The Effect of Cognitive Biases and Visceral Factors on Economics Decisions

by

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Abstract

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This work presents new evidence of effects that cognitive biases and visceral factors, particularly hunger, have on economic decisions. In Chapter 1, I test whether individuals display inattention to the decimal digits of a price (i.e. left-digit bias). Using data from a unique experiment conducted by Chetty et al. (2009), who find that tax-salience decreases demand, I find that if tax-salience shifts the price left-most digit upwards the decrease in demand is larger. This study presents new evidence on left-digit bias and also suggests that this is the main channel through which tax salience affects consumers' decisions. In Chapter 2, I motivate a new research agenda by drawing parallel evidence from psychology, economics, and neuroscience, and posing the question: does cognitive-fatigue and hunger affect time preferences? Using data from a novel laboratory experiment, I find that hunger and cognitive-fatigue exacerbate impatience. On one hand, cognitive-fatigue appears to decrease attention and increase the use of heuristics, resulting on a higher degree of utility curvature. On the other hand, hunger has a larger effect on impatience when monetary rewards are immediate, resulting in present-biased preferences. These results show that present bias is a visceral response activated when sooner rewards are immediate, and can help explain why the poor tend to make more shortsighted economic decisions.

To the village.

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It takes a village... but I only had one page!

Chapter 1

Left-digit Bias and Inattention in Retail Purchases: Evidence from a Field Experiment

1.1 Introduction

If you were to visit your favorite coffee shop and realize that the price for one cup of coffee has increased from \$3.20 to \$3.60 (call this scenario A), would you still buy that one cup of coffee? Now imagine that the price of that same cup of coffee had increased from an initial \$2.80 to \$3.15 (call this scenario B), would you still buy that same cup of coffee? While the proportional increase in price in each scenario is always the same, 12.5%, some people would answer yes to the first question and no to the latter. This is an example of left-digit bias and inattention that affects agents' economic decisions.

In scenario A, the price leftmost-digit does not change, while in scenario B the price leftmost-digit increases by one unit. If economic agents limit their attention to the leftmost-digit, they would perceive a price increase under scenario B, but not under scenario A. Given that attention is a scarce resource, it is understandable to find situations as previously described, where individuals may based their decisions on a limited amount of the "available" information (DellaVigna, 2009) or solve complex problems using heuristics (Gabaix and Laibson, 2006).

In the past decade economists have shown an increased interest in the implications of inattention on consumers' behavior.[1] Hossain and Morgan (2006) use a set of field experiments on eBay auctions to show that consumers' behavior is sensitive to the way prices are framed. Brown et al. (2010) later combine those field experiments with a natural experiment to show that "shrouded" shipping charges may lead to higher revenue for sellers. Malmendier

[1]Significant amount of evidence has shown that salience and cognitive costs play an important role in consumers' decisions in markets such as: credit cards (Ausubel, 1991) and retirement investments (Hastings and Tejeda-Ashton, 2008). See DellaVigna (2009) for a review of the literature.

and Lee (2011) use eBay data to compare prices paid in auctions with prices at which the same goods are available for immediate purchase (a.k.a."buy it now" prices) and find that, in 42% of the auctions, the final prices paid in auctions are higher than the "buy it now" prices. Chetty et al. (2009) use data from a field experiment on retail sales and observational data on alcohol sales to demonstrate that consumers under react to non-salient taxes. Also, Lacetera et al. (2012) analyze over 22 million wholesale used-car transactions and find that sale prices drop discontinuously as the odometer mileage on used cars crosses the 10,000-mile threshold.

The current literature has explored the effect of consumers inattention in "opaque" or "hard to find" components of the final price of a good (e.g. shipping charges, alternative fix prices and non-salient taxes). While some have tried to estimate the effects of inattention when the information is relevant and clearly visible, this has only been accomplished using quality metrics that we *expect* consumers to incorporate into their decision making process (e.g. odometer mileage on used cars). This study presents new evidence of inattention to prices, which are neither opaque nor hard to find.

In Section 1.2, I motivate the empirical analysis using an extension of the partial inattention framework, introduced by DellaVigna (2009), to partial inattention to digits to the right of the decimal point of the price. Lacetera et al. (2012) propose a similar approach to estimate the effect of inattention to odometer mileage in the used-car market. DellaVigna (2009) defines the value of a good, V (inclusive of price), as the sum of a visible component v and an opaque component o: $V = v + o$. Due to inattention, the perceived value of the same good is given by $\hat{V} = v + (1 - \theta)o$. The parameter θ denotes the degree of inattention, thus when $\theta = 0$ there is full attention to the opaque signal and $\hat{V} = V$ (i.e. for $\theta = 0$ this model reduces to the standard economic model). Following this framework, I define the price of a good as the sum of its dollar-value (or units to the left of the decimal point) and its cent-value (or units to the right of the decimal point). In terms of DellaVigna's framework, the dollar-value of the price can be seen as the v component of the perceived price and the cent-value of the price can be seen as the o component of the perceived price. Thus, the model assumes that the digits to the left of the decimal point receive full attention, while people may pay only partial attention to the digits to the right of the decimal point.

To test this hypothesis I use data from an experiment designed and used by Chetty et al. (2009), who show that posting tax inclusive prices cause demand to decrease by almost the same amount (about 7.6%) as a price increase of the same magnitude as the tax rate (7.375%). Under the assumption of consumers perceiving tax salience as a price increase (Chetty et al., 2009), I test whether the estimates of such an effect are significantly different between products whose digits to the left of the decimal point change versus those whose digits to the left of the decimal point do not change when posting tax inclusive prices, even though the tax rate is the same for all products. In the context of this study, I will refer to the first type of products as products with shifting dollar-value prices (SDV-prices) and second type of product as products with rigid dollar-value prices (RDV-prices).[2]

[2]From our initial example, scenario A is a case of a product with RDV-price and scenario B is a case of

This study differs from the “99-cent” marketing literature (Ginzberg, 1936; Schindler and Kibarian, 1996) since the unique experimental design does not restrict us from only considering one cent differences around the zero threshold of the price cent-value.

In Section 1.3, I discuss the details of the experiment and data. The experiment took place over a three-week period in early 2006 at a supermarket where, like in most retail stores in the United States, shelf prices exclude the sales tax which is only added at the register. To test if consumers incorporate sales taxes in purchasing decisions, the tax-inclusive price tags were displayed below the original pre-tax price tags (as shown in Figure 1.1). All products in 13 taxable categories were treated (e.g. deodorants and cosmetics). Weekly-product level scanner data was collected for the 13 treated categories and 96 other control categories, in treated store as well as two other control stores in nearby cities. This design allows me to use a difference-in-differences (DD) research design and verify the common trends conditions for the validity of the estimates by calculating difference-in-difference-in-differences (DDD).

The results are presented and discussed in Section 1.4. The results show that in treated categories products with SDV-prices seem to have a large and statistically significant decrease in sales (about 10.7%), while sales for products with RDV-prices have a small and statistically insignificant decrease in sales (about 2.44%).[3] When taking into account changes in sales for control categories (i.e. calculating DDD), I find that the decrease in sales for products with SDV-prices continues to be large (about 11.8%) and statistically significant and the decrease in sales for products with RDV-prices continues to be small and statistically insignificant (about 1.09%).[4] These results are robust when limiting the analysis to products with relatively small prices.[5] Also, when limiting the analysis to products whose pre-tax price is 20 cents below and above the unit threshold, I find that the point estimate for products with RDV-prices continues to be very small in magnitude and statistically insignificant (and increase of about 0.01%) and the point estimate for products with SDV-prices becomes larger in magnitude and more statistically significant (a decrease of about 17.68% in sales). Section 1.5, concludes and discusses the implications of the results and suggests ideas for future research.

1.2 Empirical Framework

As introduced by DellaVigna (2009), consider the value of a good, V (inclusive of price), as the sum of a visible component v and an opaque component o, $V = v + o$. Due to inattention,

a product with SDV-price.

[3]These estimates are obtained using the summary statistics shown in column 4 of Table 1.1 and the DD estimates shown in Row C of Table 1.2

[4]These estimates are obtained using the summary statistics shown in column 7 of Table 1.1 and the DD estimates shown in Row G of Table 1.2

[5]As shown in column 2 of Table 1.4, the DDD estimates show that products with SDV-prices have a statisticallt significant decrease in sales (about 10.94%) while sales for products with RDV-prices have an statistically insignificant decrease in sales (about 1.13%). Prices of most of the products sold are in average less than \$11 through the period of observation (about 86%).

the perceived value of the same good is given by $\hat{V} = v + (1-\theta)o$. The parameter $\theta \in [0,1]$ denotes the degree of inattention to the opaque component o. Thus, if $\theta = 0$ there is full attention, if $\theta = 1$ there is complete inattention, and if $\theta \in (0,1)$ there is patial attention to the opaque component o.

Following this framework, I can define the price of a good p, as the sum of its integer part (or dollar-value), $D \in Z$; and its fractional part (or cent-value), $C \in [0,1)$: $p = D + C$. In terms of DellaVigna's framework, the integer part of the price can be seen as the visible v component of the perceived price and the fractional part of the price can be seen as the opaque o component of the perceived price. Thus, the proposed framework assumes that the digits to the left of the decimal point receive full attention, while people may only pay partial attention to the digits to the right of the decimal point. Therefore, the perceived price $\hat{p}$ can be denoted as:

$$\hat{p} = D + (1-\theta)C \tag{1.1}$$

where θ is the inattention parameter as defined above.[6] If consumers display some level of inattention, $\theta = 0$, then there will be differences between the actual price of a good and the perceived price of a good that could lead to unexpected demand behavior. In other words, let $X((\,\cdot\,))$ denote the empirically observed demand. Under the proposed framework:

$$dX(p(D,C)) = \frac{\partial X}{\partial p}\Big(\frac{\partial p}{\partial D}dD + \frac{\partial p}{\partial C}dC\Big) = \frac{\partial X}{\partial p}(dD + dC) \tag{1.2}$$

$$dX(\hat{p}(D,C;\theta)) = \frac{\partial X}{\partial \hat{p}}\Big(\frac{\partial \hat{p}}{\partial D}dD + \frac{\partial \hat{p}}{\partial C}dC\Big) = \frac{\partial X}{\partial \hat{p}}(dD + (1-\theta)dC) \tag{1.3}$$

Equation 1.2 represents the change in demand given a change in price when there is full attention ($\theta = 0$) which is equivalent to the change in demand under the standard framework. Equation 1.3 represents the change in demand given a change in price when there is partial or complete inattention ($0 < \theta \leq 1$). Since the change in the cent-value of the price is being weighted by $(1-\theta)$ and $\theta \neq 0$, we would expect price increases that cause a change in D to have a larger impact on demand than price increases of the same (or larger) magnitude that only affect C. In other words, predictions of changes in demand would only be consistent with the standard model if and only if $\theta = 0$, and as a result $dX(p(D,C)) = dX(\hat{p}(D,C;\theta))$.

As noted by Lacetera et al. (2012), one may suggest that for larger prices a more appropriate specification of Equation 1.1 would be:

$$\hat{p} = \sum_{l=0}^{L}(1-\theta)^{L-l} + \sum_{r=-1}^{R}(1-\theta)^{L-r}d_r 10^r \tag{1.4}$$

where L is the base-10 power of the non-zero leftmost-digit of p; R is the base-10 power of the non-zero rightmost-digit of p; let $n \in \{l, r\}$ then d_n is the value of the digit in each base-10^n

[6] For example, consider a good whose price is \$7.79. From Equation 1.1, its price will be perceived as $\hat{p} = 7 + (1-\theta)\cdot 0.79$, where θ is the inattention parameter as defined above.

power, such that $d_n \in \{1, 2, \ldots, 9\}$ for $n = N$ and $d_n \in \{0, 1, \ldots, 9\}$ for all $n < |N|$; and θ is the inattention parameter as defined before, such that $\theta \in [0, 1]$. Note that Equation 1.4 considers the possibility of decreasing attention as we move towards digits further to the right, in both the integer and fractional part of the price.[7] Also, as the magnitude of the price increases, L, attention to the fractional part of the price practically disappears.

This study presents evidence that the innatention parameter consumers pay only partial attention to digits to the right of the decimal point (i.e. $\theta \leq 1$) by testing whether the effect of a perceived price increase of the same magnitude is different for products whose dollar-value increases, herein referred to as products with SDV-prices, versus products whose dollar-value does not change, herein referred to as products with RDV-prices.

1.3 Data[8]

Experiment

The experiment was conducted in a Northern California middle-income suburb store of a national grocery chain. The store floor space is about 42,000 sq. ft. and has weekly revenue of approximately \$300,000. About 30% of the products sold in the store are taxable. The local tax rate during the experimental period was 7.375%. This tax is only added to the total price at the register. Tax inclusive prices were posted on all the products, roughly 750, in 13 categories that occupied about half of the toiletries aisle (e.g. deodorants and cosmetics). The treated categories were selected based on the products within the categories fulfilling the following criteria: (1) not "sales leaders", given that the grocery chain managers were expecting the treatment to reduce sales; (2) relatively high prices, so that the sales tax would be nontrivial; and (3) high price elasticities, to obtain a detectable demand response to the intervention.

The intervention lasted three weeks, beginning in February 22, 2006 and ending on March 15, 2006. As shown in Figure 1.1, a tax-inclusive price tag was attached bellow the original pre-tax price tag, which was left untouched, for each of the products in the treated categories (roughly 750). According to store managers, prices are always changed on Wednesday nights and remain fixed for an entire week. This period is known as a *promotional week*. To synchronize with the store's promotional weeks, tags were printed and attached every Wednesday night during low-traffic times at the store, between 11:00 p.m. and 2:00 a.m.

[7] However, with regard to consumer prices, digits smaller than cent-units may be irrelevant since, as is common knowledge, this is the customary subunit used in retail prices and mill-units are only used for accounting purposes.

[8] Due to the nature of the data, some parts of this section are heavily borrowed from Chetty et al. (2009). See Chetty et al. (2009) for more details about the data and experimental design.

