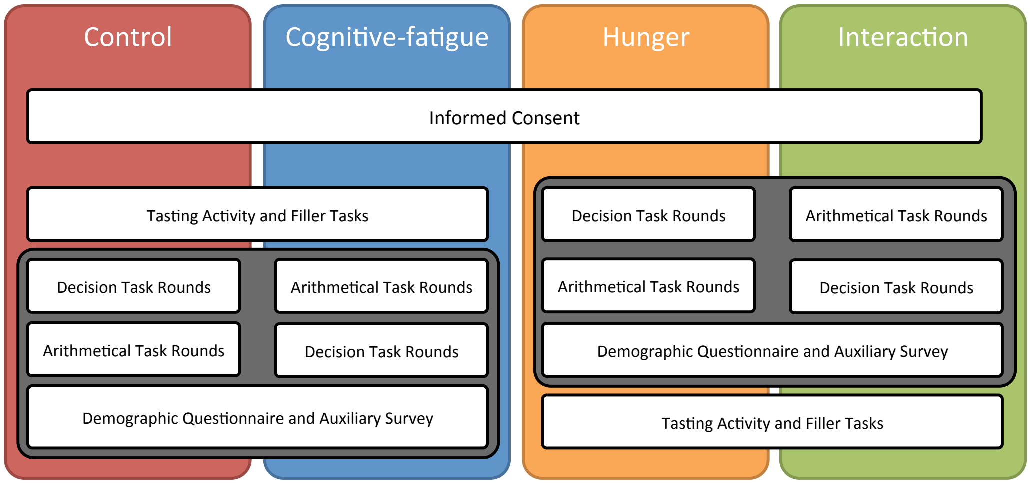

Figure 1. Experimental Design

Note: Computer-based experimental tasks (CETs) circled in gray.

Figure 2. Laboratory setup and presentation of “blind” drink for tasting activity

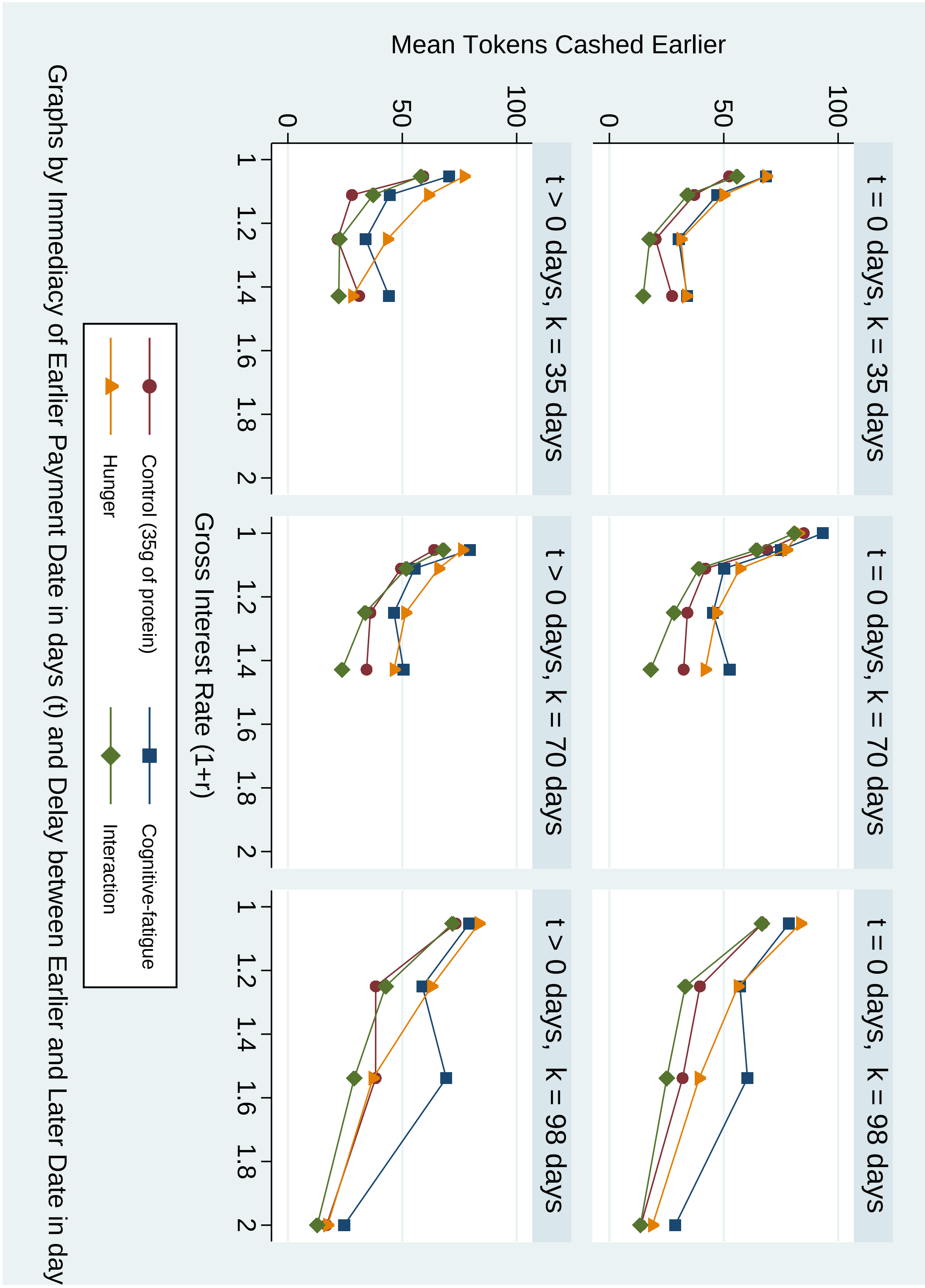

Figure 3. Mean Tokens Cashed Earlier by Gross Interest Rate

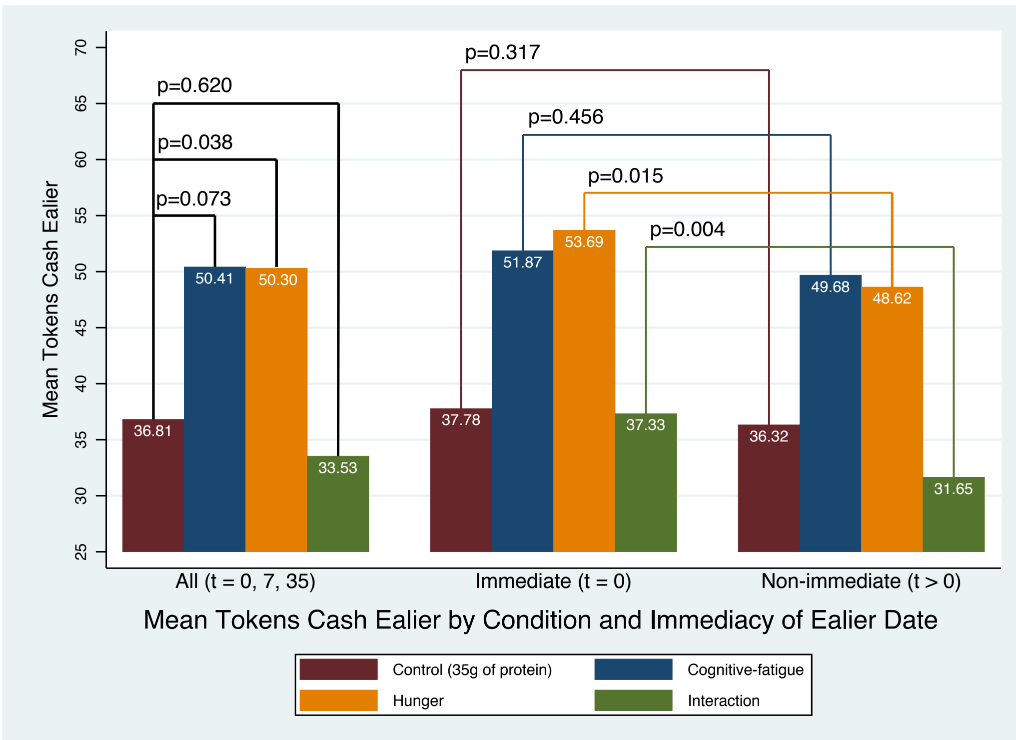

Figure 4. Mean Tokens Cashed Earlier

Notes: All budgets are constrained by 100 tokens (i.e. tokens cash earlier (or at t) + tokens cash later (or at $t+k$) = 100). Means are generated from regressions of the total number of tokens cashed earlier on condition status, with standard errors clustered at the individual level (see Table 4). The p-values for all choices correspond to the null hypotheses $H_0 : \mu_{\text{control}} = \mu_{\text{other}}$, where *other* refers to each of the non-control conditions. The p-values for immediate and non-immediate choices correspond to the null hypotheses $H_0 : \mu_{\text{t=0}} = \mu_{\text{t>0}}$ for each condition. In order to have a comparable set of choices across earlier date delay (t) and delay between earlier and later date (k), I only included the balanced combination of choice sets from Table 1 (i.e. $(1+r)$-choices with all nine (t, k)-combinations), however estimates do not significanly change if all choices are included.

