COMBINING EXPERIMENTAL METHODS WITH BIOMETRIC TOOLS TO ANALYZE FOOD-RELATED BEHAVIOR

A Dissertation

by

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ABSTRACT

This dissertation uses experimental economics methods and biometric tools to test for the consistency of individual preferences and analyze how such preferences are affected by states of cognitive impairment and resource scarcity. Across the study, emphasis is made on the effect of hunger on food choices and intertemporal decisions, along with the implementation of health-related intervention programs tailored to individuals with different health characteristics. The behavioral findings are supported by eye tracking data, which provide insightful information on how visual attention and arousal impact final food choices. The methodologies used to measure individual preferences are hypothetical and non-hypothetical, and the statistical tools used to analyze this data include econometric models for categorical and limited dependent variables in preference space and in willingness-to-pay (WTP) space.

The first essay tests the consistency of individual preferences over the same repeated choice experiment. Results based on a within-subjects design indicate that after changing the position of the same alternatives in the choice set, participants were consistent with their choices 69% of the time. Moreover, after reverting back to the identical original positions of the alternatives but randomizing the order of the choice sets, individuals' choices were consistent 67% of the time. The robustness of these results was further demonstrated by using random parameters models with flexible mixing distributions to calculate WTP for the products attributes. Importantly, none of the attributes followed a normal distribution, which highlights the importance of considering more flexible forms such as polynomials when estimating the distribution of random parameters.

The second essay tests for the presence of an anticipatory food reward effect and examines whether this effect is ubiquitous or if there are differential effects by body mass index (BMI). In a

controlled laboratory experiment, participants performed a cognitive test and a food choice task in randomized order. The results showed that overweight and obese individuals exhibited an anticipatory food reward effect, which enhanced their cognitive capacity after merely choosing a food snack that would be consumed at the end of the experimental session. This cognitive impairment induced by hunger only affected the food choices of obese individuals, who were more likely to make unhealthy food choices. This finding was complemented by eye tracking data, which indicated that the obese exhibited more arousal or engagement towards the food products under a low cognitive capacity.

Finally, the third essay consists of a laboratory experiment implemented to investigate whether inducing health related thoughts and future self-image representations influence the food choices and intertemporal decisions of overweight, obese and normal weight individuals. The results indicate that providing information about the immediate consequences associated with healthy/unhealthy habits increased the number of healthy food choices and patience level of overweight and obese individuals. However, when the obese interacted with their potential future healthier and unhealthier selves, the opposite effect was uncovered. This effect might be due to the fact that obese individuals look at the reward of becoming healthier as somewhat unattainable in the short-run, requiring more tangible or plausible immediate rewards. The behavioral findings of this essay are supported by eye tracking data, which revealed how the temptation towards unhealthy food snacks exhibited by overweight, obese, and normal weight individuals translated to their final food choices.

DEDICATION

I would like to dedicate this work and all of the efforts put forth to obtaining my doctoral degree to my beloved family. Your love has been the major spiritual support in my life and what propelled me through when I wanted to give up.

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All the work for the dissertation was completed by the student, under the advisement of Dr. Marco A. Palma of the Department of Agricultural Economics.

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1. INTRODUCTION

Neoclassical economic theory relies on the assumption that agents behave in a rational manner and act accordingly to their self-interest. However, there are numerous empirical studies whose findings seem to contradict fundamental axioms of choice theory. In this regard, behavioral economics have been used to explain why people deviate from optimal decisions and which factors affect their preferences. Factors found to influence decision-making processes include individuals' cognitive ability, emotions, visceral states, among others. Incorporating these aspects into economic theory and understanding how individuals make choices could significantly improve models of human behavior inherited from neoclassical economics.

Behavioral economics principles form the basis through which policy interventions can create substantial changes in eating behavior and food choices, providing viable solutions to combat obesity and other food-related problems. Although consumers have become increasingly aware of the damaging impacts of unhealthy behaviors, their desire to change their habits is seldom met with the proper lifestyle choices. That is, most obese individuals desire to lose weight, but find it difficult to change to healthier lifestyle habits. While behavioral economics has been previously used to "nudge" individuals into a "desirable" course of action, there is an everlasting controversy on the proper policies to adopt for obesity intervention programs. This dissertation provides valuable insights to the linkage of food choices and obesity. It combines experimental methods with biometric data to help identify potential factors affecting the consistency of food-related decisions and evaluate the effectiveness of behavioral interventions tailored to individuals with specific health characteristics.

This dissertation will examine, in three essays, the use of hypothetical and non-hypothetical economic experiments in measuring individual preferences and analyzing the mechanisms involved in food-related decision-making. Emphasis is made on improving the data collection methods, the econometric analysis of individual preferences, and the importance of fully accounting for individual and behavioral characteristics. The objectives of this work are summarized as follows:

- Test the consistency of preferences for food products in repeated choice experiments and examine the use of random parameters models with flexible mixing distributions to calculate WTP for the product attributes.
- Test for the presence of an anticipatory food reward effect in normal weight, overweight, and obese individuals, under a state of hunger.
- Examine whether inducing health-related thoughts and self-image representations influence the eating behavior and time preferences of normal weight, overweight, and obese individuals, and evaluate the effectiveness of intervention programs targeted to individuals with specific health characteristics.

Essays 1, 2, and 3 will address the objectives stated above through the implementation of hypothetical and non-hypothetical economic experiments using eye tracking. This is followed by a conclusion section, which highlights the main contributions of this work and provides directions for future research.

2. TESTING THE CONSISTENCY OF PREFERENCES IN DISCRETE CHOICE EXPERIMENTS: AN EYE TRACKING STUDY

"Inconsistency is the only thing in which men are consistent"

Horace Smith

2.1 Introduction

In stated preference mechanisms, individual valuations are estimated from ranking, rating, and choice data (Bunch et al., 1996). Discrete choice experiments (DCE) are the most commonly used stated preference approach and they have been applied to elicit valuations for environmental assets, household appliances, transportation choices, and health services (Hensher, 1994; Revelt and Train, 1998; Louviere et al., 2010; McNeil et al., 1982). One of the main reasons for the widespread use of choice experiments is the flexibility in the design of choice sets and alternatives, which allows for a wide range of information to be collected from participants (Lusk and Norwood, 2005). Although individual questions in DCEs are typically framed in a way that resembles real consumer decisions (e.g., choosing among different product alternatives) (Lusk and Schroeder, 2004), the validity and accuracy of DCEs has been under scrutiny due to their hypothetical nature.

In particular, past evidence has found that choice experiments result in inconsistent choices as consumers tend to overstate their preferences in a hypothetical setting compared to when real money is on the line (List and Gallet, 2001; Ding et al., 2005; Murphy et al., 2005; Lusk and Schroeder, 2006; Sándor and Franses, 2009). By inconsistent choices we are referring to choices that change over the course of the same choice experiment, that is, between the beginning and end of the choice sequence (Johnson and Mathews, 2001). Potential explanations for inconsistent choices in DCEs include: 1) complexity in experimental design (DeShazo and Fermo, 2002; Swait and Adamowicz, 2001), 2) changes in the combination of the attributes (Mellers et al., 1992), 3) confusion and cognitive dissonance exhibited by participants (Loomes and Sugden, 1983; Plott and Zeiler, 2005), 4) fatigue and learning effects (Johnson and Desvousges, 1997), and 5) limited experience shown by respondents (Lusk and Schroeder, 2006; Beshears et al., 2008).