Empirical Strategy

I compute and compare the effect of the intervention on demand, using a difference-in-differences (DD) estimate approach, for products with SDV-prices and products with RDV-prices. I perform the DD analysis by comparing changes in the average weekly sales between the baseline and experimental period in the *treated categories* between the *treated store* and two *control stores*. The *treated categories* are considered to be the 13 categories that occupied about half of the toiletries aisle with taxable products and whose tags were modified. Prior to the experiment, two *control stores* were chosen to match the treatment store based on demographics and other characteristics using a minimum-distance criterion.[9] It is also possible to verify the common trend condition by computing the DD estimates for *control categories*. These categories should not have been affected by the treatment. The control categories are 96 categories in the same toiletries aisle as the *treated categories* with similar taxable products (e.g. toothpaste, skin care, and shaving products). Lastly, the DD estimates for treated and control categories can be used to compute difference-in-difference-in-differences (DDD) estimates.

As noted by Gruber (1994), this estimate should be immune to product-specific and store-specific shocks, as long as there are no shocks that affect the treated store during the experimental period. Given the exogenous nature of the experiment this condition is likely to be satisfied. Thus, this estimator could be considered a more precise measurement of the effect of the intervention.

Data Description[10]

The raw scanner data, which was provided by the grocery store chain, contains information on weekly quantity sold, gross revenue, and net revenue (i.e. gross revenue minus markdown amount) for each product sold in 109 "health and beauty" categories in the three stores from the first promotional week of 2005 to the fourteenth promotional week of 2006.[11] The variables are measured net of returns. In exclude 477 observations which are cases were more items were returned than purchased within a week; nevertheless, the results would not change if I include these observations.

The scanner data, by nature, reports only items that were actually sold each week. Thus, if a certain product was not sold during a promotional week I set the quantity sold for such products to be zero during that week and impute prices for unsold items before aggregating

[9] See Chetty et al. (2009) for a detailed description of store selection and summary statistics of store and city characteristics.

[10] The strategy for cleaning the data slightly differs from the one used by Chetty et al. (2009). Using their data and code I am able to fully reproduce their results. However, using a slightly different data cleaning strategy I am also able to reproduce their results up to the first decimal point.

[11] Each product is identified by a unique Universal Product Code (UPC). See Appendix Table 1 of Chetty et al. (2009) for a list of categories. The experimental period corresponds to the eighth, ninth and tenth promotional week of 2006 in grocery store terms.

the data to the category-week-store level.[12] For such unsold items, I use the price in its last observed transaction; if the product was not sold during the previous week, the price of the product during the following week is imputed; and lastly if neither alternative is possible the average price for that product at each store is used. I categorize each observation as: a) a product with SDV-price if the dollar-value of its pre-tax unitary price is smaller than the dollar-value of its tax-inclusive unitary price at the category-week-store level, and b) a product with RDV-price if the dollar-value of its pre-tax unitary price is the same as the dollar-value of its tax-inclusive unitary price at the category-week-store level. Finally, I aggregate to the category-week-store-SDV/RDV level and compute total sold quantity, gross and net revenue, average gross and net price for each category.

Summary Statistics

As shown in Table 1.1, products with SDV-prices in treated categories sold on average 11.84 units per week in all stores while products with SDV-prices in control categories sold on average 17.85 units per week in all stores. It is not surprising to find such differences since, as requested by store managers, the treated categories contain none or very little "sale leaders". The differences in sales between the treated and control categories are also similar between treated and control stores, about 6 units more. In contrast, products with RDV-prices in treated categories seem to have similar (or slightly greater) average weekly sales volume as product with RDV-prices in control categories (15.07 units and versus 12.86 units per week, respectively). Nevertheless, the differences in sales between the treated and control categories are also similar between treated and control stores, about 3 units less.

Chetty et al. (2009) show that based on observable characteristics, such as average weekly revenue and prices, the treatment and control product groups are very similar between treatment and control stores.[13] The validity of my research design depends on maintaining this overlap even after introducing a new level of aggregation—products with SDV-prices and products with RDV-prices—since this may be may be introducing noise into the experiment randomization (e.g. price levels could be highly correlated with whether products have SDV-prices or RDV-prices). In order to show that the counterfactuals continue to be valid even under the new level of aggregation I test the null hypothesis of equality of means between baseline and experimental periods, and between control and treated stores using some "observable characteristics"; such as: i) average total number of unique products sold, ii) average gross price, and iii) average net price (i.e. gross price - markdown).

Tables A.1 - A.4 in Appendix A present the p-values for the following four null hypotheses using two-tailed t-tests for each of the aforementioned observable characteristics at the week-store-category-SDV/RDV level: (1) mean observable characteristic is equal between treated and control stores during the baseline period for treated/control categories, (2) mean observ-

[12] According to store managers it is not uncommon to have very stable inventories through the calendar year.

[13] Table 2 of Chetty et al. (2009) presents category and product level summary statistics, broken down by treatment and control product groups within each store.

able characteristic is equal between treated and control stores during experimental period for treated/control categories, (3) mean observable characteristic is equal between baseline and experimental period at control stores for treated/control categories, and (4) mean observable characteristic is equal between baseline and experimental period at the treated store for treated/control categories.

The p-values, shown in Tables A.2 - A.4, suggest that null hypotheses (2)-(4) cannot be rejected at the 10 percent (or greater) confidence level for any of the observable characteristics, in treated and control stores for both product with SDV-prices and products with RDV-prices. On the other hand, Table A.1 shows that the null hypothesis (1) cannot be rejected for most (33 out of 36) panels at the 1 percent (or greater) confidence level. It is not surprising to find a few cases in which the null hypothesis can be rejected (e.g. mean gross price for products with SDV-prices in control categories) due to the greater price variation in baseline period, which expands for 60 promotional weeks more than the experimental period, and the larger number of control categories in the sample, which are about nine times more than the treated categories. The fact that the number of null hypotheses rejected is relatively low (3 out of 144 totals), suggest that the counterfactuals are valid even after introducing the new level of aggregation.

1.4 Results

Comparison of Means

Table 1.2 shows a cross-tabulation of mean quantity sold. Columns 1 to 3 report means for products with SDV-prices, and columns 4 to 5 report means for procuts with RDV-prices. The columns split the data by control stores (columns 1 and 4), treated store (column 2 and 5), and difference over stores (columns 3 and 6). The rows split the data by baseline period (rows A and D), experimental period (rows D and E), and difference over time (row G).[14] Mean quantity sold, standard deviation of the mean quantity sold, and the number of observations are shown in each cell.

Row C presents the difference over time, i.e. change in sales between the experimental and the baseline period, for treated categories by control and treated stores; as well as the *difference-in-difference* estimates for both products with SDV-prices (SDV-DD$_{TC}$) and products with RDV-prices (RDV-DD$_{TC}$), i.e. the difference of the difference in sales over time for treated categories between the treated and control stores. During the experimental period, the sales of products with SDV-prices in treated categories increased by an average of 1.45 and 0.18 units in the control and treated stores (columns 1 and 2), respectively. Thus, for products with SDV-prices in treated categories, sales fell in the treatment store relative to

[14] Chetty et al. (2009) exclude week 7 of 2006 from the analysis since during this period a pilot, requested by store managers, was conducted to ensure that tags could be placed without disrupting business. I have included this period since this virtually does not affect the results. Also, omitting the post-experimental period (week 11 to week 14 of 2006) from the sample does not affect the results either.

the control stores (column 3) by 1.27 units on average (SDV-DD_{TC} = -1.27), with a standard error of 0.70. Meanwhile, during the experimental period, sales of products with RDV-prices in treated categories decreased by an average of 1.07 and 1.43 units in the control and treated stores (columns 5 and 6), respectively. Therefore, for products with RDV-prices in treated categories, sales fell in the treatment store relative to the control store (column 6) by only 0.37 units on average (RDV-DD_{TC} = -0.37), with a standard error of 0.82. Using the base mean quantity sold in treated categories, shown in column 3 of Table 1.1, for products with SDV-prices and RDV-prices (11.84 and 15.07 units respectively) and the aforementioned difference-in-differences results from the comparison of means, I can estimate the change in demand for products with SDV and RDV-prices in treated categories to be -10.7% and -2.44%, respectively.

In order to consider the difference-in-difference estimates to be valid the common trend condition (i.e. sales would have evolved similarly in the absence of the treatment) must hold.[15] Therefore, by comparing the change in sales between treated and control stores in the control categories (i.e. categories with products were no tax-inclusive tags were posted) I can evaluate the validity of DD_{TC} estimates. Mirrowing the estimates for treated categories presented in row C, row F presents the difference over time; as well as the *difference-in-difference* estimates for both products with SDV-prices (SDV-DD_{CC}) and products with RDV-prices (RDV-DD_{CC}). Here, I find that sales in the treated store relative to the control stores for products with SDV-prices increased by 0.75 units (SDV-DD_{CC} = 0.75), with a standard error of 0.40; and for products with RDV-prices in control categories, sales in the treated store relative to the control stores decreased by 0.22 units (RDV-DD_{CC} = -0.22), with a standard error of 0.25. The fact that these results are not statistically significantly different from zero (i.e. sales for control categories where no tax-inclusive price tags were posted evolve similarly in treated and control stores), suggest that sales for treated categories at the treatment and control stores would have moved together in the absence of an intervention.

Now, using the DD_{TC} and DD_{CC} estimates I can construct a *triple-difference* estimator (DDD) immune to store-specific shocks and product-specific shocks, as discussed above. The triple difference estimates, which are constructed by differencing out within-store and within-product time trends (DDD=DD_{CC}-DD_{TC}), are presented in row G. I find that sales for products with SDV-prices fell by 2.02 units (SDV-DDD = -2.02), with a standard error of 0.98; and for products with RDV-prices sales fell by only 0.14 units (RDV-DDD = -0.14), with a standard error of 0.98. Using the aforementioned DDD point estimates and the base means of quantity sold for all categories in all stores, shown in column 7 of Table 1.1, for products with SDV-prices and RDV-prices (17.13 and 13.16 units respectively), I can conclude that, consistent with the DD point estimates, the demand for products with SDV-prices has a statistically significant decrease of 11.8%, which is significant at the 5 percent level; while the demand for products with RDV-prices only falls by 1.09%, and is statistically insignificant.

[15]See Meyer (1995).

Regression Results

It is possible to evaluate the robustness of the DDD estimates by estimating the following equation:

$$Y = \alpha + \sum_{d=SDV,RDV} [\tau_d(S \cdot T \cdot C) + \gamma_{1d}(S \cdot T) + \gamma_{2d}(S \cdot C) + \gamma_{3d}(T \cdot C) + \beta_{1d}(S) + \beta_{2d}(T) + \beta_{3d}(C)] + \varepsilon \tag{1.5}$$

where Y denotes quantity sold; d is an index over the dummy variables for each type of product (products with SDV-prices and products with RDV-prices); S is a treatment store dummy (indicator that equals 1 if the store was treated, 0 otherwise); T is a treatment time dummy (indicator that equals 1 if the experiment took place during that week, 0 otherwise); C is a treatment category dummy (indicator that equals 1 if the category was treated, 0 otherwise); $S \cdot T$ is the interaction of the treatment store and treatment time dummies; $S \cdot C$ is the interaction of the treatment store and treatment category dummies; $T \cdot C$ is the interaction of the treatment time and treatment category dummies; and X denotes a set of additional covariates (e.g. price). The coefficients of interest in the previous regression model are τ_{SDV}=SDV-DDD and τ_{RDV}=RDV-DDD.

Table 1.3 shows the regression results from estimating Equation 1.5. Each set of estimates are obtained using three different sample definitions to check for the robustness of the results. Also, in order to simplify the results, I present the DDD estimates and the base means quantity sold per category in all categories to compute demand changes in terms of percentage points, which are reported in the following paragraphs and shown in Table 1.4.

Column 1 of Table 1.3, as expected, when estimating Equation 1.5 for the full sample, τ is equal to the DDD estimates in the comparison of means.[16] Thus, column 1 of Table 1.4 shows that: demand for products with SDV-prices decreased by 11.8%, this result is statistically significant at the 5 percent level; and demand for products with RDV-prices decreased by 1.09%, this result is statistically insignificant. Column 2 of Table 1.3 shows that estimates are stable (in both magnitude and statistical significance) when limiting the sample to products whose price was less than or equal to $11 for at least one week-store-category observation during the entire period of observation. In column 2 of Table 1.4, I estimate that demand for products with SDV-prices decreased by 10.94%, this result is statistically significant at the 5 percent level; and demand for products with RDV-prices decreased by 1.13%, this result is statistically insignificant. Also, column 3 of Table 1.3 shows that when limiting the sample to products whose pre-tax cent-value falls within 20-cents below and above the cent-value zero-threshold, the estimated decrease in demand for products with SDV-prices becomes even greater in magnitude and more statistically significant. Column 3 of Table 1.4 shows that in this case demand for products with SDV-prices decreases by 17.68%, which is statistically significant at the 1 percent level, and the estimated decrease in demand for products with RDV-prices becomes even smaller in magnitude, 0.006%, and remains statistically insignificant.

[16]Standard errors are clustered at the category level.

Robustness checks

One may be concerned that price level may be highly correlated with how consumers respond to the tax-inclusive price posting and/or with the probability of items been priced such that they can be perceived by consumers as products with SDV-prices or RDV-prices. Thus, I estimate Equation 1.5 controlling for mean price and mean price squared in each category, and including category, store, and promotional week fixed effects. Column 4 of Table1.3 shows that the estimate for products with SDV-prices remains practically unchanged and that although the estimate for products with RDV-prices becomes more negative, it remains relatively small and not significantly different from zero. Column 4 of Table 1.4 shows that under such specification demand for products with SDV-prices decreases by 11.80%, significant at the 5 percent level; and demand for products with RDV-prices has a statistically insignificant decrease of 1.91%. These results are consistent with the previous estimates.[17]

1.5 Conclusion

This study presents new evidence on left-digit bias from a quasi-random experiment, which also suggests that this is the main channel through which tax salience affects consumers' decisions. Exploiting a unique experiment, and under certain assumptions (i.e. consumers perceive tax salience as a price increase), I am able to estimate and compare the effect of a perceived price increase of the same percentage magnitude on products whose dollar-value increases versus products whose dollar-value remains the same.