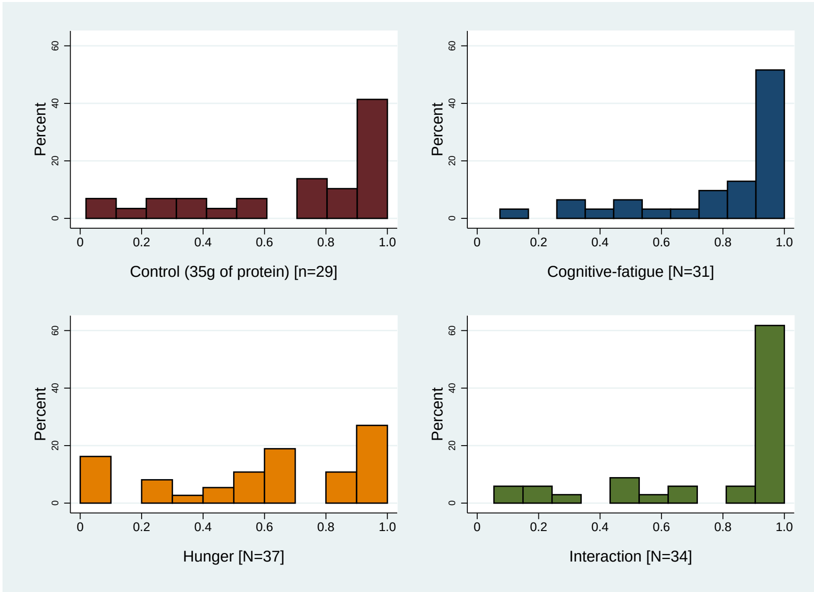

Figure 5. Percentage of Subjects by the Share of Corner Solutions Chosen

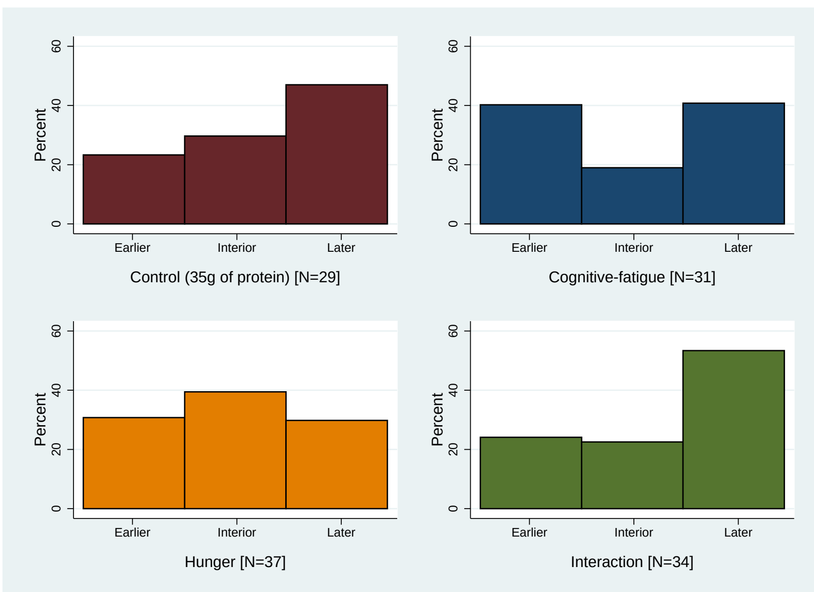

Figure 6. Percentage of Corner and Interior Solutions by Condition

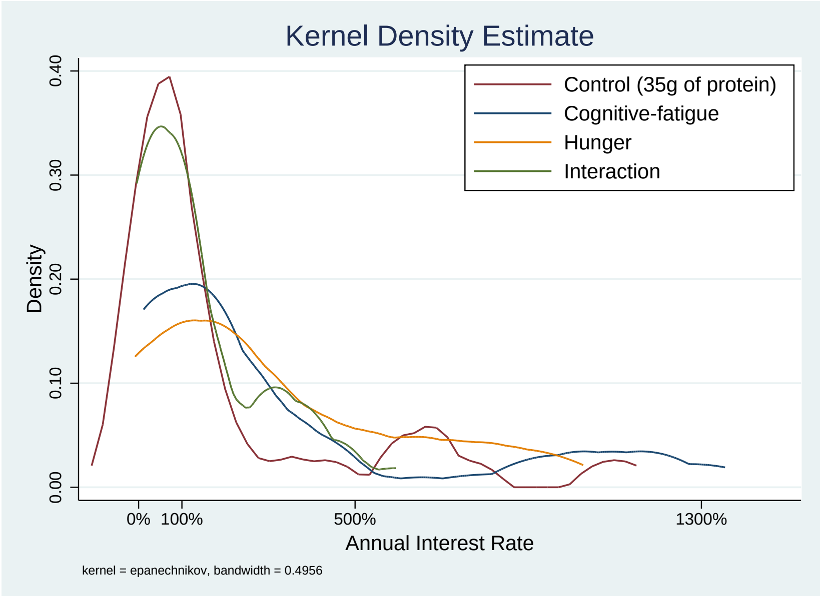

Figure 7. Kernel Density of Individual Annual Interest Rate Estimates

Note: Parameter trimmed at the 5th and 95th percentile.

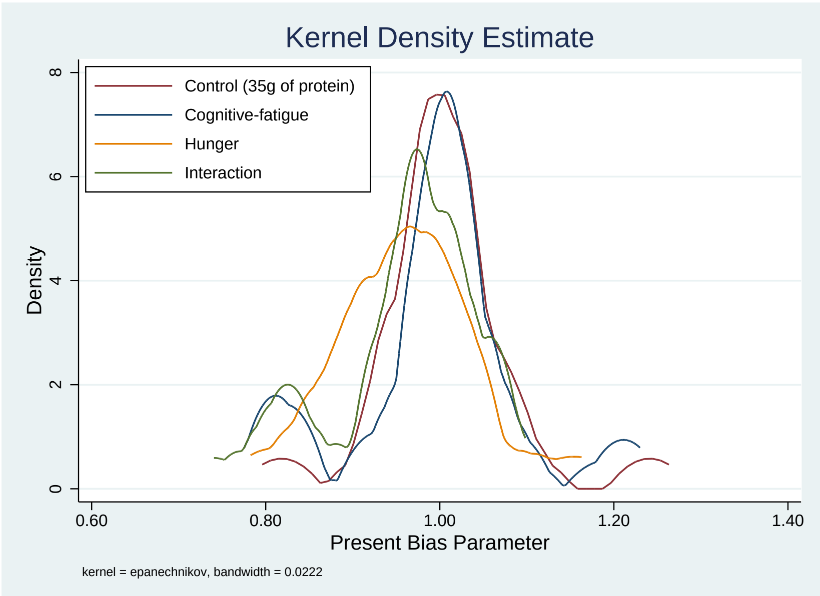

Figure 8. Kernel Density of Individual Present Bias Parameter Estimates

Note: Parameter trimmed at the 5th and 95th percentile.

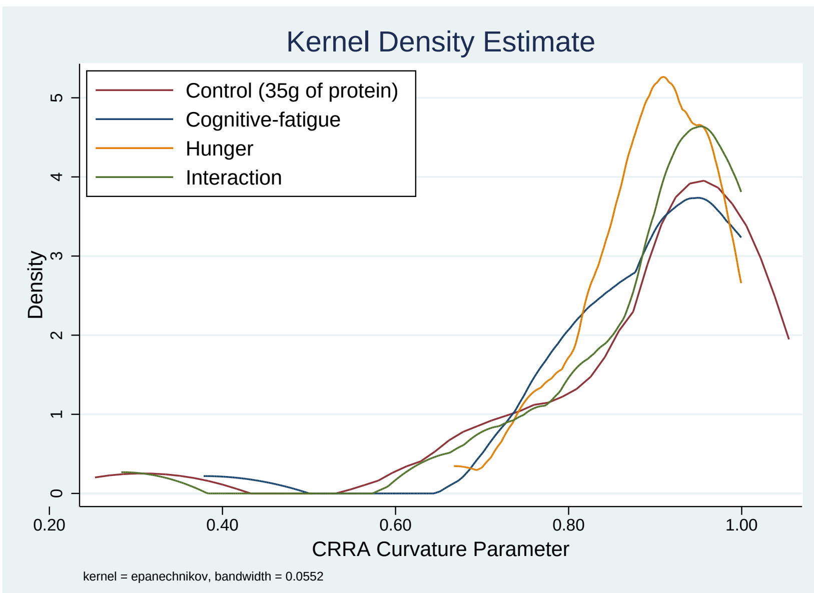

Figure 9. Kernel Density of Individual CRRA Curvature Parameter Estimates

Note: Parameter trimmed at the 5th and 95th percentile.