Specific to the decision-making process, preference inconsistencies have been attributed to the change in respondents' preferences at different stages of the process. These discrepancies can be further linked to changes in how attributes are weighted (Tversky et al., 1988), changes in how attributes are combined to form an evaluation (Mellers et al., 1992), and modifications in the way formed evaluations are translated into responses (Goldstein and Einhorn, 1987).

As a consequence, several methods for mitigating inconsistencies in choice experiments have been proposed. For example, Mowen and Gentry (1980) tried to identify inconsistencies by designing different tasks under several contexts and comparing individual versus group decisions. Furthermore, Mellers et al. (1992) conducted three experiments which used different procedures or tasks to evaluate inconsistencies and found that attribute choices changed under variations in combination rules, whereas utilities remained constant across tasks. Similar to our study, Kim et al. (2012) used eye tracking data to analyze the relationship between preference inconsistencies and subjects' visual attention. The authors found that respondents exhibited systematic preference inconsistencies when making decisions under risk partly due to changes in attention across different tasks.

Despite these efforts to diminish preference inconsistencies in stated elicitation methods, inconsistencies have been constantly observed in applied research (Tversky et al., 1990; Chu and Chu, 1990). Specifically, preferences and willingness-to-pay (WTP) elicited using choice experiments have been compared to those elicited under rankings, ratings, and experimental auctions (Caparrós et al., 2008; Corrigan et al., 2009; Su et al., 2011). The results from these comparisons are ambiguous. For example, while Boyle et al. (2001) found inconsistent estimates between ranking and choice experiments, opposite results were found by Caparrós et al. (2008).

Although past research has sought to identify the factors causing preference inconsistencies, little has been done to explore these inconsistencies in repeated choice experiments. A key assumption in most DCEs is that individuals' preferences are stable across choice sets and remain unchanged throughout a single seating experiment (Sælensminde, 1998). However, it is possible that even little details in the experimental design, such as changing the position of the alternatives within the same choice set, can hold significant effects on choices. As a result, it is common practice for DCEs to randomize the position of product alternatives. We ask the question, to what extend does the position order influences visual attention, search dynamics, and ultimately product choices and valuations? The objectives of this article are as follows. First to assess the influence of the position of the alternatives and the order of the choice sets on the consistency of individual choices. Second, to estimate random parameters models in willingness-to-pay (WTP) space using flexible mixing distributions and compare the results to commonly used normal distributions. Third, to examine the consistency in attribute attendance using eye tracking estimates.

We implement a within-subject experiment to test for the consistency of preferences over a sequence of three discrete choice experiments with identical choice sets that only differ in their position and order. Our findings suggest that preferences are consistent to a large degree in terms of direction and with similar magnitudes over the repeated choice experiments. Specifically, the results show that after changing the position of the same alternatives in the choice set, subjects consistently selected the same alternative 69% of the time. Furthermore, after reverting back to the original positions, subjects consistently selected the same alternative 67% of the time. Compared to the literature on inconsistencies for other preference elicitation methods, it is worthwhile to note that hypothetical DCEs have a high level of consistency of preferences. Moreover, the empirical results show that none of the attributes followed a normal distribution, which highlights the importance of considering more flexible forms such as polynomials when estimating the distribution of random parameters.

2.2 Methodology

2.2.1 Experimental Design

The experiment used an ABA design that included three conditions and two "distraction tasks" between each treatment (Figure 2.1). The first condition was the *baseline control,* which entailed a standard DCE containing 12 hypothetical choice sets for vegetable products in which the position of the products was randomized. In each choice set, subjects were asked to choose between three vegetable products and a "no-purchase" option. Following the general practice, the no-product alternative remained in a fixed position. Each alternative was presented in four possible positions on the computer screen: 1) upper-left corner, 2) upper-right corner, 3) lower-left corner, and 4) lower-right corner. In the second condition, the *position change treatment*, the same DCE was implemented; however, the position of the alternatives (including the no-product alternative) was again randomized for each choice set. The third condition, referred to as the *baseline treatment,* replicated the original 12 choice sets in the *baseline control* (with the exact same original positions for each alternative). In order to avoid subjects trying to memorize their choices in the baseline control and deliberately trying to match them in the baseline treatment, the order of the choice sets was randomized. Furthermore, two "distraction tasks" were included between the conditions in order to measure choice preferences after the subject's attention was diverted (by manipulating the focus of attention). The first distraction task was a cognitive function test commonly used to measure fluid intelligence independent of acquired knowledge, which was completed between the *baseline control* and the *position change treatment*. The second distraction task was a short socio-demographic survey presented between the *position change treatment* and the *baseline treatment*. All experimental materials are available in the Appendix A.1.

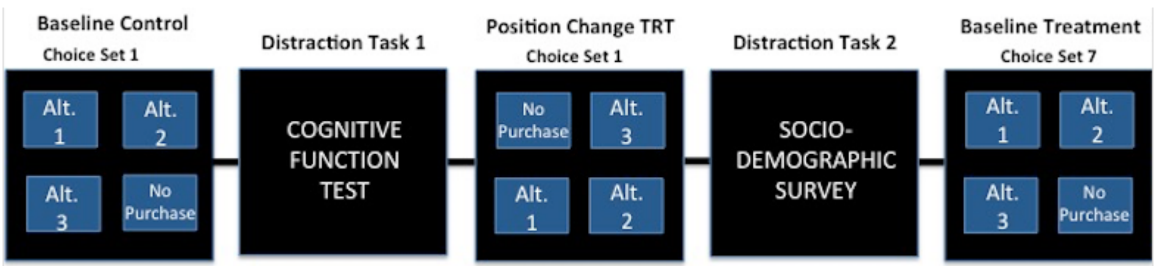

Figure 2.1. ABA Experimental procedure.

In this application, an orthogonal D-efficient fractional factorial design with no priors was generated using NGENE 1.1.2 (ChoiceMetrics, 2014). Five artichoke vegetable attributes with three levels each were used: 1) size (*small, medium, large*), 2) color (*green, purple, mixed*), 3) production method (*conventional, organic, pesticide-free*), 4) presentation form (*fresh, canned, glass*), and 5) price *($1/unit, $2/unit, $3/unit*). Pilot studies, including experimental auctions and choice experiments, were conducted to test and select product attributes and attribute levels. In order to ensure that the subject was familiar with the attributes, a review of the exact definitions of each product attribute and attribute level was presented prior to the *baseline control* condition. The final product alternatives in the experimental design included several alternatives not currently produced or available in real markets as it is the case in many DCEs. Therefore, the choices participants made were hypothetical.

2.2.2 Experimental Procedure

A within-subject design was implemented to test the consistency of choices in repeated choice experiments. In doing so, a total of 101 participants (39 male, 62 female) were recruited from the general population of a mid-size city in the Southwest United States. To qualify for the study, participants must have not had any corrective eye surgery. Subjects ranged in age from 19 to 69, with an average age of 28 years and an average income of $45,000.