Using a difference-in-difference-in-differences analysis, I estimate that the effect of a "price increase" (i.e. posting tax-inclusive prices with a tax rate of 7.375%) on demand for products with SDV-prices is consistently statistically significant and ranges in between -10.94% and -17.68%, while the effect on demand for products with RDV-prices appears to be statistically insignificant and ranges only in between -0.01% and -1.09%. This suggests that there might be a substantial level of consumer inattention to digits to the right of the price (i.e. inattention to the cent-value in the price of a good) at least for relatively small prices (i.e. average prices less than $11). It is important to note that differences between the consumer's perceived price of a good and the actual price of a good (i.e. consumers' inattention to certain visible components of the price) may lead to unexpected demand behavior. Future research could be done using larger prices to generalize these results to a broader price spectrum and test for the possibility of decreasing attention to digits to the right. Also an experimental design where only products whose price cent-value is right around the zero-threshold could allow better control for unobservable product characteristics that might be correlated with pricing schemes. Lastly, a research design where demand elasticities could be obtained could allow us to structurally estimate the parameter of inattention to price right-digits, θ.

[17] Due to space constraints I have not included regression with controls for the subsamples in columns 2 and 3 of Table 1.3 but these estimates are also consistent with those obtained in the regressions without controls.

Source: Chetty et al. (2009)

Figure 1.1: Exhibit of tax-inclusive price tags.

Table 1.1: Summary Statistics by Category.

	Treated Categories			Control Categories			All Categories
	Control Store (1)	Treated Store (2)	All Stores (3)	Control Store (4)	Treated Store (5)	All Stores (6)	All Stores (7)
Products with SDV-prices							
Av. Qty.	12.36	10.78	11.84	18.5 0	16.54	17.85	17.13
	(10.98)	(9.18)	(10.44)	(28.11)	(23.37)	(26.65)	(25.33)
Total categories	13	13	13	96	96	96	109
Products with RDV-prices							
Av. Qty.	15.47	14.29	15.07	13.50	11.55	12.86	13.16
	(18.57)	(17.03)	(18.08)	(24.67)	(19.02)	(22.99)	(22.40)
Total categories	13	13	13	87	89	89	102

Notes: Standard deviations are reported in parentheses bellow the means.

Table 1.2: Comparison of Mean Quantity Sold.

	Products with SDV-prices			**Products with RDV-prices**		
Period	Control Store (1)	Treated Stores (2)	Difference over stores (3)	Control Store (4)	Treated Stores (5)	Difference over stores (6)
Treated Categories						
A. Baseline	12.297	10.769	-1.528	15.514	14.356	-1.158
(2005:1-2006:7&2006:11-2006:14)	(0.187)	(0.187)	(0.206)	(0.237)	(0.283)	(0.224)
	[1612]	[806]	[2418]	[1612]	[806]	[2418]
B. Experimental	13.744	10.949	-2.795	14.449	12.923	-1.526
(2006:8-2006:10)	(0.499)	(0.431)	(0.811)	(1.068)	(0.823)	(0.962)
	[78]	[39]	[117]	[78]	[39]	[117]
C. Difference over time	1.447	0.18	-1.267	-1.066	-1.433	-0.367
	(0.452)	(0.401)	(0.696)	(0.910)	(0.734)	(0.820)
	[1690]	[845]	[2535]	[1690]	[845]	[2535]
Control Categories						
D. Baseline	18.540	16.541	-2.000	13.458	11.513	-1.945
(2005:1-2006:7&2006:11-2006:14)	(0.170)	(0.151)	(0.137)	(0.151)	(0.137)	(0.130)
	[11842]	[5890]	[17732]	[10491]	[5134]	[15625]
E. Experimental	17.733	16.488	-1.245	14.427	12.258	-2.169
(2006:8-2006:10)	(0.494)	(0.707)	(0.467)	(0.510)	(0.573)	(0.269)
	[573]	[285]	[858]	[511]	[252]	[763]
F. Difference over time	-0.807	-0.053	0.754	0.969	0.745	-0.224
	(0.441)	(0.601)	(0.408)	(0.446)	(0.491)	(0.257)
	[12415]	[6175]	[18590]	[11002]	[5386]	[16388]
G. DDD Estimate			**2.021**			**0.143**
			(0.979)			**(0.984)**
			[21125]			**[18923]**

Notes: Standard deviations are reported in parentheses bellow the means. Number of observations are reported in square brackets bellow the standard errors. Statistics are computed using the full sample.

Table 1.3: Triple Differences

LHS: *Quantity per Category*	(1)	(2)	(3)	(4)
SDV-DDD	-2.021**	-1.767*	-2.153***	-2.021**
	(0.979)	(0.887)	(0.704)	(0.987)
RDV-DDD	-0.143	-0.148	-0.0002	-0.251
	(0.984)	(0.980)	(0.242)	(1.031)
Price				-2.106***
				(0.162)
Price Sq.				0.037***
				(0.003)
Week, Store and Category FEs				Yes
Constant	13.458***	13.452***	3.194***	22.838***
	(0.151)	(0.151)	(0.082)	(0.922)
Observations	40048	39073	35717	40048
R-squared	2	0.01	0.09	0.71
Ho[a]: SDV-DDD - RDV-DDD = 0	0.321	0.37	0.019	0.36

Notes: Robust standard errors in parentheses (clustered at the category level). (1) full sample; (2) only products whose price was less than or equal to $10 for at least one week-store-category observation during the entire period of observation; (3) only products whose pre-tax price falls within 20-cents below or above the cent-value zero-threshold; and (4) full sample with controls and fixed effects. [a] When testing the null hypothesis of equality between coefficients—one may call this a fourth difference—it is only possible to conclude that the DDD estimate for products with SDV-prices is statistically different from the DDD estimate for products with RDV-prices when limiting the sample to products whose pre-tax cent-value falls within 20-cents below and above the cent-value zero-threshold. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 1.4: Decreased in Demand (Triple Differences)

	(1)	(2)	(3)	(4)
Products with SDV-prices				
Av. Quantity sold	17.13	16.15	12.18	17.13
DDD	-2.021**	-1.767*	-2.153***	-2.021**
Change in Demand	-11.80%	-10.94%	-17.68%	-11.80%
Products with RDV-prices				
Av. Quantity sold	13.16	13.15	2.97	13.16
DDD	-0.143	-0.148	-0.0002	-0.251
Change in Demand	-1.09%	-1.13%	-0.01%	-1.91%

Notes: Quantity sold is the average of total items sold by categories all stores. DDD estimates are equal to from Equation 5. (1) full sample; (2) only products whose price was less than or equal to $10 for at least one week-store-category observation during the entire period of observation; (3) only products whose pre-tax price falls within 20-cents below or above the cent-value zero threshold; and (4) full sample with controls and fixed effects. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Chapter 2

Hunger Games: The Effect of Hunger and Cognitive Fatigue on Time Preferences

2.1 Introduction

Does hunger affect economic decisions? The idea that behavioral biases may be at least partially mediated by visceral factors is not new (DellaVigna, 2009). A number of studies have documented how,

> "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." (Loewenstein, 1996, p. 277)

Nevertheless, not much has been done to test whether visceral factors activate behavioral biases in general.[1] In other words, does increasing the intensity of a visceral factor also affect preferences towards goods not directly associated with that visceral factor?

This study extends on this notion by drawing parallel evidence from psychology, economics, and neuroscience and presenting evidence that hunger (a visceral factor) affects choices not directly associated with hunger and leads to present-biased preferences.

To date, only a single study has shed light into the question, *does hunger indirectly affect all economic decisions?* Danziger et al. (2011) find that the percentage of favorable parole decisions fluctuates in relation to the time in which judges take a food break. Nevertheless, because of their research design, they are unable to decouple whether it was hunger or cognitive fatigue that affected the judges' decision.

[1] For example, Loewenstein et al. (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.

In order to not only estimate the effect that hunger has on economic decisions but also to isolate it from any potential effects caused by cognitive fatigue, I conducted a controlled laboratory experiment that manipulated the state of hunger and cognitive fatigue of participants making intertemporal choices. These intertemporal choices were based on Andreoni and Sprenger (2012)'s 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 payment date given that whatever is cashed on the later payment 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 the effect they have on time preferences is driven by two different mechanisms. On one hand, hunger disproportionately increases monetary impatience when choices involve immediately available monetary rewards (i.e. the effect hunger has on time preferences is concentrated on the present bias parameter). On the other hand, cognitive fatigue seems to decrease attention and increase the use of heuristics-based choices, which reflects as a decrease in the individuals responsiveness to the cost of earlier rewards (i.e. the effect cognitive fatigue has in time preferences is concentrated on the utility curvature parameter). Interestingly, the interaction of both treatments leads to an increase on present bias and an increase on heuristic based choices, which combined with the experimental parameters used results in a relatively low discounting rate. 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, as suggested by Andreoni and Sprenger (2012). These results also open the door to a new research agenda tightly interconnected with the behavioral poverty trap literature since as we know the poor are more susceptible to food insecurity and as a result more likely to frequently experience hunger. As suggested by Banerjee and Mullainathan (2007, p. 2) "...people are present-biased because they are poor, but that in turn keeps them poor. In other words the impatience that the poor often show is as much a result of their poverty as it is a cause". Thus, hunger may be a factor that feeds into this vicious cycle. This provides important insights into 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).

The remainder of the chapter is organized as follows: Section 2.2 motivates the research question and describes the related literature. Section 2.3 details the experimental design. Section 2.4 provides summary statistics. Section 2.5 discusses the results. Section 2.6 concludes.

2.2 Motivation

Proposition 1 *Hunger affects individual attitudes and preferences that are not directly associated with hunger.*

To date, only a single study has shed light into the question: does hunger indirectly affect all economic decisions? This is the field study conducted by Danziger et al. (2011) who explore whether, as many lawyers have quipped for years, *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 a break. The authors use this as evidence 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*, which could be working through fatigue or hunger. Nevertheless, because of the research design (i.e. the purpose of a *food break* is to eat a meal) they are unable to identify whether it was hunger or cognitive fatigue that affected the judges' decision.

Proposition 2 *(a) Hunger/fasting is associated with increased activity in limbic areas of the brain. These areas are preferentially activated when individuals make decisions involving immediate monetary rewards. Therefore (b) hunger may disproportionately affect choices involving immediate monetary rewards—in comparison to choices involving non-immediate monetary rewards.*

In recent decades researchers have shown an increased interest in understanding how and which brain systems are associated with individual economic decisions (Camerer et al., 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 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).

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

[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 orbitofrontal cortex (OFC) to produce representations of the expected reward value, including monetary reward value (Rolls, 1999; Rolls and Grabenhorst, 2008).

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]

There is growing evidence that psychological 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 et al., 2012). Also, Dickinson et al. (2013) find that glucose increases the likelihood of making a Bayesian choices over heuristic-based choices by up to 9%, and Kuhn et al. (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 study formally linking hunger and economic behavior. Therefore, I designed and conducted a controlled 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, the experiment was designed to explore *how cognitive fatigue and the interaction of both hunger and cognitive fatigue affect such decisions.*[4]

Proposition 3 *Hunger affects time preferences by disproportionately exacerbating impatience on immediate monetary rewards versus non-immediate monetary rewards. In other words, hungry individuals display present bias.*

Proposition 4 *Cognitive-fatigue affects time preferences by decreasing the level of attention individuals pay to the decision. In other words, cognitive-fatigued individuals will look to simplify choices by following heuristics or rules-of-thumb.*

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

[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.

[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 et al. (2009)) for a more in dept review of the literature, see DellaVigna (2009).

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 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, which directly reflects Proposition 3.

In the following section, I detail the controlled laboratory experiment used to test Proposition 1, part (b) of Proposition 2, and Proposition 3.[5]

2.3 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

[5]Testing part (a) of Proposition 2 should be the goal of future studies.

auxiliary survey, used to collect additional information on individual characteristics and dietary practices. Figure 2.1 illustrates how the ordering of these stages defines each of the cells/conditions resulting from the $2x2$-factorial design.

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 2.2). 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 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]

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

[6]Appendix B describes the application in more detail and provides the consent form and the instruction scripts used.

[7]The application also provided subjects with practice rounds for arithmetical and decision tasks.

[8]CETs are circled in gray in Figure 2.1.

[9]By selecting a random round to determine their compensation I avoid wealth effects.

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 \$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]

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 et al., 1988; Weigle et al., 2005; Astrup, 2005; Bertenshaw et al., 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] 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

[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.

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.

Decision Task

I used Andreoni and Sprenger (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

$$(1+t)c_t + c_{t+k} = m, \tag{2.1}$$

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 of m 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 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 2.1 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 payment date measure in days from the date of the experiment; k represents the delay between the earlier and the later payment date measured in days; v_t represents the earlier token cash-value, i.e. the value of each token if cashed on the earlier payment date; and v_{t+k} represents the later token cash value, i.e. the value of each token if cashed on the later payment date. Table 2.1

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

[15] Figure B.4 and Figure B.3 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.

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.

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 within a session. As illustrated in Figure 2.1 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.

Demographic Questionnaire and Auxiliary Survey

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

2.4 Summary Statistics

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 (16 out of 160 participants). Table 2.2 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 treat and refer to non-compliers as a separate group, and 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 is "Extremely", how hungry

[17] Figure B.2 provides a screenshot of the arithmetical task round as it was presented to subjects.
[18] A list of these questions is provided in Appendix B.
[19] Demographic questionnaire and auxiliary survey questions are provided in Appendix C.
[20] In the following section I compare non-compliers to the control group and find that, as one would expect, these two groups behave in a similar way.

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 [$\mu = 4.93$, 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*.

Sample

Table 2.2 summarizes subjects characteristics measured using the demographic questionnaire, auxiliary survey, filler tasks, and experimental questions. A total of 160 subjects participated

[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.

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

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 2.3 summarizes the same characteristics as Table 2.2 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]

2.5 Results

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).