Table 1—Choice Sets

t	k	v_t	v_{t+k}	$(1+r)$	Annual Rate Range		
0, 7, 35	35, 70, 98	20	25	1.25	117.82	-	575.97
0, 7, 35	35, 70, 98	19	20	1.05	20.95	-	67.41
0, 7, 35	35, 70	18	20	1.11	69.64	-	172.90
0, 7, 35	35, 70, 98	16	20	1.25	117.82	-	575.97
0, 7, 35	35, 70	14	20	1.43	389.46	-	1460.69
0, 7, 35	98.00	13	20	1.54	305.83	-	305.83
0, 7, 35	35, 70, 98	12	15	1.25	117.82	-	575.97
0, 7, 35	98	10	20	2.00	698.04	-	698.04
7	70	20	20	1.00	0.00	-	0.00

Table 2—Summary Statistics (by compliers).

	Mean			t	p-value
VARIABLE	Compliers (1)	Non-compliers (2)	Difference (3)	(4)	(5)
Male	0.462	0.294	0.167	1.312	0.191
Age	20.650	19.647	1.003	1.281	0.202
BMI	22.353	21.803	0.550	0.508	0.613
ESL	0.462	0.412	0.050	0.387	0.699
College Year [1-5][a]	2.893	2.529	0.363	1.211	0.228
Registered to Vote	0.483	0.588	-0.106	-0.821	0.413
Bus/Econ/Psych Major	0.273	0.235	0.037	0.327	0.744
STEM Major	0.203	0.235	-0.032	-0.311	0.756
Work	0.308	0.412	-0.104	-0.867	0.387
Own a credit card	0.706	0.647	0.059	0.501	0.617
Smoke	0.042	0.059	-0.017	-0.319	0.750
All-nighter	0.622	0.588	0.034	0.272	0.786
Able to maintain desired weight	0.678	0.765	-0.086	-0.723	0.471
Exercise regularly	0.573	0.647	-0.074	-0.579	0.564
Do Not Trust [payment]	0.049	0.059	-0.010	-0.175	0.861
Special Need	0.154	0.118	0.036	0.393	0.695
Donation Frequency [0-4][b]	1.754	1.353	0.401	1.272	0.205
Gambling Frequency [0-4][c]	0.280	0.063	0.217	1.464	0.145
Numeracy Score [0-5]	4.510	4.647	-0.137	-0.707	0.481
IQ Score [0-2]	1.119	1.118	0.001	0.006	0.995
Hours since last meal	9.197	1.603	7.594	5.861	0.000
Hunger level *upon arrival* [0-10][de]	5.818	3.176	2.642	4.174	0.000
Hunger level *after CETs* [0-10][de]	5.664	2.941	2.723	3.936	0.000
Hunger level *after tasting* [0-10][df]	4.928	2.250	2.678	2.760	0.007
Av. Arithmetical Score [0-4]	2.533	2.541	-0.008	-0.026	0.979
Av. Time Decision [0-45]	10.076	10.639	-0.563	-0.481	0.631
Av. Time Arithmetical [0-45]	40.173	39.853	0.320	0.303	0.762
Compensation [USD]	25.164	23.347	1.817	0.989	0.324
N	143	17			

[a] Freshman = 1, Sophomore = 2, Junior = 3, Senior = 4, and Graduate = 5.
[b] Never = 0, Once a year = 1, Once a month = 2, Once a week = 3, and More than once a week = 4.
[c] Never = 0, One hour or at least $10 per year = 1, One hour or at least $10 per month = 2, One hour or at least $10 per week = 3, More than one hour or $10 per week = 4.
[d] Not At All = 0, and Extremely = 10.
[e] Rated during auxiliary survey.
[f] Only subjects completing tasting activity after CETs were asked to rate their hunger level during the filler tasks.

Table 3—Summary Statistics (by conditions).

VARIABLE	Control (1)	Cognitive-fatigue (2)	Hunger (3)	Interaction (4)	Low-dose (5)
Male	0.379	0.581	0.459	0.412	0.500
Age	20.966	21.516	20.378	19.882	20.667
BMI	22.711	20.981	23.368	22.341	22.092
ESL	0.586	0.226	0.486	0.471	0.667
College Year [1-5][a]	2.897	3.194	2.946	2.545	2.900
Registered to Vote	0.379	0.613	0.378	0.529	0.583
Bus/Econ/Psych Major	0.310	0.161	0.432	0.235	0.083
STEM Major	0.172	0.226	0.243	0.147	0.250
Work	0.310	0.290	0.270	0.412	0.167
Own a credit card	0.793	0.677	0.676	0.676	0.750
Smoke	0.000	0.000	0.108	0.059	0.000
All-nighter	0.586	0.677	0.595	0.676	0.500
Able to maintain desired weight	0.621	0.839	0.703	0.559	0.667
Exercise regularly	0.483	0.645	0.703	0.529	0.333
Do Not Trust [payment]	0.069	0.032	0.081	0.029	0.000
Special Need	0.172	0.097	0.189	0.147	0.167
Donation Frequency [0-4][b]	1.414	1.839	1.919	1.636	2.167
Gambling Frequency [0-4][c]	0.276	0.161	0.297	0.324	0.417
Numeracy Score [0-5]	4.483	4.516	4.622	4.471	4.333
IQ Score [0-2]	1.103	1.065	1.162	1.118	1.167
Hours since last meal	10.205	8.326	9.358	8.851	9.150
Hunger level *upon arrival* [0-10][de]	5.931	5.839	5.324	6.265	5.750
Hunger level *after CETs* [0-10][de]	4.310	4.839	6.703	7.000	4.083
Hunger level *after tasting* [0-10][df]			5.278	4.545	
Av. Arithmetical Score [0-4]	2.659	2.442	2.735	2.438	2.108
Av. Time Decision [0-45]	10.224	9.029	10.646	10.664	8.999
Av. Time Arithmetical [0-45]	40.134	41.081	38.714	40.553	41.342
Experimental [USD]	25.524	25.209	27.029	23.220	23.938
N	29	31	37	34	12

[a] Freshman = 1, Sophomore = 2, Junior = 3, Senior = 4, and Graduate = 5.
[b] Never = 0, Once a year = 1, Once a month = 2, Once a week = 3, and More than once a week = 4.
[c] Never = 0, One hour or at least $10 per year = 1, One hour or at least $10 per month = 2, One hour or at least $10 per week = 3, More than one hour or $10 per week = 4.
[d] Not At All = 0, and Extremely = 10.
[e] Rated during auxiliary survey.
[f] Only subjects completing tasting activity after CETs were asked to rate their hunger level during the filler tasks.

Table 4—Mean Tokens Cashed Earlier by Condition and Immediacy of Earlier Date

Earlier Date	CONDITION		Tokens Cashed Earlier: Mean (1)	Tokens Cashed Earlier: Robust-SE (2)	$H_0 : \mu_{\mathrm{C}} = \mu_{\mathrm{O}=\{\mathrm{F,H,I}\}}$: F-statistic (3)	$H_0 : \mu_{\mathrm{C}} = \mu_{\mathrm{O}=\{\mathrm{F,H,I}\}}$: p-value (4)
All ($t = 0, 7, 35$)	C:	Control (35g of protein)	36.811	5.057	.	.
	F:	Cognitive-fatigue	50.413	5.560	3.27	0.073
	H:	Hunger	50.305	3.956	4.42	0.038
	I:	Interaction	33.533	4.241	0.25	0.620
		Observations	6934			
		R-squared	0.50			
		Clusters	131			
Immediate ($t = 0$)	C:	Control (35g of protein)	37.781	5.176	.	.
	F:	Cognitive-fatigue	51.869	5.940	3.20	0.076
	H:	Hunger	53.687	4.296	5.60	0.020
	I:	Interaction	37.329	4.971	0.00	0.950
		Observations	2310			
		R-squared	0.52			
		Clusters	131			
Non-immediate ($t > 0$)	C:	Control (35g of protein)	36.323	5.064	.	
	F:	Cognitive-fatigue	49.682	5.609	3.12	0.080
	H:	Hunger	48.621	3.904	3.67	0.058
	I:	Interaction	31.650	3.972	0.53	0.469
		Observations	4624			
		R-squared	0.50			
		Clusters	131			

Notes: Robust standard errors clustered at the individual level. Estimates are inmune to demographic control (e.g. gender, age), survey controls (e.g. order), time-of-the-day fixed effects, and/or date fixed effects.