Individuals who agreed to participate in the experiment were assigned a specific time and date that was convenient for them. Each session lasted approximately 30 minutes and a compensation of $10 was paid to subjects in exchange for their participation. Upon arriving at the session, participants signed a written consent form and were assigned an identification number to maintain anonymity. During their participation, subjects' eye movements were recorded using a Tobii TX300 eye tracking device, which was embedded in the computer and tracked gaze position using near-infrared technology at a sampling rate of 120 Hz.

Prior to the experiment, participants received general instructions and their eyes were calibrated using a nine-point calibration method. After a successful calibration, subjects started with the first of three choice experiments. Participants knew that their eye movements were being recorded during the experiment; however, they had no information on its purpose.

2.2.3 Econometric Models

To account for unobserved taste heterogeneity, a mixed logit model with flexible mixing distributions was developed following a random utility theory framework (McFadden, 1974). In the conventional mixed logit model (Revelt and Train, 1998), the utility of each alternative is specified as a function of the product attributes. Let the *n*th individual's utility of choosing option *j* in choice situation *t* be given by $U_{njt} = V_{njt} + \varepsilon_{njt}$, where V_{njt} represents the systematic portion of the utility determined by the product attributes and ε_{ijt} is a stochastic component. Assuming V_{njt} is linear in parameters, the utility function can be expressed as $U_{njt} = \beta_n' x_{njt} + \varepsilon_{njt}$, where x_{njt} represents a vector of observed attributes for individual *n* in choice set *t*, β_n is a vector of utility coefficients that vary over people, and ε_{njt} is an extreme-value distributed error term. Under this assumption, the probability that decision-maker *n* makes a sequence of choices, conditional on β_n, can be specified as:

$$L_n(\beta_n) = \prod_{t=1}^{T} Q_{nit}\,(\beta_n) \tag{2.1}$$

where $Q_{nit}(\beta_n) = \frac{e^{\beta_n' x_{nit}}}{\sum_{j\epsilon J} e^{\beta_n' x_{njt}}}$. Then, the unconditional probability of the sequence of choices takes the form:

$$P_n = \int L_{nt}(\beta) f(\beta|\theta) d\beta, \tag{2.2}$$

where $f(\beta|\theta)$ corresponds to the specified distribution of the random coefficients, and θ is a vector that describes the distribution of β_n (Train, 2009).

2.2.3.1 Econometric Models in WTP-Space with Flexible Mixing Distributions

The standard practice for application of choice models is to estimate "models in preference space", in which the utility parameters are used to calculate WTP. Let the utility for individual *n*, alternative *j*, and choice situation *t* be separable into price and non-price attributes as follows:

$$U_{njt} = -\theta_n p_{njt} + \beta_n' x_{njt} + \varepsilon_{njt} \tag{2.3}$$

where θ_n and β_n are coefficients that vary at random over individuals. The error term, ε_{njt}, is assumed to be distributed extreme value with variance: $Var(\varepsilon_{njt}) = k_n^2(\pi^2/6)$, where k_n is the scale parameter for individual *n*. In this case, the random scale parameter represents the standard deviation of the utility over different situations (Train and Weeks, 2005). Dividing the utility function (3) by the scale parameter results in a new error term that is constant across all individuals:

$$U_{njt} = -(\theta_n/k_n)p_{njt} + (\beta_n/k_n)'x_{njt} + \varepsilon_{njt} \tag{2.4}$$

where ε_{njt} is distributed type-one extreme value with constant variance $\pi/6$. Now, the utility coefficients are defined as $\gamma_n = (\theta_n/k_n)$ and $\delta = (\beta_n/k_n)$, such that the utility is specified as:

$$U_{njt} = -\gamma_n p_{njt} + \delta_n' x_{njt} + \varepsilon_{njt}. \tag{2.5}$$

The utility function described in equation (2.5) is known as the model in preference space. Under this specification, the WTP for a product attribute is calculated as the ratio of the attribute's coefficient to the price coefficient: $WTP_n = \delta_n/\gamma_n$.

Based on previous work by Cameron and James (1987), Train and Weeks (2005) constructed econometric models where the distributional assumptions and restrictions are parameterized directly on WTP and referred to them as "models in WTP space". In these models, parameter distributions are specified for the WTP and price/scale coefficient. Using the previous definition of *WTP*, the utility in equation (2.5) can be rewritten as:

$$U_{njt} = -\gamma_n p_{njt} + (\gamma_n WTP_n)'x_{njt} + \varepsilon_{njt} \tag{2.6}$$

where WTP_n corresponds to a vector of willingness-to-pay for each non-price attribute. Under this specification, the probability that the decision maker *n* chooses alternative *i* in choice set *t* becomes:

$$Q_{nit}(\beta_n) = \frac{e^{-\gamma_n(p_{nit}+WTP_n' x_{nit})}}{\sum_{j\epsilon J} e^{-\gamma_n(p_{njt}+WTP_n' x_{njt})}} \tag{2.7}$$

where β_n is defined as the vector of $\gamma_n WTP_n$. Then, the unconditional probability of the sequence of choices made by individual *n* is: $P_n = \sum_{r\in S} L_n(\beta_r) W(\beta_r|\alpha)$ where $W(\beta_r|\alpha) = e^{\alpha' z(\beta_r)} / \sum_{s\in S} \alpha' z(\beta_s)$ is the probability mass function of the cumulative distribution function F, S is the support set, and $z(\beta_r)$ corresponds to a vector capturing the distributional shape of the probability mass function.

In our application, rather than assuming a specific distribution for each parameter (such as normal or lognormal) that may be data dependent (Train and Weeks, 2005), we test more flexible distributions. We follow Train (2016) and use Legendre polynomials WTP, which implies coefficients may follow more flexible polynomial functions. Specifically, the WTP range with flexible polynomial distributions was set using two standard deviations above and below the mean WTP with normal distribution. A total of 10 random variables were specified as a sixth order polynomial so that 60 parameters were estimated. Correlation among the parameters was allowed so that 36 additional parameters were estimated. The simulated maximum likelihood was performed with 2000 random draws per individual, and the standard errors were obtained by replicating the estimation procedure over 20 new samples. A detailed explanation on the procedures for estimating random parameters with flexible distributions can be found in Train (2016). The Matlab code was adapted from Train (2016).

2.3 Results

Theoretically, the order of the choice sets and the position of the alternatives should not alter the subject's preferences; however, using eye tracking data, we report evidence that both the position in which the alternatives are presented and the order of the choice sets influence which attributes the participants pay more attention to and ultimately, their choices and valuations.

2.3.1 Eye Tracking Analysis

To analyze whether the position of the alternatives influenced subjects' visual attention, specific Areas of Interest (AOIs) were created for the alternatives in each choice set. Overall, the time subjects spent evaluating the different choice sets quickly decayed as they progressed through the experiment (Figure 2.2). This result goes in line with previous research that found a decrease in time visit duration over the course of the choice experiment (Rasch et al., 2015) and is evident specifically in the case of the *baseline control*. For instance, this outcome can be attributed to potential learning and fatigue effects acquired by participants as they view the choice sets.