Non-parametrical Analysis

Figure 2.3 graphs the mean tokens cashed earlier for non-compliers and each of the conditions by the delay of the earlier payment date.[25] In order to have a comparable set of choices across immediacy of the earlier payment date (t) and delay between earlier and later payment date (k), I only included the balanced combination of convex budgets from Table 2.1 (i.e. $(1+r)$-budgets in all nine (t, k)-choice sets), however estimates do not significantly

[24] Due to limited resources, I only collected data for 12 subjects under the low-protein control condition. 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 will be discussed in the following section.

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

change if all choices are included. The means are also presented in Table 2.4.[26]

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 payment date ($t = 0, 14, 28$), we find that subjects under the control condition cashed 36.81 [SE = 5.054] earlier tokens in average. Consistent with predictions, subjects under the cognitive-fatigue [$\mu_F = 50.41$, SE = 5.557] and hunger [$\mu_H = 50.31$, SE = 3.954] conditions cash significantly more tokens earlier ($p = 0.072$ and $p = 0.037$, respectively). Subjects under the interaction condition [$\mu_I = 33.53$, SE= 4.238], i.e. those that received both the cognitive-fatigue and hunger treatment, seem to cash slightly less tokens earlier ($p = 0.620$). The fact that the number of tokens cashed earlier in average by non-compliers is slightly higher [$\mu_N = 40.35$, SE = 6.362] than the number of tokens cashed earlier by subjects under the control condition, but not statistically different ($p = 0.664$), is not surprising.[27] Lastly, as one would expect, subjects under the low-protein control condition seem to cash slightly more tokens earlier [$\mu_L = 38.89$, SE = 8.027]; however the difference is not statistically significant ($p = 0.827$).

Result 1 *Consistent with predictions: (a) subjects under the control condition display relative low levels of monetary impatience, and (b) cognitive-fatigue and hunger exacerbate monetary impatience.*

Present Bias — As I discussed in Section 2.2, an individual displays present-biased preferences if, relative to immediate outcomes ($t = 0$), she/he disproportionately discounts non-immediate outcomes ($t > 0$). In Figure 2.3 and Table 2.4, I contrast the effects including only choices with immediate earlier payments (t=0) against the effects including only choices with non-immediate earlier payments (t=7,35). This can 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 payment date was immediate, than if the earlier payment date was non-immediate, only for subjects under the hunger [$\mu_{H_{t=0}} - \mu_{H_{t=7,35}} = 5.07$, $p < 0.05$] and interaction [$\mu_{I_{t=0}} - \mu_{I_{t=7,35}} = 5.68$, $p < 0.01$] condition.

Result 2 *Consistent with predictions, hunger exacerbates monetary impatience significantly more when the earlier payment date is immediate.*

Corner Effects — These non-parametrical aggregate results, by nature, lack individual heterogeneity details. Less than 18.3% of subjects (24 out of 131) in the four main conditions (i.e. control, cognitive-fatigue, hunger, and interaction) have no interior choices in all 55

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

[27] Recall that non-compliers include subjects that received the cognitive-fatigue treatment, which we expected to increase monetary impatience.

convex budgets, which is consistent with linear preferences. However, when plotting the percentage of subjects by their total corner solutions, i.e. all tokens cashed earlier or all tokens cashed later, in each of these conditions there are some differences (see Figure 2.4).[28] Almost twice as many subjects (32.3%) have no interior choices under the cognitive-fatigue condition, compare to the control (17.2%). This is not the case under the hunger (13.5%) and the interaction condition (11.8%). Additionally, Figure 2.5 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 2.5 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%, $p < 0.05$).

Result 3 *The cognitive-fatigue effect appears to be driven by an increase in corner solutions, which is consistent with the a priori expectation that cognitive fatigue would decrease the level of attention or increase the use of heuristics (i.e. subjects cash either all tokens earlier or all tokens later as a way to simplify the decision problem).*

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 payment 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 2.5).

In summary, cognitive fatigue and hunger (Proposition 1) increase monetary impatience. While hunger has a significantly larger effect when choices involve immediate monetary rewards (Proposition 3), cognitive-fatigue does not. Also, the cognitive-fatigue effect appears to be driven by an increase in corner solutions (Proposition 4), i.e. subjects choose all-earlier or all-later token allocations perhaps as a way to simplify the decision problem. Both of these

[28]From this point forward I will discuss only the four main conditions. Appendix F a comparison between the subjects under the control condition, subjects under the low-dose condition, and non-compliers.

results suggest that hunger and cognitive fatigue affect time preferences through different mechanisms, which we will further explore in the following section.

Parametrical Analysis

Following Andreoni and Sprenger (2012)'s CTB methodology, I estimate the time preference parameters for subjects under control and each of the treatment (cognitive-fatigue and hunger) and interaction conditions.[29] 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):

$$U(c_t, c_{t+k}) = \frac{1}{\alpha} c_t^{\alpha} + \beta\delta^k \frac{1}{\alpha} c_{t+k}^{\alpha}, \tag{2.2}$$

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 E.2 subject to the future value Equation 2.1 yields to the tangency condition

$$\frac{c_t}{c_{t+k}} = \begin{cases} (\beta\delta^k(1+r))^{\left(\frac{1}{\alpha-1}\right)} & \text{if } t = 0 \\ (\delta^k(1+r))^{\left(\frac{1}{\alpha-1}\right)} & \text{if } t > 0 \end{cases}, \tag{2.3}$$

and the demand for tokens cashed earlier

$$c_t = \begin{cases} \dfrac{m(\beta\delta^k(1+r))^{\left(\frac{1}{\alpha-1}\right)}}{1+(1+r)(\beta\delta^k(1+r))^{\left(\frac{1}{\alpha-1}\right)}} & \text{if } t = 0 \\ \dfrac{m(\delta^k(1+r))^{\left(\frac{1}{\alpha-1}\right)}}{1+(1+r)(\delta^k(1+r))^{\left(\frac{1}{\alpha-1}\right)}} & \text{if } t > 0 \end{cases}. \tag{2.4}$$

[29] As noted in the previous subsection, I will only include the 131 subjects under the four main conditions in the parametrical analysis since subjects under the low-dose condition and non-compliers behave relatively similar to those under the control condition. Appendix F presents a brief parametrical comparison between the subjects under the control condition, subjects under the low-dose condition, and non-compliers.

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

$$c_t = \left[\frac{m(\beta_C^\tau \delta_C^k (1+r))^{\left(\frac{1}{\alpha_C - 1}\right)}}{1+(1+r)(\beta_C^\tau \delta_C^k (1+r))^{\left(\frac{1}{\alpha_C - 1}\right)}}\right] \cdot \mathbb{C} + \left[\frac{m(\beta_F^\tau \delta_F^k (1+r))^{\left(\frac{1}{\alpha_F - 1}\right)}}{1+(1+r)(\beta_F^\tau \delta_F^k (1+r))^{\left(\frac{1}{\alpha_F - 1}\right)}}\right] \cdot \mathbb{F} + \left[\frac{m(\beta_H^\tau \delta_H^k (1+r))^{\left(\frac{1}{\alpha_H - 1}\right)}}{1+(1+r)(\beta_H^\tau \delta_H^k (1+r))^{\left(\frac{1}{\alpha_H - 1}\right)}}\right] \cdot \mathbb{H} + \left[\frac{m(\beta_I^\tau \delta_I^k (1+r))^{\left(\frac{1}{\alpha_I - 1}\right)}}{1+(1+r)(\beta_I^\tau \delta_I^k (1+r))^{\left(\frac{1}{\alpha_I - 1}\right)}}\right] \cdot \mathbb{I} + \epsilon, \tag{2.5}$$

where τ is an indicator for whether or not the earlier payment 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

In Figure 2.6 I plot the mean number of tokens cashed earlier against the gross interest rate, $((1 + r))$.[30] I plot separate points for each condition and separate graphs by both the experimental values of the earlier payment date in days ($t = 0, 7, 35$) and the experimental values of the delay between the earlier and the later payment in days ($k = 35, 70, 98$). Consistent with the non-parametrical analysis, 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 payment date is immediate ($t = 0$). 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 with the interest rate.[31]

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 2.6 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

[30]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.

[31]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 payment date is immediate ($t = 0$), versus non-immediate ($t = 7, 35$).

interaction conditions.[32]

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 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. This result is consistent with other cognitive biases in which subjects seem to follow heuristics or rules-of-thumb to simplify the decision problem.

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).[33] 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.

[32]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 E.

[33]They estimate the annual interest rate at 37.1% [SE = 0.091].

Result 4 *(a) The hunger effect seems to be concentrated in the present bias parameter (β), while (b) the cognitive-fatigue effect, although only marginally significant, seems to be concentrated on the utility curvature parameter (α).*

It is worth highlighting that my 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.[34] This provides additional evidence for the validity and consistency of the CTB methodology.

Individual Estimates

Table 2.7 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).[35] 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 median 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 2.7, Figure 2.8, and Figure 2.9 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.

[34] They estimate $\hat{\beta}$ at 1.007 [SE = 0.006] and $\hat{\alpha}$ at 0.897 [SE = 0.009].

[35] Andreoni and Sprenger (2012) are also unable to estimate parameters for 10 out of 97 subjects.

- 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.

2.6 Conclusion

In summary, cognitive fatigue and hunger increase monetary impatience and affect time preferences. 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 (i.e. hungry individuals display present-bias preferences and satiated individuals do not). This is consistent with the initial proposition that hunger is linked to brain activity in areas of the brain that are disproportionately activated when immediate rewards are available. 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 corner solutions. This is also consistent with the initial proposition that cognitive-fatigue decreases individuals' attention, who then look to simplify choices by following heuristics or rules-of-thumb (e.g. choosing all-earlier or all-later token allocations). These results suggest that hunger and cognitive fatigue affect time preferences through different mechanisms, which can explain the conflicting results from the interaction condition. Also, while the effect that hunger has on time preferences is significant and consistent independent of the approach (non-parametrical or parametrical) and the aggregation level, the effect that cognitive-fatigue has on time preferences seems to be only marginally significant at the aggregate level and fades when looking at individual level parameters. Therefore, perhaps a better approach to study the effects of cognitive-bias on decision making would be to test for utility maximization consistency a la Choi et al. (2014).

This study contributes to the field of behavioral economics by proving that present bias is a visceral response activated when earlier rewards are actually immediate. These results also open the door to a new research agenda that could help explain why the poor tend to make more shortsighted 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. Another goal, would be to identify the mechanisms through which hunger and cognitive fatigue affect decisions. Particularly, testing Proposition 2 and mapping the link between hunger, brain activity, and decision-making.

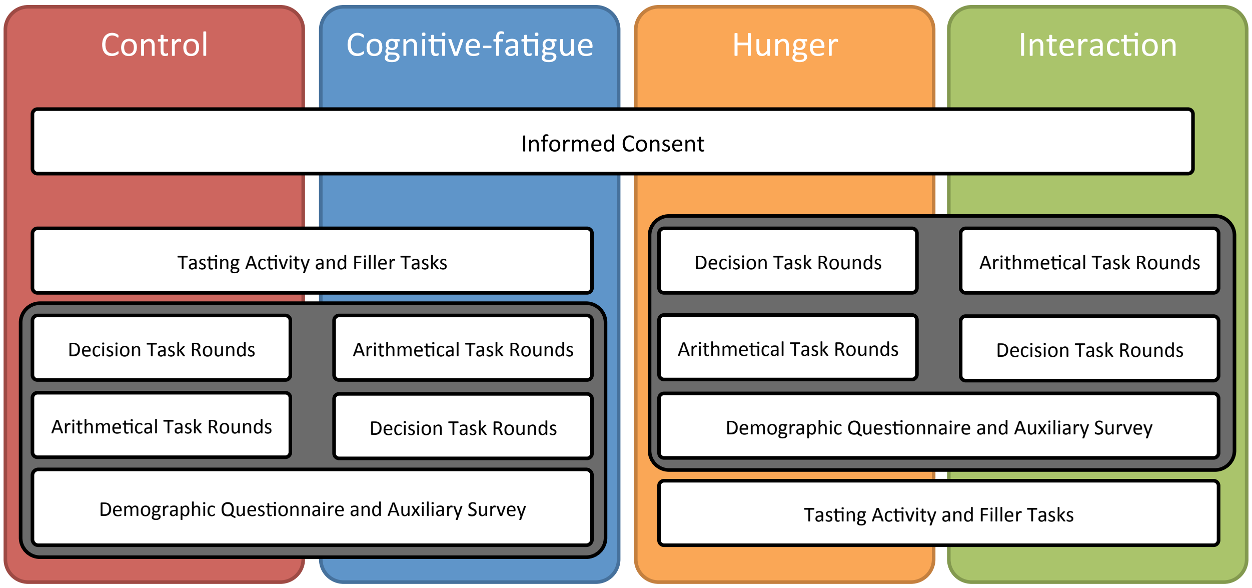

Figure 2.1: Experimental Design.
Note: Computer-based experimental tasks (CETs) circled in gray.

Figure 2.2: Laboratory setup and presentation of “blind” drink for tasting activity.