Table 5—Corner Effects

	Share of Corner Solutions	
VARIABLES	Patient (1)	Impatient (2)
Cognitive-fatigue Effect	0.169**	-0.062
	(0.069)	(0.089)
Hunger Effect	0.074	-0.190**
	(0.061)	(0.078)
Interaction Effect	0.007	0.032
	(0.059)	(0.082)
Constant: Control (35g of protein)	0.233***	0.470***
	(0.046)	(0.064)
Observations	7064	7064
R-squared	0.02	0.03

Notes: Robust standard errors, in parenthesis, clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1.

Table 6—Aggregate Parameter Estimates by Condition

		Aggregate		H_0 : $\text{Parameter}_{\text{C}}$=$\text{Parameter}_{\text{O}=\{\text{F,H,I}\}}$	
CONDITION		Parameter (1)	Robust-SE (2)	F-statistic (3)	p-value (4)
Annual discount rate					
C:	Control (35g of protein)	0.730	0.229	.	.
F:	Cognitive-fatigue	1.646	0.589	2.10	0.147
H:	Hunger	1.480	0.338	3.37	0.067
I:	Interaction	0.607	0.164	0.19	0.661
Present bias: $\hat{\beta}$					
C:	Control (35g of protein)	1.001	0.011	.	.
F:	Cognitive-fatigue	0.993	0.025	0.09	0.769
H:	Hunger	$0.952^{\dagger\dagger\dagger}$	0.014	7.23	0.007
I:	Interaction	$0.974^{\dagger\dagger}$	0.011	2.95	0.086
CRRA curvature: $\hat{\alpha}$					
C.	Control (35g of protein)	$0.867^{\ddagger\ddagger\ddagger}$	0.021	.	.
F.	Cognitive-fatigue	$0.806^{\ddagger\ddagger\ddagger}$	0.024	3.71	0.054
H.	Hunger	$0.844^{\ddagger\ddagger\ddagger}$	0.017	0.72	0.397
I.	Interaction	$0.891^{\ddagger\ddagger\ddagger}$	0.013	0.96	0.327
	Observations	7064			
	R-squared	0.59			
	Clusters	131			

Notes: Robust standard errors clustered at the individual level. ††† p<0.01, †† p<0.05, † p<0.1 for null hypothesis of no present bias (i.e. $H_0 : \beta = 1$). ‡‡‡ p<0.01, ‡‡ p<0.05, ‡ p<0.1 for null hypothesis of linear utility (i.e. $H_0 : \alpha = 1$).

Table 7—Individual Parameter Estimates by Condition

CONDITION		N	Median	5th Percentile	95th Percentile	Max	Min
Annual discount rate							
C:	Control (35g of protein)	26	0.800	0.112	7.501	-0.589	11.005
F.	Cognitive-fatigue	26	1.315	0.116	11.953	0.114	13.547
H:	Hunger	32	1.803	-0.057	8.697	-0.083	10.27
I:	Interaction	28	0.728	0.117	4.081	-0.044	5.946
Present bias: $\hat{\beta}$							
C:	Control (35g of protein)	26	1.001	0.915	1.106	0.818	1.241
F.	Cognitive-fatigue	27	1.001	0.816	1.192	0.775	1.23
H:	Hunger	33	0.959	0.795	1.145	0.783	1.163
I:	Interaction	26	0.980	0.801	1.063	0.741	1.098
CRRA curvature: $\hat{\alpha}$							
C:	Control (35g of protein)	24	0.941	0.658	0.999	0.308	0.999
F.	Cognitive-fatigue	28	0.930	0.766	0.999	0.378	0.999
H:	Hunger	32	0.905	0.762	0.999	0.667	0.999
I:	Interaction	28	0.943	0.673	0.999	0.283	0.999

Notes: Due to lack of choice variation, it was not possible to estimate parameters for 3 subjects under the control condition, 2 subjects under the cognitive-fatigue condition, and 2 subjects under the interaction condition (in total 7 out of the 131 subjects under all four main conditions). Parameter estimates for some subjects result in extreme outliers due to the limited number of observations per subject, therefore parameters were trim at the 5th and 95th percentiles loosing 12 more observations for each parameter.

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APPENDICES FOR ONLINE PUBLICATION

A. Server-based Application

Consent Form

My name is Lydia Ashton; I am a graduate student researcher in the Agricultural and Resource Economics department. My advisor is Professor Sofia Villas-Boas in the Department of Agricultural and Resource Economics. I would like to invite you to take part in my study, which examines how people make decisions and will be conducted at the Experimental Social Science Lab (aka Xlab) at the University of California at Berkeley. at the University of California at Berkeley.

If you agree to take part, you will be asked to complete some questionnaires. The total time expected for completion of these activities should be about 60 to 90 minutes.. During the study, we may ask you to complete different tasks (e.g. arithmetical problems, economic decisions, food/drink tasting activity). We will also ask you to answer a survey with some demographic questions.

There are no direct benefits to you from this research. It is our hope that the research will benefit the scientific community and lead to a greater understanding of how individuals make decisions. There is little risk to you from taking part in this research. As with all research, there is a chance that confidentiality could be compromised; however, we are taking precautions to minimize this risk.

Your study data will be handled as confidentially as possible. The data will be stored in a password-protected computer in a secured location. Each person will have his/her own (anonymous) code number. Your name and other identifying information about you will not be used in the research. The information collected for payment and administrative purposes (name, student id, e-mail) will be kept in a separate password-protected location and the records linking your personal information to your code number will be destroyed after all payments are processed.

We will save data, using the anonymous code number, for use in future research done by others or myself but this data will not be linked to your personal information.

The total compensation you will receive will vary, depending on your experimental decisions/responses. The average compensation will be approximately $15/hr with a minimum of $10. We will send your compensation by Paypal today and/or in a future date (this will be determined by your responses through the survey). Although you may refuse to answer some question(s), you will not receive payment if you do not complete the study.

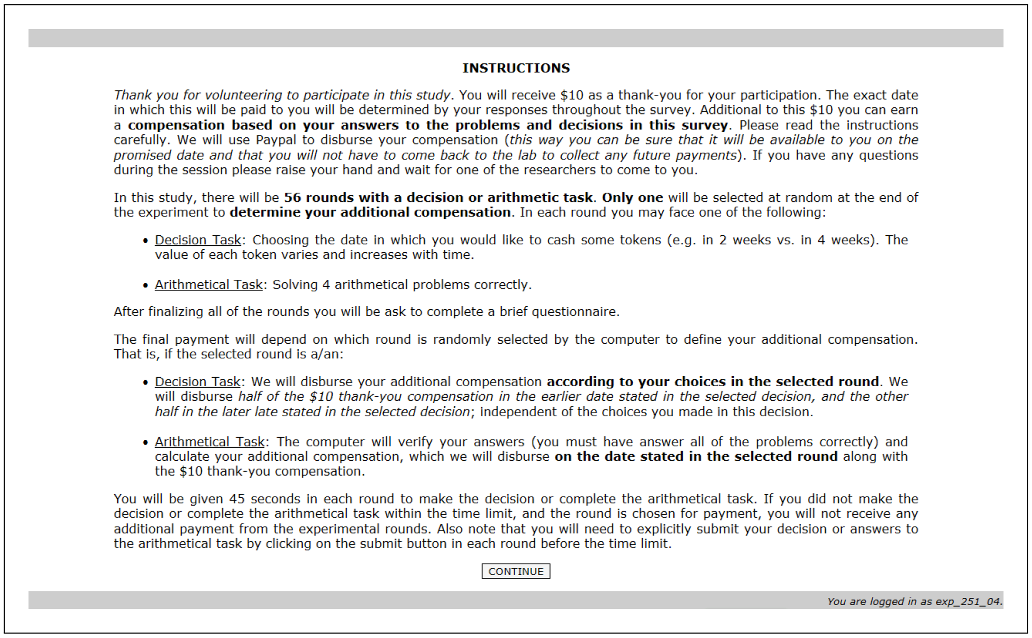
Please understand that your participation in this study is completely voluntary. You are free to decline to take part in the project. You can decline to answer any questions and are free to stop taking part in the project at any time. Whether or not you choose to participate in the research and whether or not you choose to answer a question or continue participating in the project, there will be no penalty to you or loss of benefits to which you are otherwise entitled.