Figure 2.3 shows the eye tracking metrics and the choices made by participants by treatment and position. The values in red, green, and blue represent estimates for the *baseline control*, *position change treatment*, and *baseline treatment*, respectively. Panel A displays the total amount of time (in seconds) spent on each position by treatment. In all conditions, the longest amount of time was spent on the upper-left position (4.62 s, 2.71 s, and 2.49 s), followed by the upper-right (3.62, 2.31, and 2.11), lower-left (3.26, 1.99, and 1.80), and the lower-right (0.57, 1.88, 0.27). Moreover, it appears that the alternatives located in the upper positions, especially the upper left position, received the highest attention in terms of how often subjects looked at those alternatives (Panel B). This result ties into the relationship between the position of the alternatives and the frequency of choices. Panel C shows the proportion of chosen alternatives for each screen position. On average, subjects tend to choose the products located in the upper positions more often, with a higher inclination towards the alternative in the upper right position.

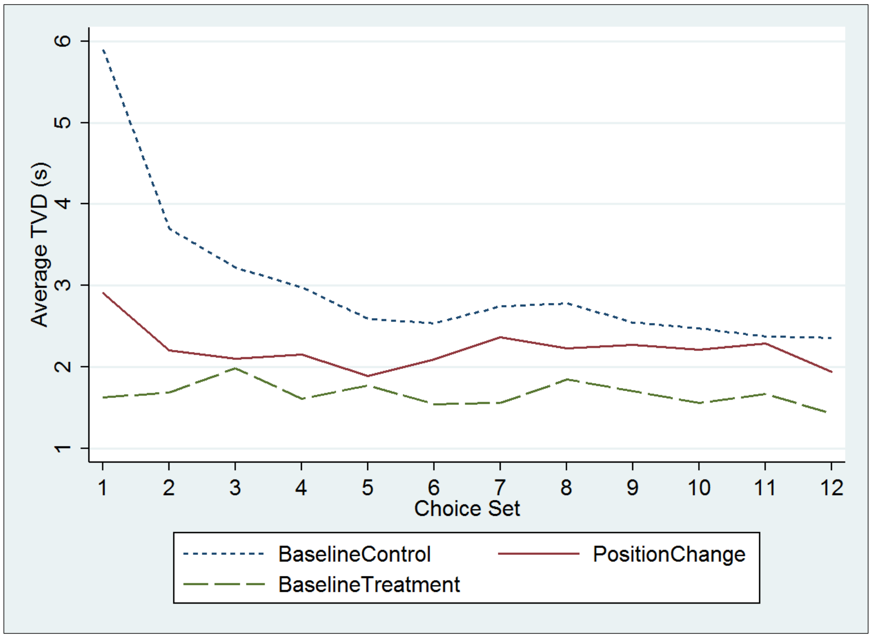

Figure 2.2. Time visit duration for each choice set by treatment.

2.3.2 Consistency in Choices

To gather a better understanding on the influence of the experimental design on consumer choices, we calculate the level of consistency across treatments. Our experimental design allows for a comparison of the consistency in choices, since the product alternatives and choice sets were identical for each treatment, except for the position change and the choice set order. After changing the position of the alternatives in the choice set, subjects consistently selected the same alternative 69% of the time. Furthermore, after reverting back to the identical original positions (*baseline treatment*) and randomizing the order of the choice sets, subjects consistently selected the same alternative 67% of the time. Subjects made the same choice for all three choice sets 57.34% of the time. The consistency level of the DCE choices is high relative to the consistency in other preference elicitation mechanisms, which report consistency levels below 50% in risk related tasks (Lichtenstein and Slovic, 1973; Grether and Plott, 1979). Johnson and Mathews (2001) designed two contingent valuation experimental surveys (an environmental and health survey) to test for consistency of choices. The authors reported a consistency of less than 10% among environmental respondents and 40% among health patients.

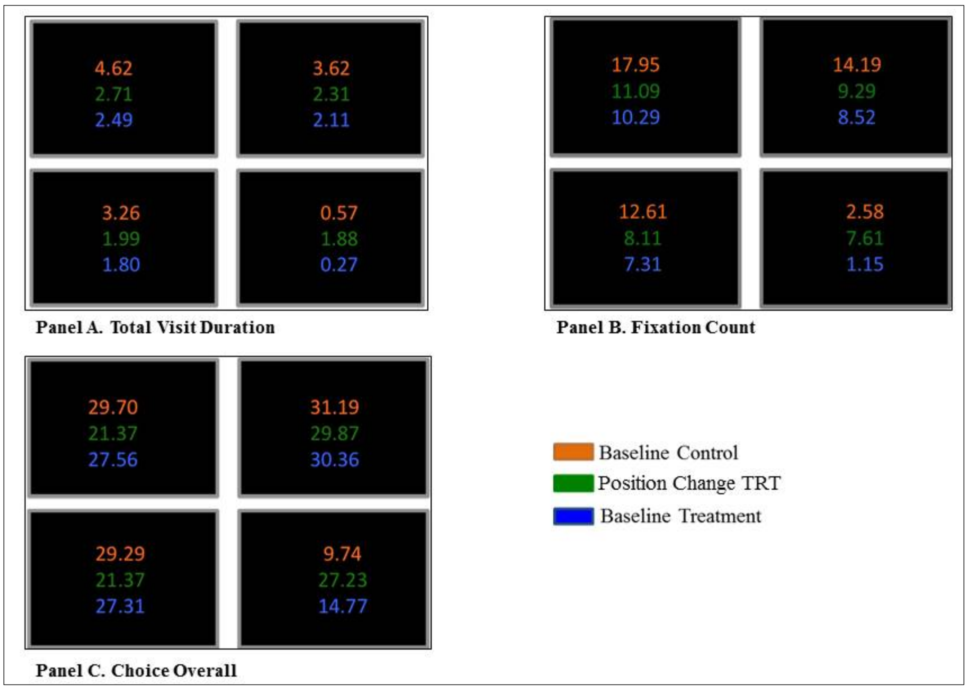

Figure 2.3. Eye tracking metrics by treatment and position.

In order to determine potential causes for preference inconsistencies, we estimate the level of consistency for each choice set. Figure 2.4 displays the consistency level between the *baseline control* and the *position change treatment*. Results show that after changing the position of the alternatives, the level of consistency increases up until the third-choice set, after which it starts to decrease. This decrease in consistency for the latter choice sets may be due to fatigue effects or tiredness exhibited by respondents (Figure 2.2). Similarly, Figure 2.5 shows the consistency level between the *baseline control* and the *baseline treatment*. Recall that these treatments differ only in the order in which the choice sets were presented. In this case, we compared the consistency of choices after the order of the choice sets was altered compared to its original order in the *baseline control*. Besides the dramatic decay in the consistency of the fourth-choice set, the results appear to follow an increasing trend. This increasing trend in the consistency level may be due to the fact that preferences are being constructed as the choice experiment progresses since respondents have more time to think about and react to the trade-offs they are facing (Johnson and Mathews, 2001).

Moreover, we explore whether the consistency level is correlated with the cognitive ability and demographic characteristics of the respondents. Recall that subjects performed a cognitive test (first distraction task) which measured their fluid intelligence independent of knowledge. Results from a Poisson regression for the number of consistent choices (Table 2.1) show that cognitive ability does not affect the level of consistency of preferences. Also, none of the demographic variables were found to be statistically significant. Importantly, the *baseline treatment* variable is not statistically significant, meaning that randomizing the order of the choice sets has the same impact on the consistency level as randomizing the position of the alternatives. These results suggest that consistency in choices does not depend on intrinsic characteristics of the participants or their cognitive ability but might be more generalizable towards preferences of the actual products or the choice tasks.