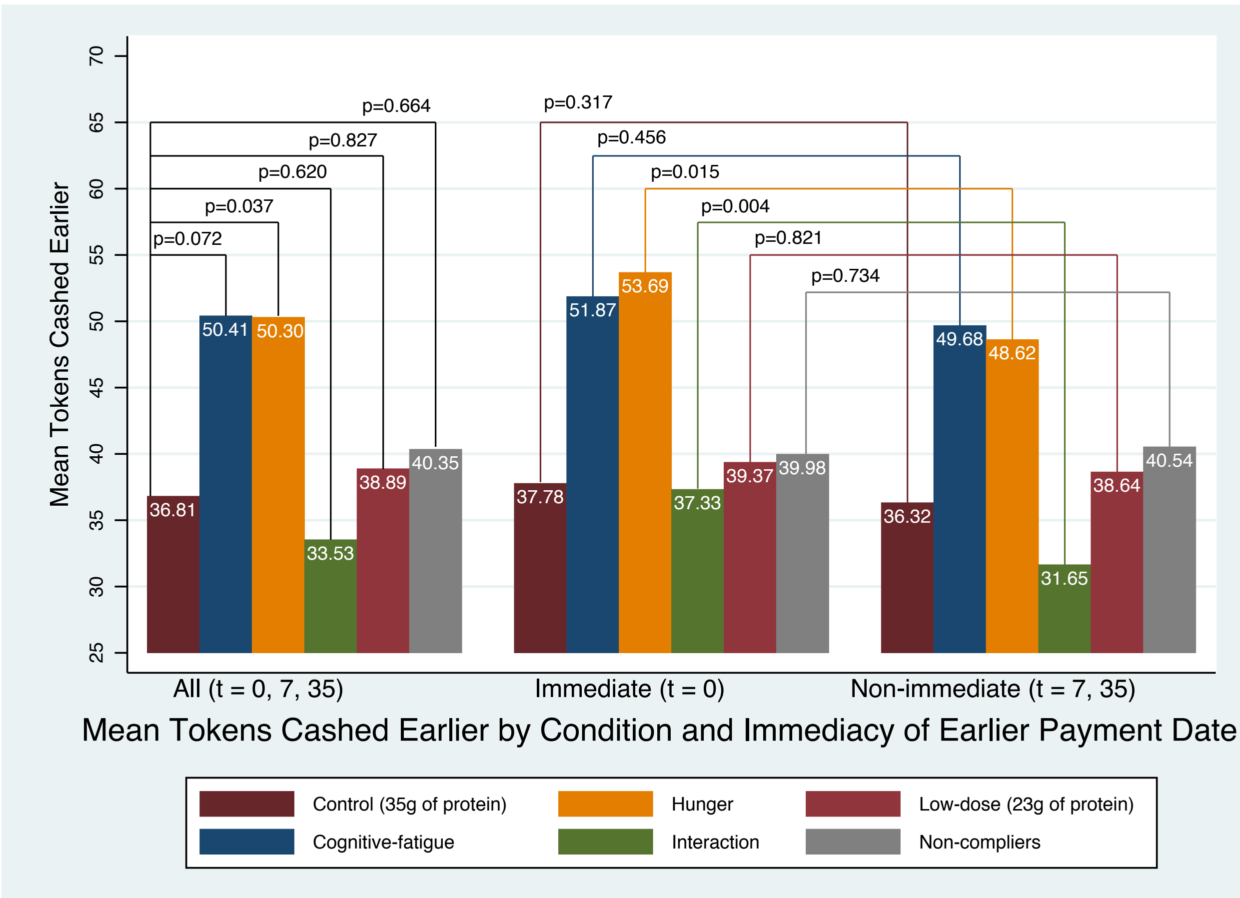

Figure 2.3: Mean Tokens Cashed Earlier

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 cash on the earlier payment date on condition status, with standard errors clustered at the individual level (see Table 2.4). 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 and non-compliers. The p-values for immediate and non-immediate choices correspond to the null hypotheses $H_0 : \mu_{\text{immediate}} = \mu_{\text{non-immediate}}$ for each condition. In order to have a comparable set of choices across earlier payment date delay (t) and delay between earlier and later payment date (k), I only included the balanced combination of choice sets from Table 2.1 (i.e. $(1+r)$-choices with all nine (t, k)-combinations), however estimates do not significanly change if all choices are included.

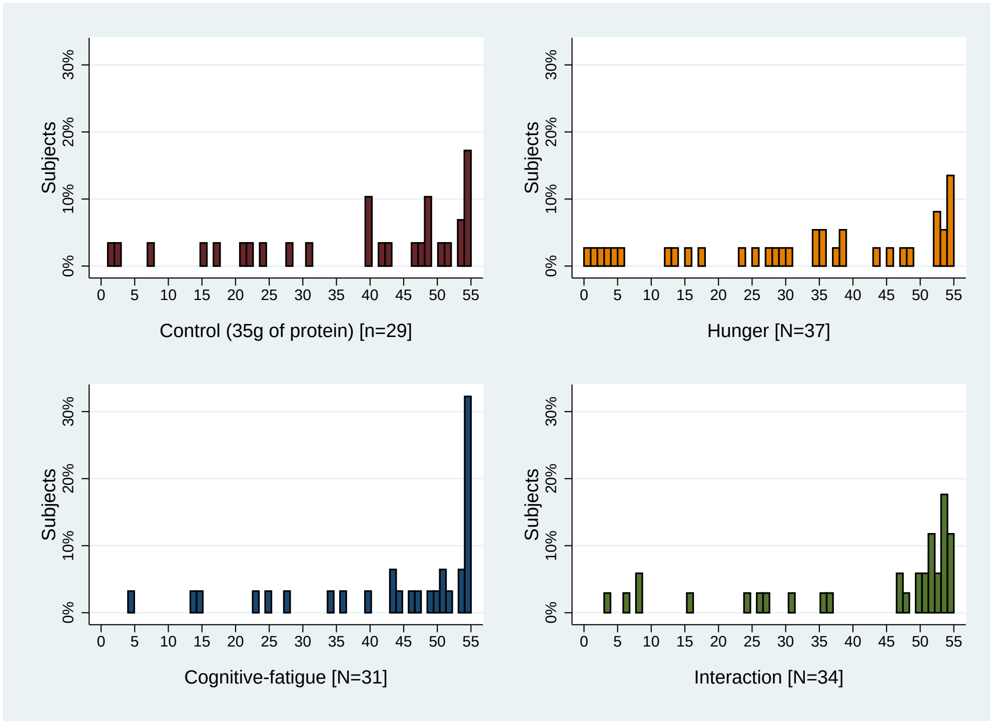

Figure 2.4: Percentage of Subjects by Total Corner Solutions (out of 55 choice sets)

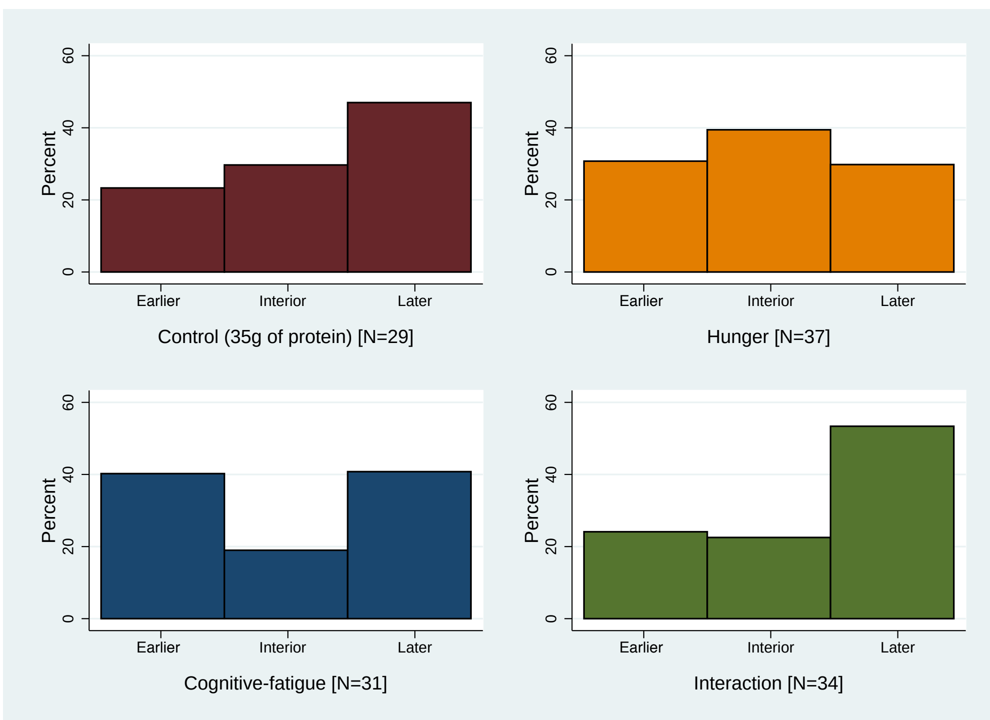

Figure 2.5: Percentage of Corner and Interior Solutions by Condition

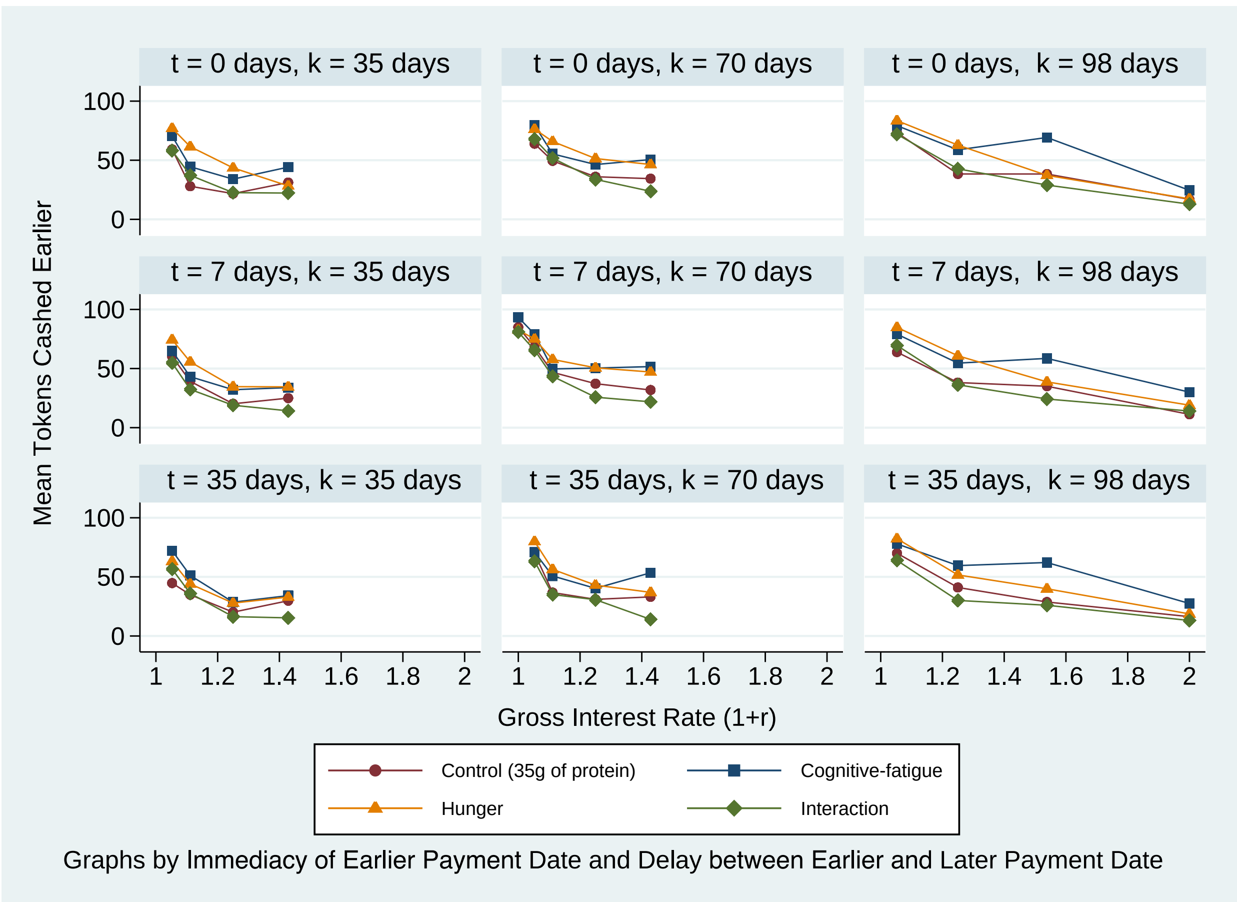

Figure 2.6: Mean Tokens Cashed Earlier by Gross Interest Rate

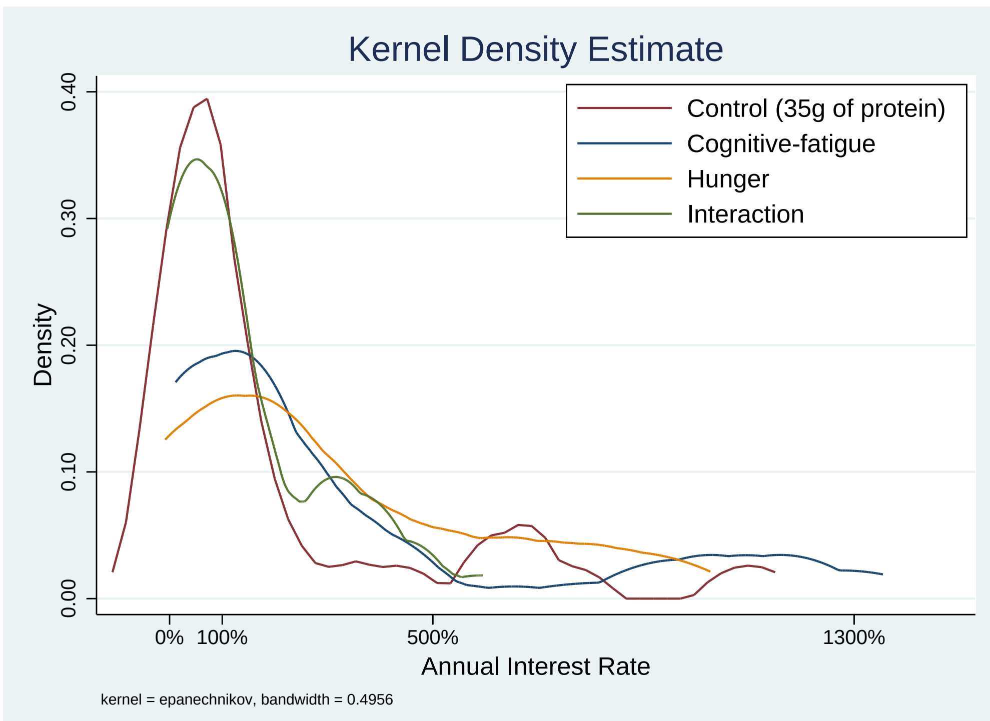

Figure 2.7: Kernel Density of Individual Annual Interest Rate Estimates
Note: Parameter trimmed at the 5th and 95th percentile.