If you have any questions about the research, you may telephone me at (510) 394-XXXX or contact me by e-mail at lydia.ashton@berkeley.edu. You may also contact my advisor, Sofia Villas-Boas at (510) 643-XXXX/sberto@berkeley.edu.

If you have any question regarding your treatment or rights as a participant in this research project, please contact the University of California at Berkeley's, Committee for Protection of Human Subjects at (510) 642-XXXX, subjects@berkeley.edu.

If you agree to participate, please check the box below.

[] I certify that I am 18 years old or older, I have read the consent form, I do not have any food allergies or sensitivities, and I have not been diagnose with diabetes or hyperglycemia, and agree to take part in this research.



INSTRUCTIONS

Thank you for volunteering to participate in this study. You will receive $10 as a thank-you for your participation. The exact date in which this will be paid to you will be determined by your responses throughout the survey. Additional to this $10 you can earn a **compensation based on your answers to the problems and decisions in this survey**. Please read the instructions carefully. We will use Paypal to disburse your compensation (*this way you can be sure that it will be available to you on the promised date and that you will not have to come back to the lab to collect any future payments*). If you have any questions during the session please raise your hand and wait for one of the researchers to come to you.

In this study, there will be **56 rounds with a decision or arithmetic task**. **Only one** will be selected at random at the end of the experiment to **determine your additional compensation**. In each round you may face one of the following:

- Decision Task: Choosing the date in which you would like to cash some tokens (e.g. in 2 weeks vs. in 4 weeks). The value of each token varies and increases with time.
- Arithmetical Task: Solving 4 arithmetical problems correctly.

After finalizing all of the rounds you will be ask to complete a brief questionnaire.

The final payment will depend on which round is randomly selected by the computer to define your additional compensation. That is, if the selected round is a/an:

- Decision Task: We will disburse your additional compensation **according to your choices in the selected round**. We will disburse *half of the $10 thank-you compensation in the earlier date stated in the selected decision, and the other half in the later late stated in the selected decision*; independent of the choices you made in this decision.
- Arithmetical Task: The computer will verify your answers (you must have answer all of the problems correctly) and calculate your additional compensation, which we will disburse **on the date stated in the selected round** along with the $10 thank-you compensation.

You will be given 45 seconds in each round to make the decision or complete the arithmetical task. If you did not make the decision or complete the arithmetical task within the time limit, and the round is chosen for payment, you will not receive any additional payment from the experimental rounds. Also note that you will need to explicitly submit your decision or answers to the arithmetical task by clicking on the submit button in each round before the time limit.

CONTINUE

You are logged in as exp_251_04.

Figure A1. Screenshot of Instructions

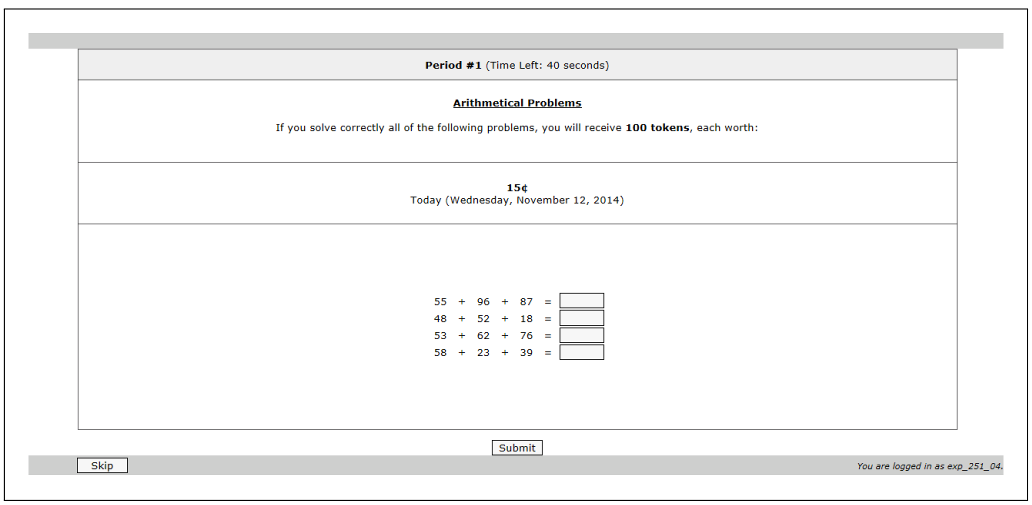


Figure A2. Screenshot of Arithmetical Round

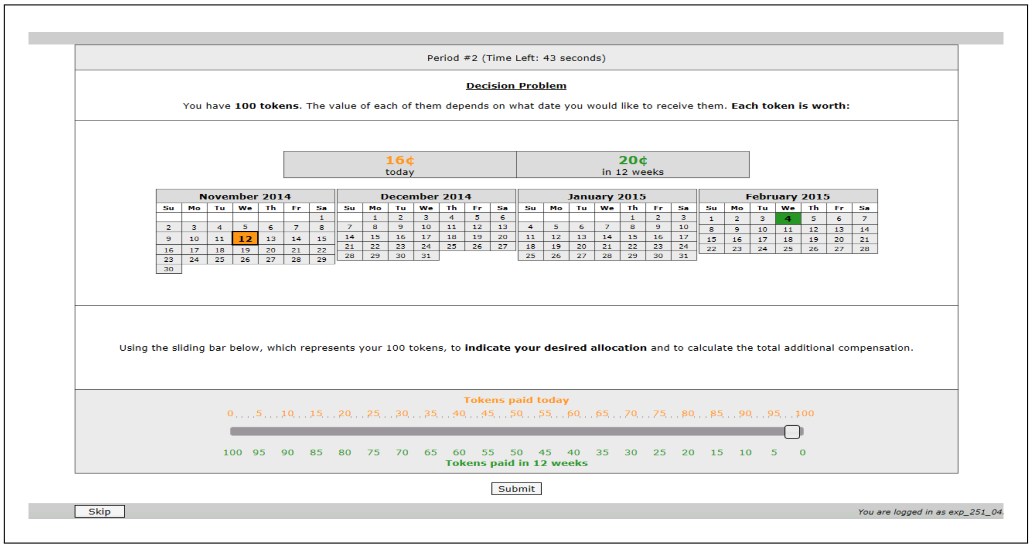


Figure A3. Screenshot of Decision Round (before decision)

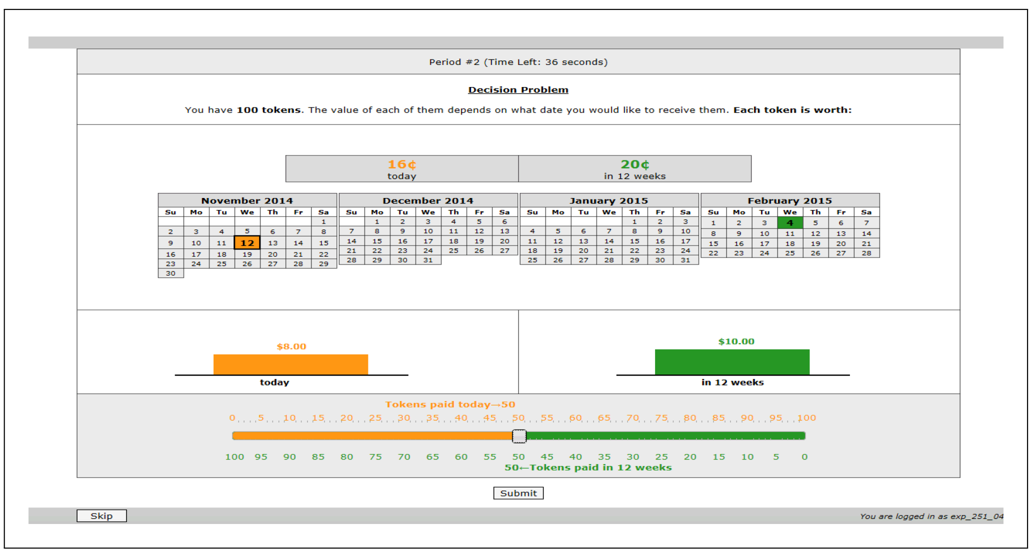


Figure A4. Screenshot of Decision Round (during/after decision)

Tasting Activity

Please read this instructions carefully. You will have about 15 minutes to:

1. Go to the table on the left side of the lab (behind the partition), take one of the bottles on the table and **drink all** of its contents as quickly as possible.