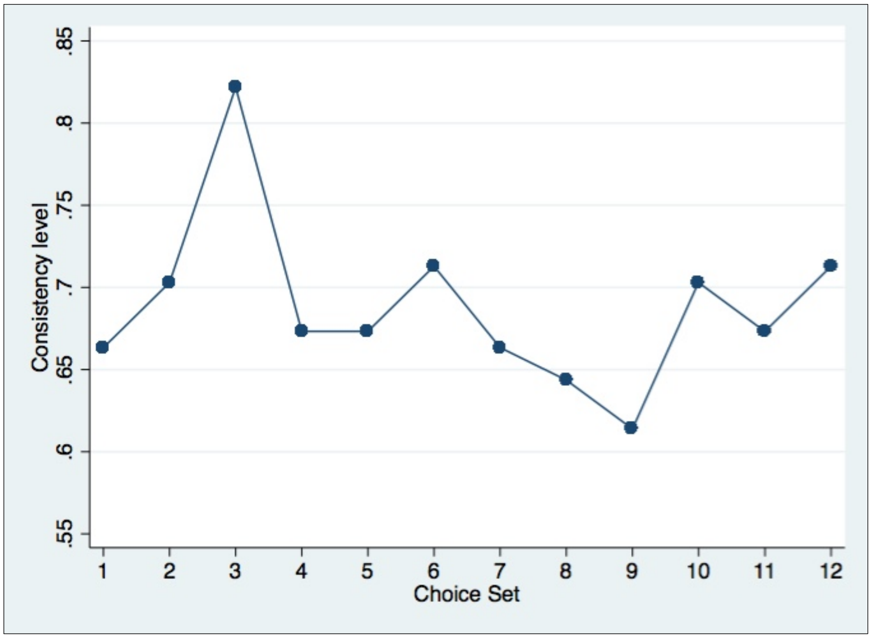

Figure 2.4. Consistency level between baseline control and position change treatment by choice set.

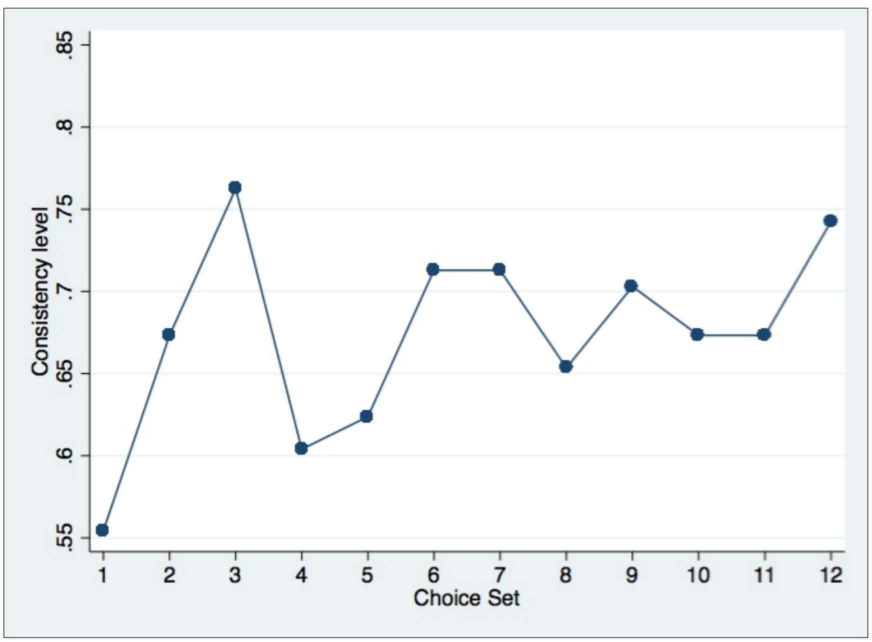

Figure 2.5. Consistency level between baseline control and baseline treatment by choice set.

Table 2.1. Poisson Regression on the Number of Consistent Choices

Variable	Coefficient	S.E.
Baseline treatment [a]	-0.0208	0.0494
Cognitive ability	0.0293	0.0214
Age	0.0018	0.0029
Male	0.0508	0.0532
Race: Hispanic	-0.0466	0.0753
Other	-0.0315	0.0580
Education: Some bachelor's degree	0.0981	0.2733
Some graduate school or more	0.1327	0.2731
Income ($40,000 - $100,000)	0.1489	0.0616
Income (> $100,000)	-0.0905	0.1351
Constant	1.6681 ***	0.3289

[a] This variable represents the consistency level after the alternatives were reverted to the same position but the order of the choice sets was randomized.

Note: *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

2.3.3 Consistency in Attribute Attendance

When looking at the product attributes, eye tracking data revealed that the percentage of times respondents spent evaluating each attribute was consistent across treatments (Figure 2.6). On average, respondents spent more time looking at the color of the products (about 28% of the time for all conditions) suggesting that color is the most important attribute considered by subjects when making artichoke choices. This result is supported by previous research showing that visual attention reflects respondents' preferences and attribute weights in a multi-attribute choice task (Kim et al., 2012). After the color of the product, subjects tended to pay more attention to its packaging and size and they spent less time looking at the price.[1] This result points out the fact that the relative ranking of visual attention is maintained throughout the choice experiments,

[1] A possible explanation for the lower amount of time spent looking at the price compared to the other product attributes is the familiarity with this attribute. It is reasonable to think that since individuals compare product prices on a regular basis, they might not need as much time to process price information.

meaning that respondents seem to be consistent in what attributes are relevant to make their choices.

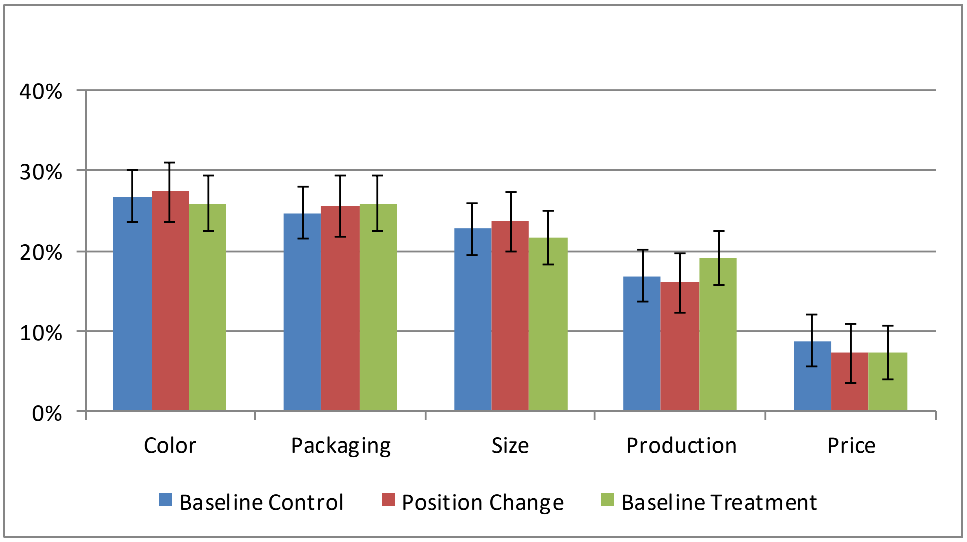

Figure 2.6. Eye tracking percentage of time spent on each attribute weighted by choice set.