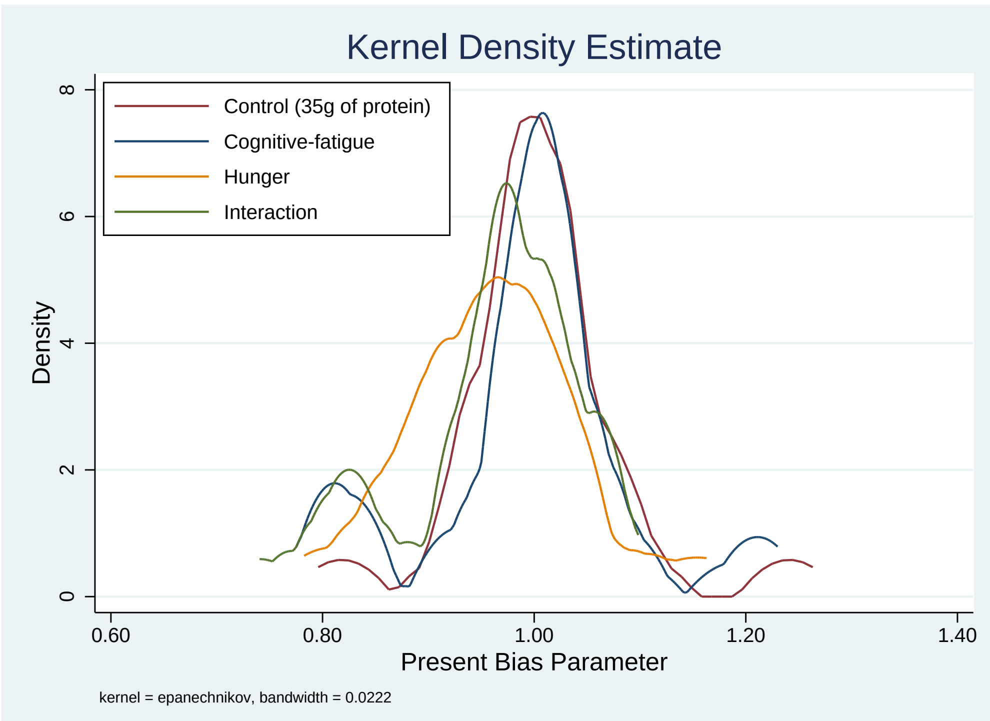

Figure 2.8: Kernel Density of Individual Present Bias Parameter Estimates
Note: Parameter trimmed at the 5th and 95th percentile.

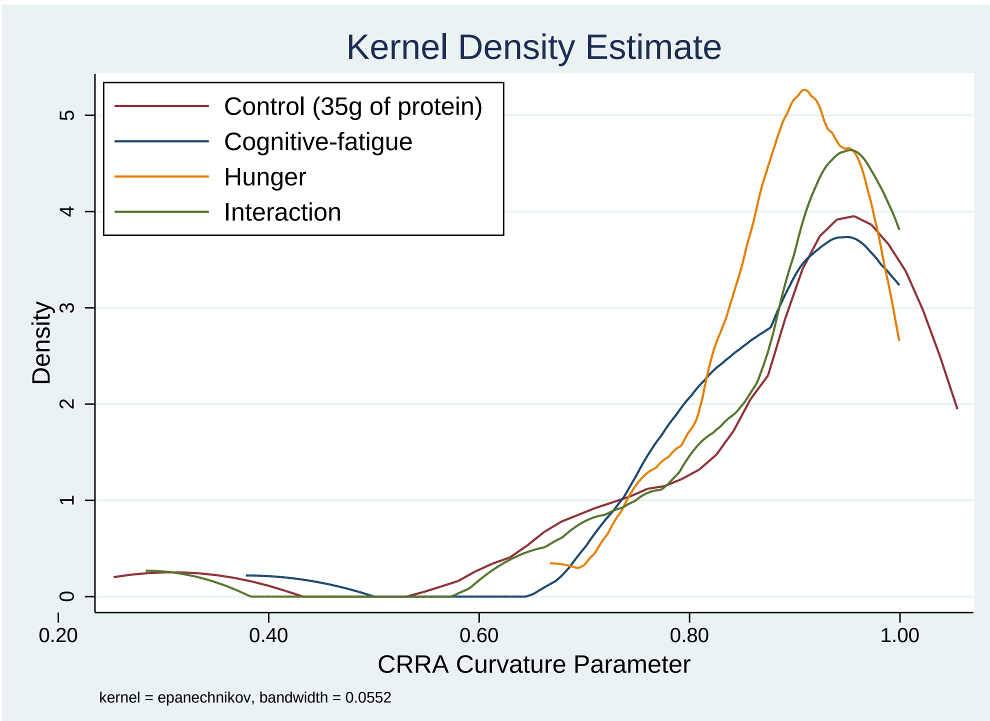

Figure 2.9: Kernel Density of Individual CRRA Curvature Parameter Estimates

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

Table 2.1: 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 2.2: 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][d]	4.510	4.647	-0.137	-0.707	0.481
IQ Score [0-2][e]	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][fg]	5.818	3.176	2.642	4.174	0.000
Hunger level *after CETs* [0-10][fg]	5.664	2.941	2.723	3.936	0.000
Hunger level *after tasting* [0-10][fh]	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] Score was calculated using answers from question 21 to 25.
[e] Score was calculated using answers from question 29 and 30.
[f] Not At All = 0, and Extremely = 10.
[g] Rated during auxiliary survey.
[h] Only subjects completing tasting activity after CETs were asked to rate their hunger level during the filler tasks.

Table 2.3: 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][d]	4.483	4.516	4.622	4.471	4.333
IQ Score [0-2][e]	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][fg]	5.931	5.839	5.324	6.265	5.750
Hunger level *after CETs* [0-10][fg]	4.310	4.839	6.703	7.000	4.083
Hunger level *after tasting* [0-10][fh]			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] Score was calculated using answers from question 21 to 25.
[e] Score was calculated using answers from question 29 and 30.
[f] Not At All = 0, and Extremely = 10.
[g] Rated during auxiliary survey.
[h] Only subjects completing tasting activity after CETs were asked to rate their hunger level during the filler tasks.

Table 2.4: Mean Tokens Cashed Earlier by Condition and Immediacy of Earlier Payment Date

			Tokens Cashed Earlier		$H_0 : \mu_C = \mu_{O=\{F,H,I,L,I\}}$	
			Mean	Robust-SE	F-statistic	p-value
DATE	CONDITION		(1)	(2)	(3)	(4)
All (t=0,7,35)	C:	Control (35g of protein)	36.811	5.054	.	.
	F:	Cognitive-fatigue	50.413	5.557	3.28	0.072
	H:	Hunger	50.305	3.954	4.42	0.037
	I:	Interaction	33.533	4.238	0.25	0.620
	L:	Low-dose (23g of protein)	38.886	8.027	0.05	0.827
	N:	Non-compliers	40.352	6.362	0.19	0.664
		Observations	8483			
		R-squared	0.50			
		Clusters	160			
Immediate (t=0)	C:	Control (35g of protein)	37.781	5.173	.	.
	F:	Cognitive-fatigue	51.869	5.937	3.20	0.076
	H:	Hunger	53.687	4.294	5.60	0.019
	I:	Interaction	37.329	4.969	0.00	0.950
	L:	Low-protein Control (23g)	39.373	6.887	0.03	0.854
	N:	Non-compliers	39.980	6.691	0.07	0.795
		Observations	2825			
		R-squared	0.51			
		Clusters	160			
Non-immediate (t=7,35)	C:	Control (35g of protein)	36.323	5.063	.	
	F:	Cognitive-fatigue	49.682	5.607	3.13	0.079
	H:	Hunger	48.621	3.937	3.68	0.057
	I:	Interaction	31.650	3.970	0.53	0.469
	L:	Low-dose (23g of protein)	38.645	8.713	0.05	0.818
	N:	Non-compliers	40.538	3.970	0.27	0.601
		Observations	5658			
		R-squared	0.50			
		Clusters	160			

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 2.5: Corner Effects

	Share of Corner Solutions	
	Patient	Impatient
VARIABLES	(1)	(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 2.6: Aggregate Parameter Estimates by Condition

		Aggregate		H_0 : Parameter$_{\mathrm{C}}$=Parameter$_{\mathrm{O}=\{\mathrm{F,H,I}\}}$	
		Parameter	Robust-SE	F-statistic	p-value
CONDITION		(1)	(2)	(3)	(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 2.7: 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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Appendix A

Two-Tailed t-test on Observables

Table A.1: H_0: Mean observable characteristic is equal between the treated and control stores during the baseline period for treated/control categories.

	Treated Categories			Control Categories		
	(1)	(2)	(3)	(4)	(5)	(6)
Products with SDV-prices						
→ Total Unique Products Purchased	0.103	0.289	0.168	0.086	0.279	0.873
→ Av. Unitary Gross Price	0.154	0.133	0.914	0.053	0.002	0.36
→ Av. Unitary Net Price	0.117	0.266	0.724	0.044	0.002	0.317
Products with RDV-prices						
→ Total Unique Products Purchased	0.547	0.547	0.002	0.071	0.065	0.734
→ Av. Unitary Gross Price	0.012	0.012	0.576	0.02	0.056	0.006
→ Av. Unitary Net Price	0.078	0.078	0.317	0.046	0.111	0.025

Notes: Two-sided p-values are reported.
Unitary Net Price = Unitary Gross Price - Unitary Discount. the means.

Table A.2: H_0: Mean observable characteristic is equal between the treated and control stores during the experimental period for treated/control categories.

	Treated Categories			Control Categories		
	(1)	(2)	(3)	(4)	(5)	(6)
Products with SDV-prices						
→ Total Unique Products Purchased	0.373	0.47	0.409	0.707	0.625	0.871
→ Av. Unitary Gross Price	0.483	0.859	0.377	0.564	0.7	0.977
→ Av. Unitary Net Price	0.405	0.728	0.335	0.517	0.534	0.993
Products with RDV-prices						
→ Total Unique Products Purchased	0.904	0.904	0.67	0.603	0.607	0.907
→ Av. Unitary Gross Price	0.564	0.564	0.835	0.834	0.866	0.729
→ Av. Unitary Net Price	0.577	0.577	0.838	0.998	0.966	0.904

Notes: Two-sided p-values are reported.
Unitary Net Price = Unitary Gross Price - Unitary Discount. the means.

Table A.3: H_0: Mean observable characteristic is equal between the baseline and experimental period at the control stores for treated/control categories.

	Treated Categories			Control Categories		
	(1)	(2)	(3)	(4)	(5)	(6)
Products with SDV-prices						
→ Total Unique Products Purchased	0.292	0.295	0.384	0.723	0.73	0.627
→ Av. Unitary Gross Price	0.871	0.789	0.671	0.94	0.702	0.732
→ Av. Unitary Net Price	0.875	0.801	0.735	0.881	0.383	0.882
Products with RDV-prices						
→ Total Unique Products Purchased	0.689	0.689	0.231	0.431	0.443	0.226
→ Av. Unitary Gross Price	0.55	0.55	0.936	0.564	0.491	0.191
→ Av. Unitary Net Price	0.842	0.842	0.38	0.614	0.546	0.334

Notes: Two-sided p-values are reported.
Unitary Net Price = Unitary Gross Price - Unitary Discount. the means.

Table A.4: H_0: Mean observable characteristic is equal between the baseline and experimental period at the treated store for treated/control categories.

	Treated Categories			Control Categories		
	(1)	(2)	(3)	(4)	(5)	(6)
Products with SDV-prices						
→ Total Unique Products Purchased	0.896	0.839	0.932	0.731	0.491	0.514
→ Av. Unitary Gross Price	0.47	0.301	0.376	0.833	0.46	0.926
→ Av. Unitary Net Price	0.385	0.24	0.313	0.937	0.372	0.884
Products with RDV-prices						
→ Total Unique Products Purchased	0.513	0.513	0.798	0.607	0.606	0.283
→ Av. Unitary Gross Price	0.561	0.561	0.909	0.355	0.345	0.139
→ Av. Unitary Net Price	0.909	0.909	0.547	0.298	0.288	0.182

Notes: Two-sided p-values are reported.
Unitary Net Price = Unitary Gross Price - Unitary Discount. the means.

Appendix B

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.