2. After you have finished the drink, **hand the empty container to the researcher** . The researcher will then hand a paper survey and a pen to you.

3. Come back to your desk and **complete the paper survey.**

4. After the time runs out click 'submit' to continue to the next task

Please note that if you finish the paper survey before the time runs you will have to wait to be able to click 'submit'.

Submit

You are logged in as exp_251_04.

Figure A5. Screenshot of Tasting Activity Instructions

Congratulations! You have completed the experiment. Thank you for your participation.

The round selected for payoff: 4.

You had 100 tokens to allocate between two dates at which you wish to receive the tokens.

Each token allocated to be received on Wednesday, December 10, 2014, is worth 20¢ while each token allocated to be received on Wednesday, December 24, 2014, is worth 25¢

You have chosen to allocate 0 tokens to be received on Wednesday, December 10, 2014 and 100 to be received on Wednesday, December 24, 2014.

Thus, you will receive additional $0 on Wednesday, December 10, 2014 and $25 on Wednesday, December 24, 2014.

Together with your participation fees, your total earnings from this session: $35 ($5 on Wednesday, December 10, 2014 and $30 on Wednesday, December 24, 2014).

Please kindly provide the following details:

Name:

Email (we will use this email to send your compensation via Paypal):

Student ID:

Submit

You are logged in as exp_251_04.

Figure A6. Screenshot of First Experimental Earnings Report

Again, thank you for your participation, and your total payment is $35 ($5 on Wednesday, December 10, 2014 and $30 on Wednesday, December 24, 2014).

You are logged in as exp_251_04.

Figure A7. Screenshot of Last Experimental Earnings Report

B. Robustness Checks

In this appendix, I present a summarized version of extensive methodology used byAndreoni and Sprenger (2012) to etimate the aggregate-level parameters and present the corresponding estimates.

In CTB, subjects choose a combination of c_t and c_{t+k} continously along the convex budget set

$$(1+r)c_t + c_{t+k} = m, \tag{B1}$$

where c_t and c_{t+k} represent the experimental earnings at an earlier and a later date, respectively. The experimental earnings are determined by choosing how many tokens of a total allocation of 100 tokens, they want *cash* on an earlier and/or a later payment date. The value of each token depends on which date the token is cash, and tokens cash on later dates generally have larger values. The choice sets used in the present study were chosen to resemble those used by Andreoni and Sprenger (2012), nevertheless the application design allows for better control of order effects and anchoring effects, since it presents each choice set as an independent round and facilitates the randomization of the order of all choices for each subject and well as randomly resetting the default allocation point for each round.[35]

First, a time separable CRRA utility function with (β-δ)-parameters is used,

$$U(c_t, c_{t+k}) = \frac{1}{\alpha}(c_t - \gamma_1)^\alpha + \beta(c_{t+k} - \gamma_2)^\alpha, \tag{B2}$$

where δ is the discount factor; β is the present bias parameter; c_t and c_{t+k} represent the experimental earnings at t and $t+k$, respectively; α is the CRRA curvature parameter; and γ_1 and γ_2 represent the Stone-Geary background consumption parameters. This form captures the present-biased time preferences, when $\beta < 1$; but can also be reduced to exponential discounting, when $\beta = 1$. Maximizing Equation B2 subject to the future value Equation B1 yields to the tangency condition

$$\frac{c_t - \gamma_1}{c_{t+k} - \gamma_2} = \begin{cases} (\beta\delta^k(1+r))^{\left(\frac{1}{\alpha-1}\right)} & \text{if } t = 0 \\ (\delta^k(1+r))^{\left(\frac{1}{\alpha-1}\right)} & \text{if } t > 0 \end{cases}, \tag{B3}$$

[35] Figure A4 and Figure A3 provide a screenshot of the decision rounds before and after a choice is made.

and the intertemporal formulation of a Stone-Geary linear demand for c_t,
(B4)

$$c_t = \begin{cases} \left[\dfrac{\gamma_1}{1+(1+r)(\beta\delta^k(1+r))^{\left(\frac{1}{\alpha-1}\right)}}\right] + \left[\dfrac{((m-\gamma_2)\beta\delta^k(1+r))^{\left(\frac{1}{\alpha-1}\right)}}{1+(1+r)(\beta\delta^k(1+r))^{\left(\frac{1}{\alpha-1}\right)}}\right] & \text{if } t=0 \\ \left[\dfrac{\gamma_1}{1+(1+r)(\delta^k(1+r))^{\left(\frac{1}{\alpha-1}\right)}}\right] + \left[\dfrac{((m-\gamma_2)\delta^k(1+r))^{\left(\frac{1}{\alpha-1}\right)}}{1+(1+r)(\delta^k(1+r))^{\left(\frac{1}{\alpha-1}\right)}}\right] & \text{if } t>0 \end{cases}.$$

An alternate functional form for utility is used to check the robustness of the results, constant absolute risk aversion (CARA). When restricting $\gamma_1 = \gamma_2$ the background parameters are dropped in the exponential form. Therefore, the marginal condition can be written as

$$\exp(-\rho(c_t - c_{t+k})) = \begin{cases} \beta\delta^k(1+r) & \text{if } t=0 \\ \delta^k(1+r) & \text{if } t>0 \end{cases}, \tag{B5}$$

where ρ represents the coefficient of absolute risk aversion in the utility formulation $u(c_t) =$ -exp$(-\rho c_t)$. This can be reduce to the tangency condition

$$c_t - c_{t+k} = \frac{\ln\,\beta}{-\rho}\cdot \mathbb{1}_{t=0} + \frac{\ln\,\delta}{-\rho}\cdot k + \frac{1}{-\rho}\cdot \ln(1+r), \tag{B6}$$

and rearrange to the solution function

$$c_t = \big(\frac{\ln\beta}{-rho}\big)\cdot\frac{\mathbb{1}_{t=0}}{-\rho} \tag{B7}$$

Table B1 presents the joint estimates for the annual discount rate, $(1-\delta)^{365}-1$; the present bias parameter, $\hat{\beta}$; the CRRA or CARA utility function curvature, $\hat{\alpha}$ or $\hat{\rho}$ respectively; and the Stone-Geary background consumption parameter(s) estimated or used, $\hat{\gamma_1}$ and $\hat{\gamma_2}$.[36][37]

[36] This table mirrors Andreoni and Sprenger (2012)'s Table 2.

[37] I use condition indicators on each of the time preference parameters (discount rate, present bias, and utility function curvature) to generate the joint estimates, i.e. I multiply each parameter of interest (by an indicator variable for each condition.

Table B1—Aggregate Parameters Estimates by Condition

CONDITION	NLS (1)	NLS (2)	NLS (3)	Tobit (4)	NLS (5)	Tobit (6)	Tobit (7)	Tobit (8)
Annual discount rate								
Control	0.525	0.735	0.730	0.832	0.710	0.804	0.784	0.805
	(0.168)	(0.206)	(0.229)	(0.447)	(0.318)	(0.419)	(0.411)	(0.350)
Cognitive-fatigue	1.034	1.485	1.646	2.589	1.818	2.468	2.390	2.164
	(0.305)	(0.503)	(0.589)	(1.102)	(0.646)	(1.016)	(0.979)	(0.865)
Hunger	1.045	1.387	1.480	2.215	1.629	2.091	2.047	1.904
	(0.222)	(0.302)	(0.338)	(0.535)	(0.370)	(0.493)	(0.483)	(0.442)
Interaction	0.435	0.608	0.607	0.716	0.543	0.674	0.659	0.684
	(0.135)	(0.165)	(0.164)	(0.290)	(0.231)	(0.278)	(0.274)	(0.234)
Present bias: $\hat{\beta}$								
Control	1.001	0.999	1.001	1.015	1.013	1.015	1.015	1.009
	(0.004)	(0.010)	(0.011)	(0.020)	(0.015)	(0.019)	(0.019)	(0.016)
Cognitive-fatigue	0.998	0.990	0.993	0.996	0.997	0.996	0.997	0.994
	(0.006)	(0.022)	(0.025)	(0.040)	(0.027)	(0.037)	(0.037)	(0.033)
Hunger	0.989	0.949	0.952	0.956	0.956	0.956	0.956	0.955
	(0.004)	(0.014)	(0.015)	(0.020)	(0.015)	(0.019)	(0.019)	(0.017)
Interaction	0.994	0.974	0.974	0.974	0.980	0.975	0.976	0.974
	(0.004)	(0.010)	(0.011)	(0.017)	(0.015)	(0.017)	(0.017)	(0.014)
CRRA/CARA curvature: $\hat{\alpha}/\hat{\rho}$								
Control	0.925	0.932	0.867	0.978	0.562	0.839	0.008	0.007
	(0.013)	(0.012)	(0.021)	(0.005)	(0.050)	(0.032)	(0.002)	(0.001)
Cognitive-fatigue	0.881	0.888	0.806	0.976	0.499	0.825	0.009	0.008
	(0.022)	(0.019)	(0.024)	(0.004)	(0.051)	(0.028)	(0.001)	(0.001)
Hunger	0.892	0.911	0.845	0.979	0.582	0.847	0.008	0.007
	(0.016)	(0.015)	(0.017)	(0.004)	(0.034)	(0.024)	(0.001)	(0.001)
Interaction	0.932	0.941	0.891	0.984	0.614	0.879	0.006	0.005
	(0.012)	(0.010)	(0.013)	(0.003)	(0.033)	(0.021)	(0.001)	(0.001)
$\hat{\gamma}_1$ or $\hat{\gamma}_1 = \hat{\gamma}_2$	2.8453	2.846	0	-0.01	-11.13	-11.13	—	—
	(0.323)	(0.332)	—	—	—	—	—	—
$\hat{\gamma}_2$	0.496							
	(1.108)							
R^2/LL	0.59	0.59	0.59	-12477.4	0.58	-8410.4	-14272.0	-12649.6
N	7064	7064	7064	7064	7064	7064	7064	7064
Uncensored	-	-	-	1981	-	1981	1981	1981
Clusters	131	131	131	131	131	131	131	131