Table 2.2 shows the time in milliseconds (ms) that subjects spent looking at the attributes of the chosen and non-chosen products for consistent and inconsistent choices. In both cases, after changing the position of the alternatives and the order of the choice sets, during consistent choices with respect to the choices in the *baseline control,* the time spent looking at the chosen product was significantly higher compared to the no-chosen products. However, there was no difference between the total visit duration between chosen and no-chosen products for inconsistent choices. The results of the visual attention time imply that it was more difficult for inconsistent subjects to differentiate between products. This may be indicative of a more difficult choice (i.e. the evaluated products may be closer to indifference). For example, when making purchasing decisions, people might find it harder to choose among three varieties of red apples versus choosing between three completely different fruit products (e.g., red apple, banana, and orange).

Table 2.2. Total Visit Duration by Consistency and Treatment

	Position Change Treatment				Baseline Treatment			
	Consistent Subjects		Inconsistent Subjects		Consistent Subjects		Inconsistent Subjects	
Total Visit Duration	Mean	S.E.	Mean	S.E.	Mean	S.E.	Mean	S.E.
Chosen Product	3.7151	0.1887	2.4848	0.2051	2.8336	0.1649	2.7897	0.2239
Not Chosen Product	1.7560	0.0687	2.6581	0.1608	2.2454	0.1016	2.5522	0.1673
p-Value	0.0000		0.9123		0.0013		0.0780	

2.3.4 WTP Estimates

Table 2.3 displays the mean and standard deviation of WTP space models assuming the coefficients for all attributes follow flexible polynomial distributions. Although the inconsistency in subjects' choices was substantially smaller compared to other preference elicitation methods, it was enough to vary the mean and distributions of WTP for each attribute across treatments. Specifically, in the case of the "no-product" estimate, both the magnitude and sign of the coefficient changed with respect to the *baseline control* (see Table 2.4 for *p-values* from Mann-Whitney tests across treatments). That is, when keeping the exact same position of the alternatives (*baseline control* and *treatment*), subjects were more likely to choose one of the product alternatives over the "no-product" option; however, the opposite effect was found after changing the position of the alternatives. Essentially, including the no product alternative in the randomization of the position made it more likely to be chosen. However, this inconsistent behavior was exhibited only for the "no product" alternative. Regarding the specific attributes of the products, preferences for the green and large artichokes changed as they carried the highest price premiums ($1.20 and $0.87, respectively) after the position of the alternatives was modified. On the contrary, for the attributes describing fresh, glassed, and pesticide-free artichokes, the mean price premiums significantly decreased after changing both the order of the choice sets and the position of the alternatives. The WTP estimates following normal distributions are displayed in Table A1 in Appendix A.

Table 2.3. Parameter Estimates of WTP Space Models with Flexible Six-Degree Polynomial Distributions

	Baseline Control			Position Change Treatment			Baseline Treatment		
				WTP Means					
	Coefficient		SE	Coefficient		SE	Coefficient		SE
Green	0.8514	***	0.2399	1.2046	***	0.1515	0.4390	***	0.1361
Mixed	1.0232	***	0.1668	1.0310	***	0.0100	0.6293	***	0.1108
Fresh	3.3346	***	0.4249	2.7962	***	0.3436	2.6590	***	0.2475
Glassed	1.7522	***	0.2071	1.5075	***	0.2671	1.4028	***	0.1932
Small	-1.9810	***	0.3061	-1.3209	***	0.3807	-0.8517	***	0.1897
Large	0.3190	***	0.2319	0.8680	***	0.2115	0.8146	***	0.1052
Organic	1.8008	***	0.2657	1.9324	***	0.2418	1.3405	***	0.0571
Pest-free	1.8401	***	0.2448	1.6248	***	0.3061	0.8155	***	0.1269
No-prod	-2.5519	***	0.9346	0.1675	***	0.1309	-1.1994	***	0.4209
Price	0.7240	***	0.1022	0.8382	***	0.0704	1.0816	***	0.1049
				WTP Standard Deviations					
Green	1.1912	***	0.1743	0.7957	***	0.1194	0.5783	***	0.1017
Mixed	0.7853	***	0.0957	0.0228	***	0.0053	0.2688	***	0.0577
Fresh	2.4689	***	0.2985	2.5311	***	0.2841	1.9421	***	0.2157
Glassed	1.1197	***	0.1892	1.2462	***	0.1400	1.1781	***	0.1659
Small	1.3482	***	0.2301	1.1535	***	0.2945	0.9035	***	0.1516
Large	0.7861	***	0.1498	1.1952	***	0.2633	0.5274	***	0.1051
Organic	1.5094	***	0.2189	2.0251	***	0.2914	0.2433	***	0.0256
Pest-free	0.9601	***	0.1607	1.7469	***	0.2275	0.5383	***	0.1265
No-prod	3.3024	***	0.6439	0.4789	***	0.0584	2.4807	***	0.3059
Price	0.4157	***	0.1115	0.3623	***	0.1072	0.3992	***	0.3992
NOBS			4848			4848			4848
Log Likelihood			-1038.09			-1100.29			-1059.75

Note: *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Individual WTP were estimated for each attribute and they were used to show the distributions of WTP by treatment (Figures 2.7, 2.8, and 2.9). Consistent with the findings in Train (2016), none of the attributes follow normal distributions, which highlights the importance of using flexible mixing distributions rather than imposing more restrictive distributional forms. The distributions of WTP estimates differed significantly for nearly all attributes after changing the order of the choice sets and the position of the alternatives, which reinforces the notion that choices are influenced by the position of the alternatives and the order of the choice sets.

Table 2.4. Mann-Whitney Tests Across Treatments

	Baseline Control vs. Position Change Treatment	Baseline Control vs. Baseline Treatment	Position Change Treatment vs Baseline Treatment
		p-values	
Green	0.0000	0.0008	0.0000
Mixed	0.0435	0.0000	0.0000
Fresh	0.0176	0.0105	0.4207
Glassed	0.0355	0.0088	0.3012
Small	0.0000	0.0000	0.0000
Large	0.0000	0.0000	0.3411
Organic	0.0661	0.0323	0.0000
Pest-free	0.0274	0.0000	0.0000
No-prod	0.0000	0.0002	0.0000
Price	0.0000	0.0000	0.0000