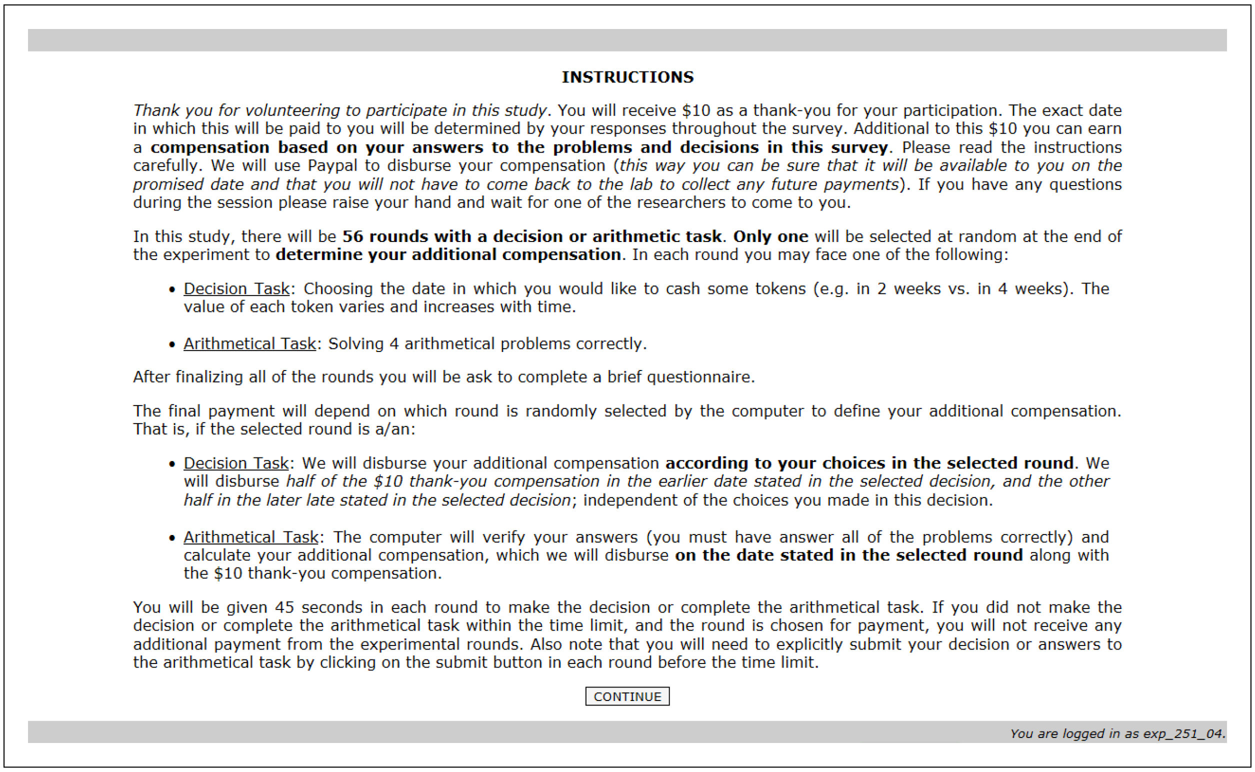
Please understand that your participation in this study is completely voluntary. You are free to decline to take part in the project. You can decline to answer any questions and are free to stop taking part in the project at any time. Whether or not you choose to participate in the research and whether 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:

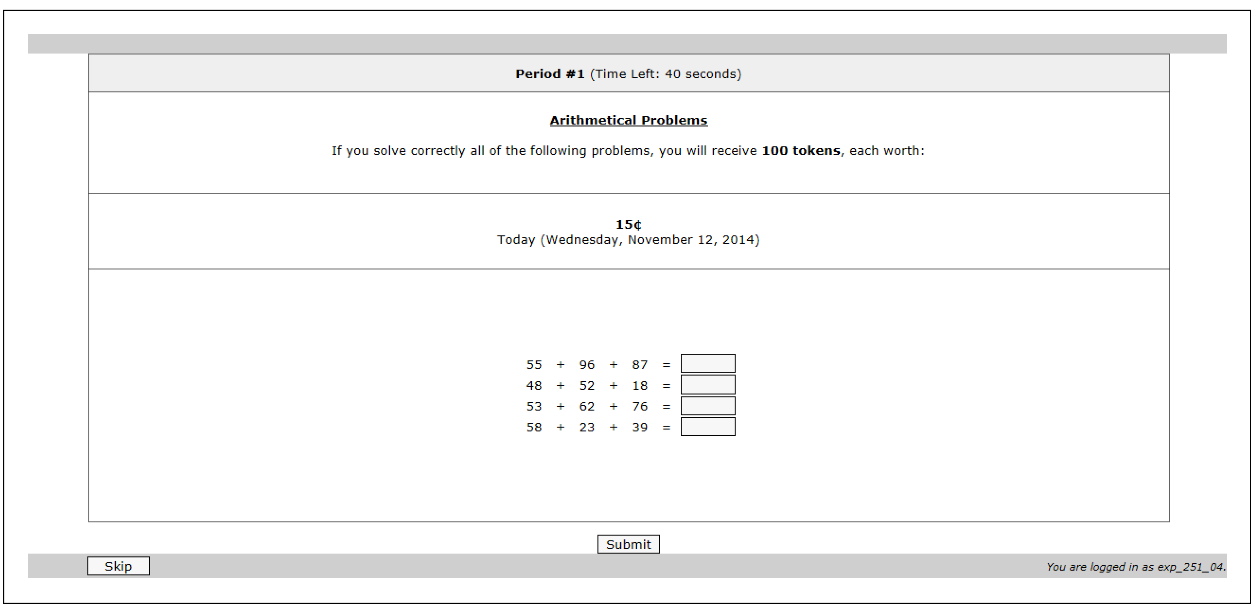
- Decision Task: We will disburse your additional compensation **according to your choices in the selected round**. We will disburse *half of the $10 thank-you compensation in the earlier date stated in the selected decision, and the other half in the later late stated in the selected decision*; independent 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 B.1: Screenshot of Instructions.



Period #1 (Time Left: 40 seconds)

Arithmetical Problems

If you solve correctly all of the following problems, you will receive **100 tokens**, each worth:

15¢
Today (Wednesday, November 12, 2014)

55 + 96 + 87 =
48 + 52 + 18 =
53 + 62 + 76 =
58 + 23 + 39 =

Submit

Skip

You are logged in as exp_251_04.

Figure B.2: Screenshot of Arithmetical Round.

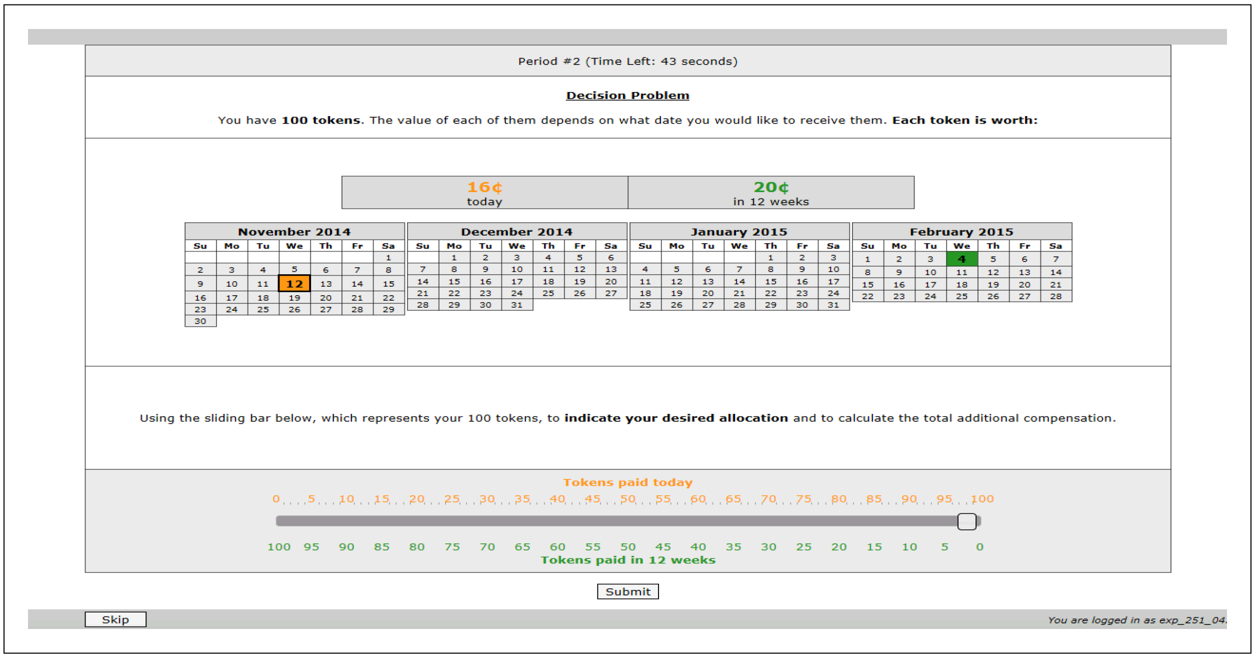


Figure B.3: Screenshot of Decision Round (before decision).

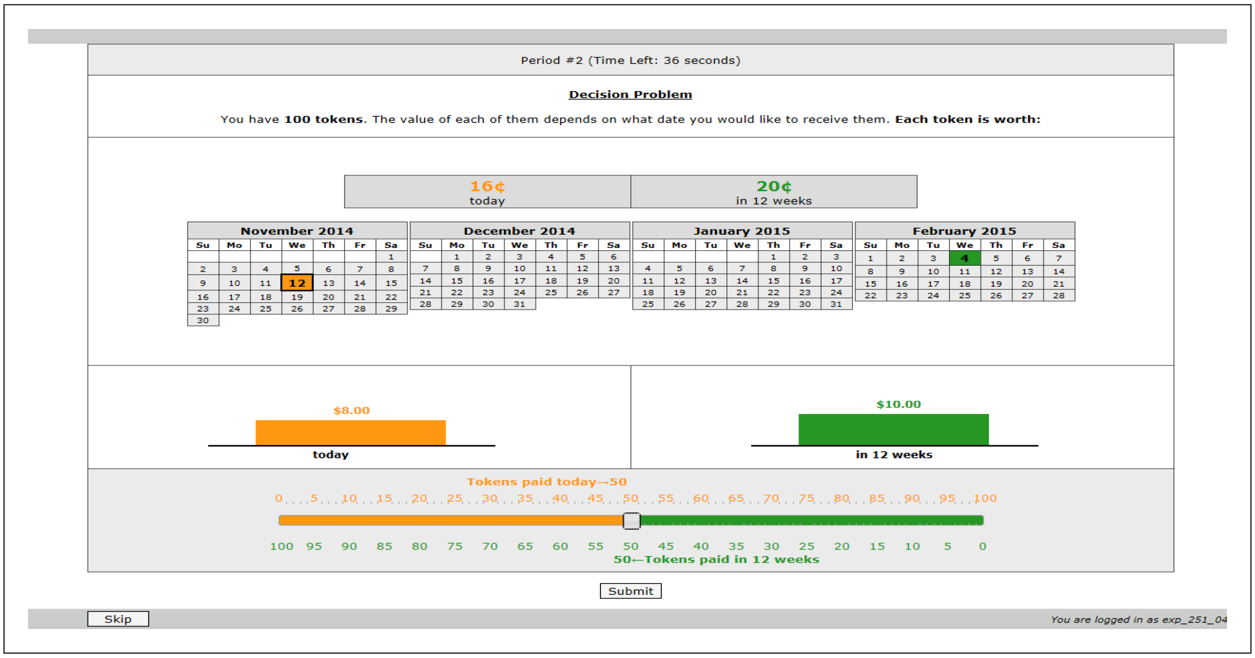


Figure B.4: Screenshot of Decision Round (during/after decision).

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 B.5: 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 B.6: 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 B.7: Screenshot of Last Experimental Earnings Report.

Appendix C

Demographic Questionnaire and Auxiliary Survey

1. Gender
   ☐ Male ☐ Female

2. Age
   [ ] years

3. Height
   [ ] ☐ft/☐cm

4. Weight
   [ ] ☐lbs/☐kg

5. Year in school
   ☐ Freshman ☐ Sophomore ☐ Junior ☐ Senior ☐ Graduate

6. Is English your second language?
   ☐ Yes ☐ No

7. What is your major?
   [ ]

8. Approximately, how much do you spend in an average month on all your living expenses (housing, clothing, groceries, dinning, entertainment, etc.)? [If a range (e.g. 10-15) please enter the average (e.g. 12.5).]
   $[ ]

9. Approximately, how much do you spend in an average month on food (include groceries and dinning)? [If a range (e.g. 10-15) please enter the average (e.g. 12.5).]
   $[ ]

10. Are you registered to vote?
☐ Yes ☐ No

11. Do you work?
☐ Yes ☐ No

12. If you work, how many hours per week do you work? [If a range (e.g. 10-15) please enter the average (e.g. 12.5).]
[ ] hours

13. If you work, how much do you earn per hour? [If a range (e.g. 10-15) please enter the average (e.g. 12.5).]
$[ ] per/hour

14. Do you smoke?
☐ Yes ☐ No

15. If yes, have you ever tried quitting?
☐ Yes ☐ No

16. If no, have you ever smoked but successfully quit?
☐ Yes ☐ No

17. How frequently do you buy lottery tickets (e.g. Power Ball) and/or gamble (e.g. online poker)?
☐ Never
☐ Once a year
☐ Once a month
☐ Once a week
☐ More than once a week

18. Do you donate money or your time (i.e. volunteer) to charitable organizations on a regular basis?
☐ Never
☐ One hour or at least $10 per year
☐ One hour or at least $10 per month
☐ One hour or at least $10 per week
☐ More than one hour or $10 per week

19. Do you trust that your study earnings will be paid on the designated dates?
☐ Yes ☐ No

20. Were there any special circumstances, such as special need for the money at a particular time?
☐ Yes ☐ No

21. If you buy a drink for 85 cents and pay with a one-dollar bill, how much change would you get?
[ ] cents

22. A shop is selling all items at half price. If before, a sofa cost $250, how much does it cost now (do not include taxes)?
$[ ]

23. If the chance of getting a disease were 10 percent, how many people out of 1,000 would get the disease?
[ ]

24. If 5 people all have the winning numbers in the lottery and the prize is $2 million, how much would each person get?
$[ ]

25. Let's say you have $200 in a savings account and the account earns 10 percent interest per year (there is no periodical compounding). What would be the balance in the account after a year?
$[ ]

26. Have you ever pulled an all-nighter to study for an exam (forgoing sleep to study the night before the exam)?
☐ Yes ☐ No

27. Do you exercise regularly?
☐ Yes ☐ No

28. Do you find that you are able to maintain the body weight that you like?
☐ Yes ☐ No

29. A bat and a ball cost $1.10 in total. The bat costs a dollar more than the ball, how much does the bat cost?
$[ ]

30. If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets?
[ ]

31. Do you have a credit card?
☐ Yes ☐ No

32. Complete the following sentences:
I am indifferent between receiving $20 dollars today or receiving $[ ] in one week.
I am indifferent between receiving $20 dollars today or receiving $ [ ] in one month.

33. In the box below, please try to describe what you were thinking when you were making decisions?
    [ ]

34. What do you think this experiment is about?
    [ ]

35. On a scale from 0 to 10, where 0 is "Not At All" and 10 is "Extremely":
    How hungry are you now?

Not at all - 0	1	2	3	4	5	6	7	8	9	10 - Extremly
○	○	○	○	○	○	○	○	○	○	○

    How hungry where you when you first arrived to the experiment?