Notes: Standard errors, clustered at the individual level and calculated via the delta method, in parenthesis. Annual discount rate calculated as $(\frac{1}{\delta})^{365}$. (1) Unrestricted CRRA regression of Equation B4. (2) CRRA regression of Equation B3 with restriction $\gamma_1 = \gamma_2$. (3)-(4) CRRA regression of Equation B4 and B3, respectively, with restriction $(\frac{1}{\delta})^{365} = 0$. (5)-(6) CRRA regression of Equation B4 and B3, respectively, with restriction $(\frac{1}{\delta})^{365} = -11.13$ (the negative of the average reported daily food expenditures*). (7)-(8) CARA regression of equation B7 and B6, respectively. *The sample reported a significanly higher average daily spending ($31.21) than Andreoni and Sprenger (2012)'s sample, who noted that the CRRA curvature parameter was very sensitive increasing values of γ.

C. Low-dose Condition Subjects and Non-compliers

Given the hypothesis that less protein would results in higher levels of hunger, it is not surprising to find that subjects under the low-dose condition (23g of protein) cash slightly more tokens earlier (Table C1) than subjects under the control condition (Table 4), however the difference is not statistically significant. Similarly, the present bias parameter for subjects under the low-dose condition is imprecisely estimated below 1 (Table C2). Also, as shown in Section III, the only difference between compliers and non-compliers is that non-compliers report lower levels of hunger. Therefore, one would expect non-compliers without cognitive fatigue to behave similar to compliers under the control condition, and non-compliers with cognitive fatigue to behave similar to compliers under the cognitive-fatigue condition. In fact, if we compare the results presented in Table C1 and Table 6 against the results presented in Table 4 and Table C2, respectively, we can see that this is true in both cases.

Table C1—Mean Tokens Cashed Earlier by Condition and Immediacy of Earlier Payment Date

			Tokens Cashed Earlier	
Earlier Payment	CONDITION		Mean (1)	Robust-SE (2)
All ($t = 0, 7, 35$)	L:	Low-dose (23g of protein)	38.886	8.146
	NC:	Non-compliers (without cognitive-fatigue)	32.419	8.863
	NF:	Non-compliers (with cognitive-fatigue)	51.804	7.163
		Observations	1549	
		R-squared	0.49	
		Clusters	29	
Immediate ($t = 0$)	L:	Low-protein Control (23g)	39.373	6.995
	NC:	Non-compliers (without cognitive-fatigue)	32.810	9.220
	NF:	Non-compliers (with cognitive-fatigue)	50.331	8.445
		Observations	515	
		R-squared	0.48	
		Clusters	29	
Non-immediate ($t > 0$)	L:	Low-dose (23g of protein)	38.645	8.844
	NC:	Non-compliers (without cognitive-fatigue)	32.223	8.754
	NF:	Non-compliers (with cognitive-fatigue)	52.540	6.637
		Observations	1034	
		R-squared	0.49	
		Clusters	29	

Notes: Robust standard errors clustered at the individual level. Estimates are immune to demographic control (e.g. gender, age), survey controls (e.g. order), time-of-the-day fixed effects, and/or date fixed effects.

Table C2—Estimates and Treatment Effects on Aggregate Parameter Estimates

CONDITION		Parameter: Coefficient (1)	Parameter: Robust-SE (2)
Annual discount rate			
L:	Low-dose (23g of protein)	0.907	0.386
NF:	Non-compliers (with cognitive-fatigue)	1.984	0.753
NC:	Non-compliers (without cognitive-fatigue)	0.515	0.329
Present bias: $\hat{\beta}$			
L:	Low-dose (23g of protein)	0.984	0.018
NF:	Non-compliers (with cognitive-fatigue)	1.025	0.043
NC:	Non-compliers (without cognitive-fatigue)	1.025	0.012
CRRA curvature: $\hat{\alpha}$			
L:	Low-dose (23g of protein)	0.892	0.022
NF:	Non-compliers (with cognitive-fatigue)	0.797	0.053
NC:	Non-compliers (without cognitive-fatigue)	0.862	0.032
	Observations	1578	
	R-squared	0.57	
	Clusters	29	

Notes: Robust standard errors clustered at the individual level.

D. Individual Parameter Estimates

Table D1—Individual Parameter Estimates

Condition	Subject ID	Annual Rate	$\hat{\beta}$	$\hat{\alpha}$	Proportion of Responses: Interior	Zero Earlier	All Earlier
Control	153		.000	-27.041	.000	.000	1.000
	145	1.816	.970	.949	.000	1.000	.000
	61	.378	.970	.955	.000	.836	.164
	130	.117	1.001	.999	.000	.982	.018
	158	.707	.999	1.000	.000	.836	.164
	15	11.005	1.045	.826	.018	.200	.782
	94	.118	1.001	.999	.018	.964	.018
	123	1.524	1.030	.963	.055	.545	.400
	70	.982	.966	.969	.073	.545	.382
	67	6.355	1.007	.901	.109	.255	.636
	46	.119	1.018	.998	.109	.873	.018
	22	.113	1.000	.999	.109	.873	.018
	27	.313	1.012	.999	.127	.764	.109
	21	.117	1.016	.999	.145	.818	.036
	37	.280	.950	.935	.218	.655	.127
	119	1.004	.944	.946	.236	.473	.291
	122	.878	.915	.915	.273	.400	.327
	56	1.705	.963	.934	.273	.364	.364
	48	.723	1.000	1.000	.273	.600	.127
	45	7.501	.818	.701	.436	.091	.473
	92	1.145	.942	.967	.491	.273	.236
	126	2.813	.994	.870	.564	.164	.273
	141	.553	1.063	.855	.600	.364	.036
	9	.521	1.009	.996	.618	.327	.055
	75	6.312	1.106	.760	.691	.055	.255
	97	4.275	1.241	.658	.727	.091	.182
	117				.873	.000	.127
	42	1.350	1.060	.758	.964	.018	.018
	18	-.589	1.079	.308	.982	.018	.000

Table D2—Individual Parameter Estimates

Condition	Subject ID	Annual Rate	$\hat{\beta}$	$\hat{\alpha}$	Proportion of Responses: Interior	Zero Earlier	All Earlier
Cognitive-fatigue	31		.000	-27.041	.000	.000	1.000
	80	10.455	1.230	.870	.000	.273	.727
	60	1.137	1.019	.952	.000	.636	.364
	105	1.948	.816	.961	.000	.382	.618
	41	.444	.975	.977	.000	.782	.218
	132	.707	.733	.999	.000	.582	.418
	125	.117	1.001	.999	.000	.982	.018
	129	.116	1.001	.999	.000	.982	.018
	131	.117	1.001	.999	.000	.982	.018
	147	.119	1.001	.999	.000	.982	.018
	23		.000	-21.535	.018	.000	.982
	66	.306	.987	.999	.018	.818	.164
	86	.904	1.001	.824	.055	.545	.400
	12	8.335	.824	.850	.073	.164	.764
	13	.120	1.001	.999	.073	.909	.018
	8	.886	1.005	.970	.091	.691	.218
	152	59.594	.997	.773	.109	.091	.800
	68	1.177	1.053	.860	.145	.418	.436
	107	1.186	1.075	.985	.164	.509	.327
	51	11.953	1.192	.860	.200	.127	.673
	40	1.445	1.019	.937	.218	.473	.309
	73	10.421	1.024	.992	.218	.109	.673
	63	1.814	.972	.910	.273	.327	.400
	28	3.135	1.093	.800	.345	.291	.364
	47	4.745	1.038	.924	.382	.091	.527
	156	13.547	.925	.808	.491	.036	.473
	146	17.817	.934	.896	.545	.000	.455
	95	1480.669	.002	-.966	.582	.000	.418
	77	2.835	.775	.794	.727	.000	.273
	137	3.372	.831	.766	.745	.164	.091
	6	3.184	1.042	.378	.927	.036	.036