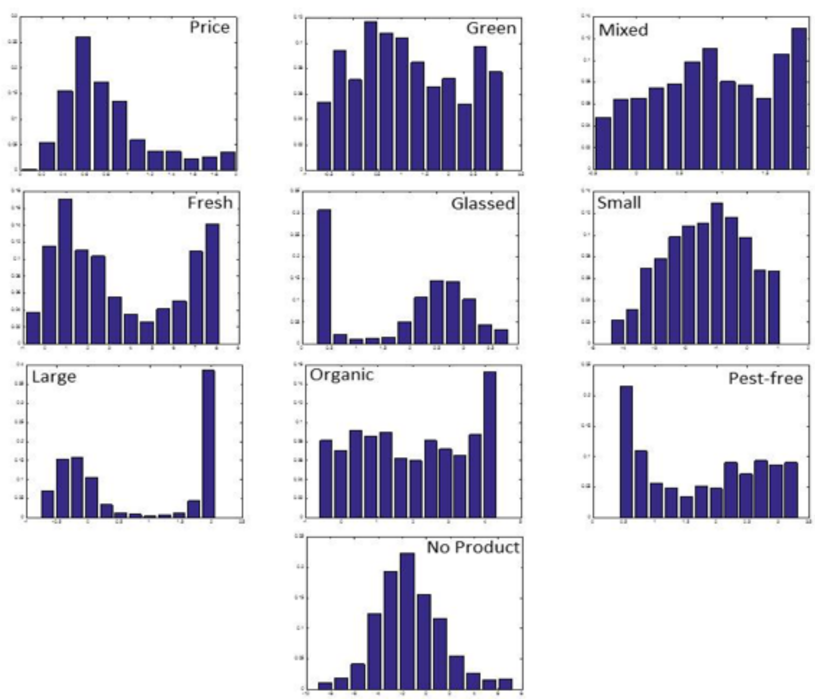

Figure 2.7. WTP distributions of artichoke attributes for baseline control.

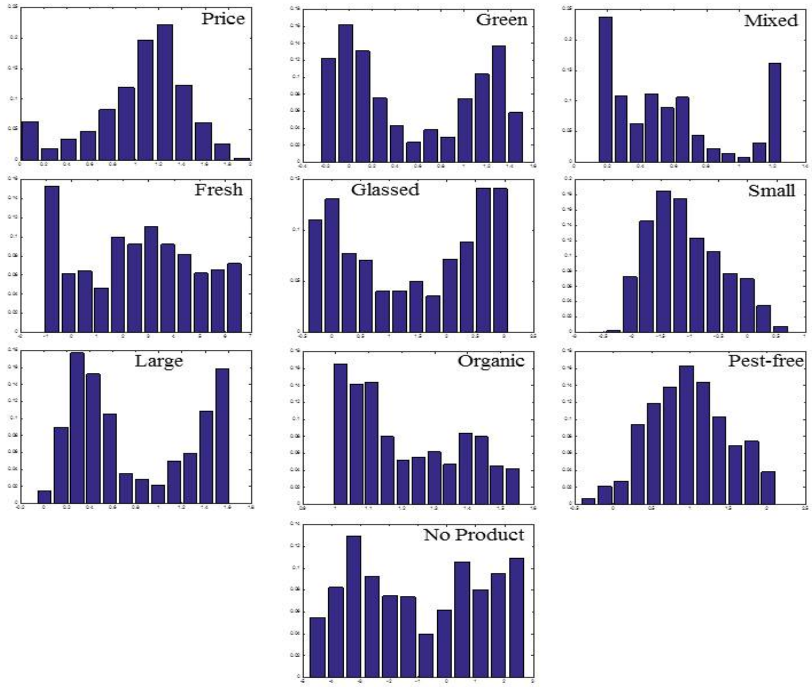

Figure 2.8. WTP distributions of artichoke attributes for position change treatment.

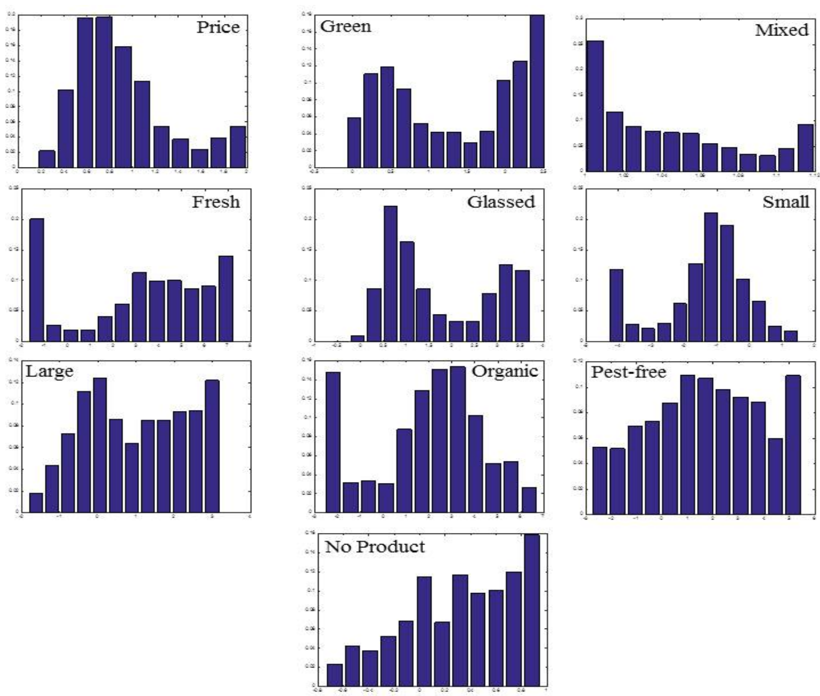

Figure 2.9. WTP distributions of artichoke attributes for baseline treatment.

Table 2.5 presents the WTP correlations between attributes. For the *baseline control*, statistically significant correlations between attributes include: subjects who preferred small artichokes were willing to pay price premiums for organic and pesticide-free artichokes (0.52 and 0.53, respectively); people who liked glassed products had preference for fresh (0.41) but disliked pesticide-free artichokes (-0.49). Moreover, subjects who preferred large artichokes expressed price discounts for mixed-color artichokes (-0.66). In the *position change treatment*, fewer significant correlations and for different attributes were found compared to the *baseline control*. Here, individuals who expressed price premiums for green artichokes preferred small and organic artichokes (0.49 and 0.39 respectively). Also, subjects who preferred organic artichokes liked pesticide-free artichokes (0.55) but dislike glassed artichokes (-0.39).

For the *baseline treatment*, statistically significant and negative correlation was found between green and pesticide-free artichokes (-0.73). Similar to the *baseline control*, respondents who liked fresh artichokes expressed premiums for glassed artichokes; however, here the correlation was stronger compared to the other treatment. These results indicate significant changes in preferences for attributes across treatments, which affirms the significance of the effect of minor changes in the experimental design on elicited preferences in DCEs.

2.4 Conclusions

We have discussed a few areas where the design of DCEs along with the estimation of WTP parameters could be improved. This article contributes to the literature by testing the consistency of preferences in repeated choice experiments, and by applying estimation methods in WTP space with flexible mixing distributions. First, it highlights the importance of the position of the alternatives and the order of the choice sets in the experimental design. In particular, the results show that participants were consistent with their choices 69% after the position of the alternatives in the same choice set was altered, and 67% of the time after the order of the choice sets was randomized. Randomizing the position does not fix the problem, since subjects still chose a different option, even when the options are identical. However, it is noteworthy that inconsistent choices seem to be closer in preference. That is, participants had a more difficult time choosing when the choices where not consistent. Second, the results from the random parameters models suggest that although the relatively high levels of consistency were not enough to keep WTP estimates constant across choice experiments, the "no product" option was the only parameter that differed in terms of size and magnitude. Finally, the article underlines the importance of utilizing less restrictive distributional specifications of the random parameters as the shape of the distributions of WTP did not appear normal for any of the coefficients.