Not at all - 0	1	2	3	4	5	6	7	8	9	10 - Extremly
○	○	○	○	○	○	○	○	○	○	○

36. At what time was the last meal you had before coming to this experiment (approximately)?
    [ ]:[ ] ☐am/☐pm

37. What was the last meal you had before coming to this experiment?
    ☐ Breakfast
    ☐ Lunch
    ☐ Snack
    ☐ Dinner (today)
    ☐ Dinner (the night before)

38. If you ate/drank anything before coming to the experiment, what did you eat/drink?
    [ ]

39. In average, how many meals do you have per day?
    [ ] meals/dat

40. Approximately, at what time do regularly you eat
    breakfast? [ ]:[ ] ☐am/☐pm
    lunch? [ ]:[ ] ☐am/☐pm
    dinner? [ ]:[ ] ☐am/☐pm

41. Do you call yourself a foodie?
    ☐ Yes ☐ No

Appendix D

Filler Tasks

PLEASE, ENTER YOUR COMPUTER NUMBER IN THIS BOX ➔ [ ]

TASTING ACTIVITY

Please fill out this survey **after finishing your drink**.

1. Do you drink flavored drinks (soda, non-fresh squeezed fruit juices, hot/cold coffee, hot/cold tea, etc.)? [ ] Yes [ ] No
   a. If yes, approximately how many 12 oz. (average medium cup) flavored drinks do you drink in a day? _______
   b. If yes, how many of these are sweetened? _______
   c. If yes, how many of these are caffeinated? _______
2. How much would you be willing to pay for this drink? $ ___.__
3. Do you think the ingredients used in this drink are...?
   a. Organic [ ] Yes [ ] No
   b. Fair-trade [ ] Yes [ ] No
   c. All-natural [ ] Yes [ ] No
4. How much **more** would you be willing to pay for this drink if you knew the ingredients were...?
   a. Organic $ ___.__
   b. Fair-trade $ ___.__
   c. All-natural $ ___.__
5. Did you know that when you buy a bottled drink you pay a deposit for the recyclable container (a.k.a. CRV in California)? [ ] Yes [ ] No
6. Do you know how much the CRV is? _______ cents
7. How many calories do you think this drink has? _______ calories
8. Approximately, how many 8 oz. glasses of water do you drink in a day? _______
9. Indicate how much do you disagree/agree with the following sentences using a scale from 1 to 7, where **1 means "Strongly disagree", 4 means "Neither",** and **7 means "Strongly agree"**:
   a. I really care about the environment: [1] [2] [3] [4] [5] [6] [7]
   b. Food produced using GMOs should be labeled: [1] [2] [3] [4] [5] [6] [7]
   c. Buying fair-trade products can help small farms: [1] [2] [3] [4] [5] [6] [7]
10. Answer the following questions using a scale from 1 to 7, where **1 means "Very little", 4 means "Indifferent",** and **7 "Very much"**:
    a. How much did you like the drink? [1] [2] [3] [4] [5] [6] [7]
    b. How much do you care about your weight? [1] [2] [3] [4] [5] [6] [7]
    c. How much effort do you put on your diet? [1] [2] [3] [4] [5] [6] [7]
11. What do you think about the presentation of the drink? ____________________________
    ____

Figure D.1: Filler Tasks for Subjects Completing Tasting Activity Before CETs.

PLEASE, ENTER YOU RCOMPUTER NUMBER IN THIS BOX ➔ [ ]

TASTING ACTIVITY

Please fill out this survey **after finishing your drink**.

1. Do you drink flavored drinks (soda, non-fresh squeezed fruit juices, hot/cold coffee, hot/cold tea, etc.)? [ ] Yes [ ] No
    a. If yes, approximately how many 12 oz. (average medium cup) flavored drinks do you drink in a day? _______
    b. If yes, how many of these are sweetened? _______
    c. If yes, how many of these are caffeinated? _______

2. How much would you be willing to pay for this drink? $ ___.__

3. Do you think the ingredients used in this drink are…?
    a. Organic [ ] Yes [ ] No
    b. Fair-trade [ ] Yes [ ] No
    c. All-natural [ ] Yes [ ] No

4. How much **more** would you be willing to pay for this drink if you knew the ingredients were…?
    a. Organic $ ___.__
    b. Fair-trade $ ___.__
    c. All-natural $ ___.__

5. Did you know that when you buy a bottled drink you pay a deposit for the recyclable container (a.k.a. CRV in California)? [ ] Yes [ ] No

6. Do you know how much the CRV is? _______ cents

7. How many …
    a. calories do you think this drink has? _______ calories
    b. sugar do you think this drink has? _______ grams
    c. fat do you think this drink has? _______ grams
    d. protein do you think this drink has? _______ grams

8. Approximately, how many 8 oz. glasses of water do you drink in a day? _______

Figure D.2: Filler Tasks for Subjects Completing Tasting Activity After CETs (page 1).

9. Indicate how much do you disagree/agree with the following sentences using a scale from 1 to 7, where **1 means "Strongly disagree", 4 means "Neither",** and **7 means "Strongly agree"**:
   a. I really care about the environment: [1] [2] [3] [4] [5] [6] [7]
   b. Food produced using GMOs should be labeled: [1] [2] [3] [4] [5] [6] [7]
   c. Buying fair-trade products can help small farms: [1] [2] [3] [4] [5] [6] [7]

10. Can you guess the flavor of the drink? ____________________________

11. What do you think about the presentation of the drink? ____________________________
____

12. Please complete the following activity (one person will be chosen at random, if that person was able to find all of the words he/she will receive an additional $5):

poetry word soup

P	O	E	T	R	Y	B	L	A	Q	Q	G	J	X	Y
E	X	L	X	H	W	H	M	K	E	A	Q	P	R	N
R	M	R	R	Z	B	S	Y	T	M	H	P	E	W	O
S	E	S	V	O	U	D	I	P	R	C	G	J	S	U
O	F	O	D	T	H	R	I	H	E	A	I	E	E	F
N	C	F	B	Z	W	P	Y	V	M	R	S	P	H	T
I	S	P	P	X	H	M	A	I	Z	R	B	V	E	Z
F	T	U	O	V	E	Q	E	T	E	D	B	O	A	V
I	E	K	E	E	L	M	Q	V	E	Q	O	X	L	W
C	N	C	X	E	T	S	A	L	S	M	F	T	N	E
A	N	N	M	I	T	S	K	Y	P	P	K	Y	I	O
T	O	W	Q	A	O	A	O	W	T	F	E	J	J	Q
I	S	A	N	H	S	I	M	I	L	E	P	E	Q	V
O	M	Z	Q	T	S	O	O	Y	K	P	U	C	C	P
N	A	E	T	P	U	H	E	H	C	E	D	O	I	H

EPIC
HYPERBOLE
IMAGERY
METAPHOR
ODE
PERSONIFICATION
POETRY
POETS
RHYME
SIMILE
SONNETS
SPEECH
STANZA
VERSE
WRITE

Figure D.3: Filler Tasks for Subjects Completing Tasting Activity After CETs (page 2).

13. On a scale from 0 to 10, where 0 is "Not At All" and 10 is "Extremely", how hungry are you now?
Not at all – [0] [1] [2] [3] [4] [5] [6] [7] [8] [9] [10] – Extremely

14. Answer the following questions using a scale from 1 to 7, where **1 means "Very little", 4 means "Indifferent",** and **7 "Very much"**:

a.	How much did you like the drink (overall)?	[1] [2] [3] [4] [5] [6] [7]
b.	How much did you like the flavor of the drink?	[1] [2] [3] [4] [5] [6] [7]
c.	How much do you care about your weight?	[1] [2] [3] [4] [5] [6] [7]
d.	How much effort do you put on your diet?	[1] [2] [3] [4] [5] [6] [7]
e.	The drink helped me feel satiated	[1] [2] [3] [4] [5] [6] [7]

Figure D.4: Filler Tasks for Subjects Completing Tasting Activity After CETs (page 3).

Appendix E

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

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

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.[1]

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

$$U(c_t, c_{t+k}) = \frac{1}{\alpha}(c_t - \gamma_1)^\alpha + \beta(c_{t+k} - \gamma_2)^\alpha, \tag{E.2}$$

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; 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 E.2 subject to the future value Equation E.1 yields to the tangency condition

$$\frac{c_t - \gamma_1}{c_{t+k} - \gamma_2} = \begin{cases} (\beta\delta^k(1+r))^{\left(\frac{1}{\alpha-1}\right)} & \text{if } t = 0 \\ (\delta^k(1+r))^{\left(\frac{1}{\alpha-1}\right)} & \text{if } t > 0 \end{cases}, \tag{E.3}$$

[1]Figure B.4 and Figure B.3 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,

$$c_t = \begin{cases} \left[\dfrac{\gamma_1}{1+(1+r)(\beta\delta^k(1+r))^{\left(\frac{1}{\alpha-1}\right)}}\right] + \left[\dfrac{((m-\gamma_2)\beta\delta^k(1+r))^{\left(\frac{1}{\alpha-1}\right)}}{1+(1+r)(\beta\delta^k(1+r))^{\left(\frac{1}{\alpha-1}\right)}}\right] & \text{if } t=0 \\ \left[\dfrac{\gamma_1}{1+(1+r)(\delta^k(1+r))^{\left(\frac{1}{\alpha-1}\right)}}\right] + \left[\dfrac{((m-\gamma_2)\delta^k(1+r))^{\left(\frac{1}{\alpha-1}\right)}}{1+(1+r)(\delta^k(1+r))^{\left(\frac{1}{\alpha-1}\right)}}\right] & \text{if } t>0 \end{cases}. \quad \text{(E.4)}$$

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

$$\exp(-\rho(c_t - c_{t+k})) = \begin{cases} \beta\delta^k(1+r) & \text{if } t=0 \\ \delta^k(1+r) & \text{if } t>0 \end{cases}, \quad \text{(E.5)}$$

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

$$c_t - c_{t+k} = \frac{\ln\,\beta}{-\rho}\cdot \mathbb{1}_{t=0} + \frac{\ln\,\delta}{-\rho}\cdot k + \frac{1}{-\rho}\cdot \ln(1+r), \quad \text{(E.6)}$$

and rearrange to the solution function

$$c_t = (\frac{\ln\beta}{-rho})\cdot\frac{\mathbb{1}_{t=0}}{-\rho} \quad \text{(E.7)}$$

Table E.1 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 $\hat{\gamma_2}$.[2,3]

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

[3] 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 E.1: 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 E.4. (2) CRRA regression of Equation E.3 with restriction $\gamma_1 = \gamma_2$. (3)-(4) CRRA regression of Equation E.4 and E.3, respectively, with restriction $(\frac{1}{\delta})^{365} = 0$. (5)-(6) CRRA regression of Equation E.4 and E.3, respectively, with restriction $(\frac{1}{\delta})^{365} = -11.13$ (the negative of the average reported daily food expenditures*). (7)-(8) CARA regression of equation E.7 and E.6, 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.

Appendix F

Low-dose Condition Subjects and Non-compliers

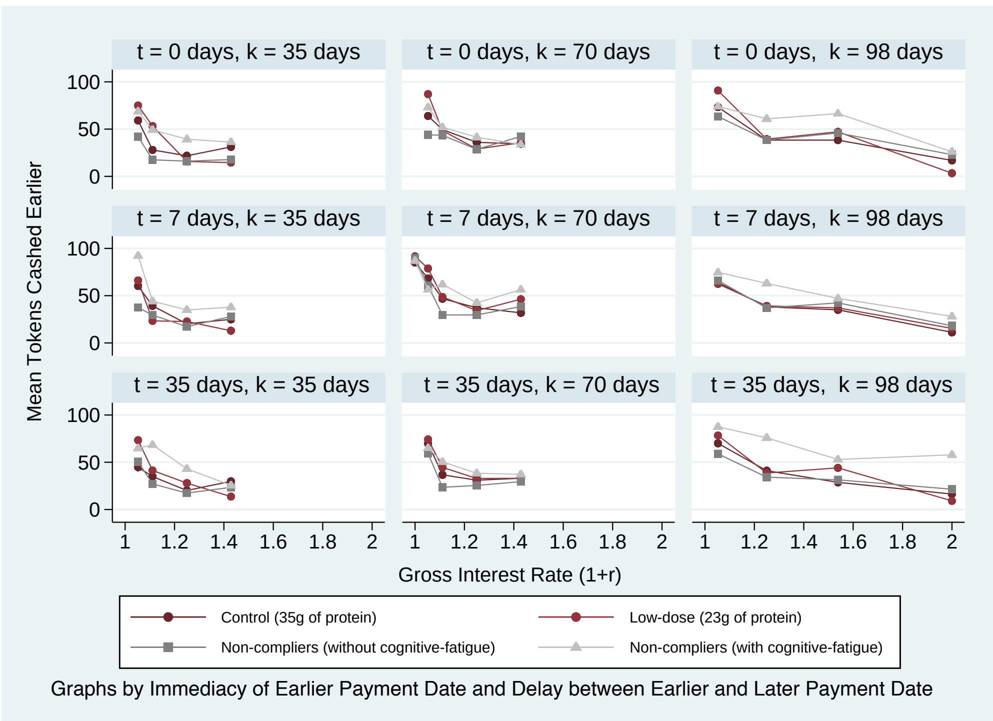


Figure F.1: Mean Tokens Cash Sooner by Gross Interest Rate

Table F.1: Estimates and Treatment Effects on Aggregate Parameter Estimates

		Parameter	
		Coefficient	Robust-SE
CONDITION		(1)	(2)
Annual discount rate			
C:	Control (35g of protein)	0.730	0.230
L:	Low-dose (23g of protein)	0.907	0.386
NC:	Non-compliers (without cognitive-fatigue)	0.515	0.329
NF:	Non-compliers (with cognitive-fatigue)	1.984	0.753
Present bias: $\hat{\beta}$			
C:	Control (35g of protein)	1.001	0.011
L:	Low-dose (23g of protein)	0.984	0.018
NC:	Non-compliers (without cognitive-fatigue)	1.025	0.012
NF:	Non-compliers (without cognitive-fatigue)	1.025	0.043
CRRA curvature: $\hat{\alpha}$			
C.	Control (35g of protein)	0.867	0.021
L:	Low-dose (23g of protein)	0.892	0.022
NC:	Non-compliers (without cognitive-fatigue)	0.862	0.032
NF:	Non-compliers (without cognitive-fatigue)	0.797	0.053
	Observations	3144	
	R-squared	0.55	
	Clusters	58	

Notes: Robust standard errors clustered at the individual level.