Table D3—Individual Parameter Estimates

Condition	Subject ID	Annual Rate	$\hat{\beta}$	$\hat{\alpha}$	Proportion of Responses: Interior	Zero Earlier	All Earlier
Hunger	108	$2.180e^{11}$	7.096	.762	.000	.073	.927
	65	8.697	.559	.790	.000	.182	.818
	157	1.076	.996	.984	.000	.745	.255
	134	.117	1.001	.999	.000	.982	.018
	139	.117	1.001	.999	.000	.982	.018
	32	7.799	1.163	.873	.036	.236	.727
	50	.723	1.004	1.000	.036	.782	.182
	121	1.107	.876	.941	.055	.564	.382
	144	1.816	.970	.949	.055	.400	.545
	120	2.190	.783	.999	.055	.400	.545
	49	1.059	.882	.953	.127	.527	.345
	96	5.717	.935	.880	.145	.200	.655
	69	3.133	.971	.970	.182	.255	.564
	76	.856	.995	.961	.218	.636	.145
	104	3.041	.955	.860	.309	.200	.491
	30	-.083	.940	.880	.309	.582	.109
	36	5.000	.898	.917	.327	.127	.545
	58	.922	1.003	.931	.364	.400	.236
	114	4.227	.905	.945	.364	.127	.509
	109	8.514	.903	.902	.382	.000	.618
	1	.523	1.061	.928	.382	.582	.036
	34	-.631	.658	.667	.455	.436	.109
	43	1.789	.906	.919	.473	.200	.327
	33	1.464	1.012	.961	.491	.309	.200
	62	2.517	.959	.871	.509	.164	.327
	90	4.179	1.007	.848	.545	.127	.327
	52	7.543	.927	.768	.582	.000	.418
	20	.217	.944	.836	.691	.291	.018
	111	3.454	.795	.778	.727	.073	.200
	127	6.194	.878	.860	.764	.018	.218
	39	1.354	1.052	.876	.782	.036	.182
	142	2153.365	.852	-.041	.909	.000	.091
	59	-.057	1.032	.908	.927	.073	.000
	29	10.270	1.001	.147	.945	.018	.036
	11	1.011	.950	.875	.964	.036	.000
	102	-.930	1.145	-4.268	.982	.018	.000
	159	-.992	1.252	.048	1.000	.000	.000

Table D4—Individual Parameter Estimates

					Proportion of Responses		
Condition	Subject ID	Annual Rate	$\hat{\beta}$	$\hat{\alpha}$	Interior	Zero Earlier	All Earlier
Interaction	25	.670	.952	.965	.000	.673	.327
	84	.226	1.037	.982	.000	.836	.164
	83	2.192	1.000	.999	.000	.400	.600
	113	.116	1.001	.999	.000	.982	.018
	136	-1.000	2.190	.820	.018	.982	.000
	74	.298	.994	.951	.018	.855	.127
	78	1.101	.945	.963	.018	.600	.382
	99	1.114	.948	.979	.018	.600	.382
	160	.187	.987	1.000	.018	.945	.036
	87	.199	.986	1.000	.018	.945	.036
	148	5.946	.737	.873	.036	.200	.764
	116	3.043	.824	.945	.036	.273	.691
	128	-1.000	14.549	.283	.055	.945	.000
	14	4.081	.821	.929	.055	.218	.727
	154	.675	.906	.954	.055	.564	.382
	26	.885	.943	.970	.055	.600	.345
	3	.214	.977	.999	.073	.873	.055
	57				.073	.745	.182
	54	.732	1.054	.966	.091	.764	.145
	2	.128	.974	.975	.091	.873	.036
	124	2.208	1.001	1.000	.127	.436	.436
	79	2.981	1.063	.889	.145	.327	.527
	53	-.044	1.916	.973	.145	.855	.000
	151	3.919	.741	.836	.327	.145	.527
	72	.724	1.098	1.000	.345	.527	.127
	138	.788	.983	.922	.436	.418	.145
	88	-.755	1.373	.690	.509	.491	.000
	101	.447	1.041	.942	.527	.345	.127
	81	1.015	.801	.762	.564	.218	.218
	143	2.140	.941	.880	.709	.091	.200
	85	3.724	1.047	.779	.855	.000	.145
	93	.554	.855	.848	.855	.018	.127
	106	.356	1.004	.673	.891	.091	.018
	110	14.148	.706	-.668	.945	.000	.055

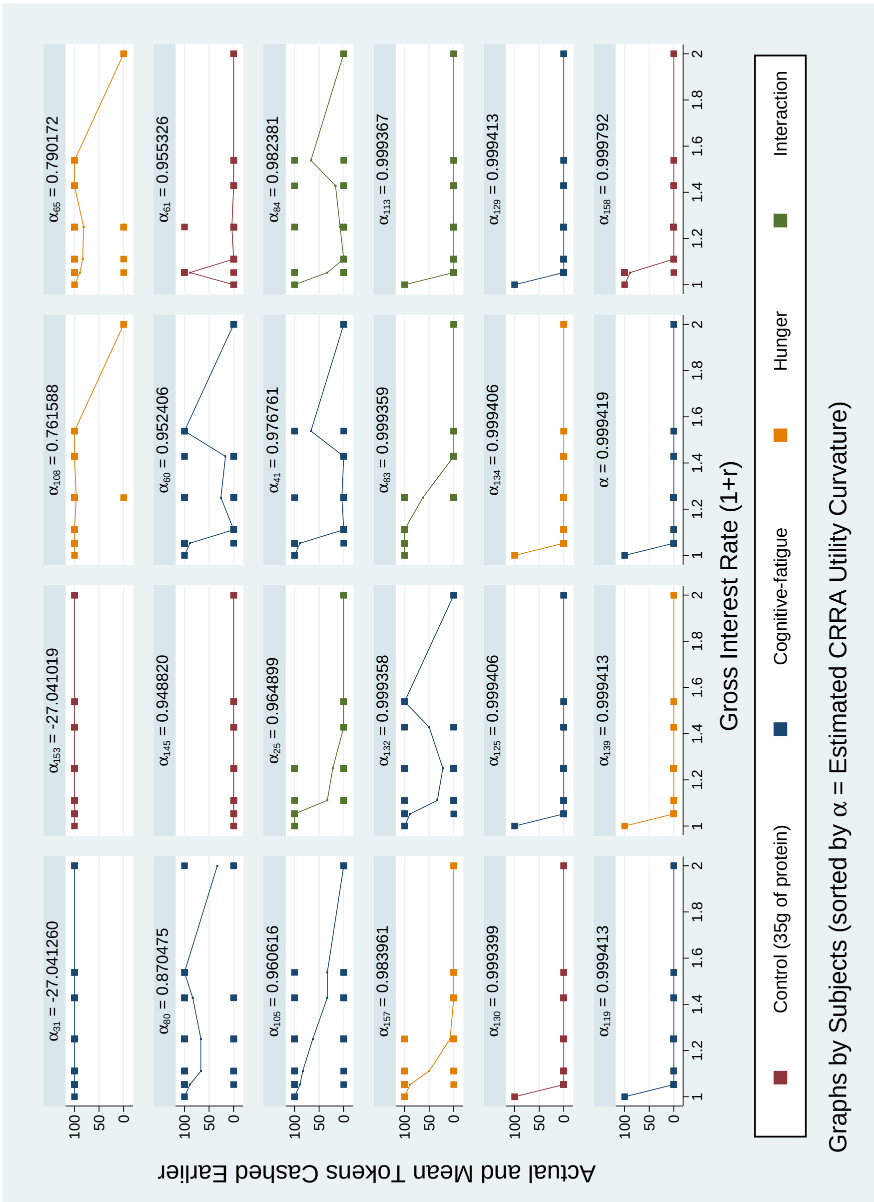


Figure D1. Actual and MEan Tokens Cashed Earlier by Subjects without Interior Solutions