The knowledge that even minor changes in the experimental design could significantly affect individuals stated preferences warrants more attention to detail when designing DCEs to elicit individuals' valuations. That being said, rather than simply 'randomizing' the position of the alternatives and the order of the choice sets as it is common practice in the field, they should be taken in consideration as part of the experimental design in order to obtain more stable preference parameter estimates. Furthermore, more flexible forms such as polynomials should be considered when estimating the distribution of random parameters in order to obtain sufficient information on the actual distribution of WTP and better align empirical results with theoretical expectations.

Table 2.5. WTP Correlations between Artichoke Attributes

Baseline Control

	green	mixed	fresh	glassed	small	large	organic	pest-free	noprod
green	1.0000	0.0162	-0.2298	0.0503	0.1587	0.4124	-0.0753	0.0895	0.0523
mixed	0.0162	1.0000	-0.0911	0.1709	0.1988	-0.6615	0.2333	0.0076	-0.0330
fresh	-0.2298	-0.0911	1.0000	0.4058	-0.0490	-0.1574	-0.4143	-0.1094	0.1118
glassed	0.0503	0.1709	0.4058	1.0000	0.1712	0.0030	-0.3691	-0.4902	0.6627
small	0.1587	0.1988	-0.0490	0.1712	1.0000	-0.2933	0.5163	0.5345	0.1732
large	0.4124	-0.6615	-0.1574	0.0030	-0.2933	1.0000	-0.4714	-0.3962	0.0153
organic	-0.0753	0.2333	-0.4143	-0.3691	0.5163	-0.4714	1.0000	0.5095	-0.1500
pest-free	0.0895	0.0076	-0.1094	-0.4902	0.5345	-0.3962	0.5095	1.0000	-0.2731
noprod	0.0523	-0.0330	0.1118	0.6627	0.1732	0.0153	-0.1500	-0.2731	1.0000

Position Change Treatment

	green	mixed	fresh	glassed	small	large	organic	pest-free	noprod
green	1.0000	-0.4246	-0.2538	-0.3438	0.4863	0.3778	0.3939	0.1932	0.2716
mixed	-0.4246	1.0000	-0.2452	0.1817	-0.2982	0.1625	-0.2218	0.1936	-0.0325
fresh	-0.2538	-0.2452	1.0000	0.2457	-0.2647	-0.2625	0.0762	0.0241	-0.2634
glassed	-0.3438	0.1817	0.2457	1.0000	0.0570	-0.0889	-0.3877	-0.1572	-0.0316
small	0.4863	-0.2982	-0.2647	0.0570	1.0000	0.1892	0.1830	-0.2648	0.1750
large	0.3778	0.1625	-0.2625	-0.0889	0.1892	1.0000	-0.1920	-0.2217	-0.1729
organic	0.3939	-0.2218	0.0762	-0.3877	0.1830	-0.1920	1.0000	0.5470	-0.1722
pest-free	0.1932	0.1936	0.0241	-0.1572	-0.2648	-0.2217	0.5470	1.0000	0.1971
noprod	0.2716	-0.0325	-0.2634	-0.0316	0.1750	-0.1729	-0.1722	0.1971	1.0000

Baseline Treatment

	green	mixed	fresh	glassed	small	large	organic	pest-free	noprod
green	1.0000	0.3593	-0.1600	-0.1202	0.2194	-0.2335	-0.0821	-0.7338	0.3218
mixed	0.3593	1.0000	0.0585	-0.0603	0.2775	0.0797	0.0660	-0.4088	0.3887
fresh	-0.1600	0.0585	1.0000	0.5819	-0.0573	-0.0156	0.2261	0.2591	0.3142
glassed	-0.1202	-0.0603	0.5819	1.0000	0.0176	-0.0867	-0.3715	0.0504	0.5276
small	0.2194	0.2775	-0.0573	0.0176	1.0000	-0.2255	0.1572	-0.0007	0.2505
large	-0.2335	0.0797	-0.0156	-0.0867	-0.2255	1.0000	-0.1099	0.1415	0.1980
organic	-0.0821	0.0660	0.2261	-0.3715	0.1572	-0.1099	1.0000	0.0870	-0.2842
pest-free	-0.7338	-0.4088	0.2591	0.0504	-0.0007	0.1415	0.0870	1.0000	-0.3455
noprod	0.3218	0.3887	0.3142	0.5276	0.2505	0.1980	-0.2842	-0.3455	1.0000

3. THE EFFECT OF FOOD ANTICIPATION ON COGNITIVE ABILITY IN THE PRESENCE OF HUNGER

3.1 Introduction

Resource scarcity in the form of financial constraints, time pressure, sleep deprivation, and high cognitive load can severely impede cognitive capacity, resulting in suboptimal behavior (Shiv and Fedorikhin, 1999; Shah et al., 2012; Mani et al., 2013; Mullainathan and Shafir, 2013; Deck and Jahedi, 2015). Scarcity, of any kind, creates a tendency to seize all available mental resources to focus on the most salient problem, leaving less available resources for other tasks (Shah et al., 2012). Diminished resource capacity affects behavior in various ways. For instance, low-income individuals are often preoccupied about financial and budgetary concerns which leads them to take high-interest loans (Shah et al., 2012), purchase lottery tickets (Haisley et al., 2008), fail to enroll in welfare assistance programs (Bertrand et al., 2004), and make shortsighted economic decisions (i.e. be more impatient) (Haushofer and Fehr, 2014; Carvalho et al., 2016). Restrained eaters focus more on food-related cues (Radel and Clément-Guillotin, 2012), are more impatient (Ashton, 2015), and overeat under high cognitive load (Ward and Mann, 2000). Likewise, individuals experiencing work overload often rely on deadline extensions that can buy them additional time (Perlow, 1999), while the sleep deprived make more risky choices in gambling tasks (Castillo et al., 2017; Ferrara et al., 2015; McKenna et al., 2007; Killgore et al., 2006).

Despite the plethora of research examining how resource scarcity influences individual behavior, prior studies offer little evidence on one of the most common forms of scarcity, namely food deprivation. To date, only a few studies have analyzed the effect of food deprivation on non-hunger related decisions. For example, Ashton (2015) conducted a controlled laboratory experiment to test whether time preferences fluctuate as a result of changes in the hunger level of participants. The author finds that hunger increases impatience towards immediate monetary rewards. Similarly, De Ridder et al. (2014) manipulated the state of hunger of subjects to examine whether hunger affects strategic decisions made under uncertainty. They find that hunger improves, rather than compromise, individual decisions with uncertain outcomes. Contrary to the previous studies, Danziger et al. (2011) conducted a natural field experiment and observe how judicial rulings change in relation to the time at which judges take a food break. The authors report an increase in the proportion of favorable rulings at the very beginning of the work day or after a food break (i.e. when judges are not hungry). They attribute this effect to the restoration of judges' mental resources following the food break.

A key contribution to this literature is the fact that cognitive or mental resources can be replenished through the supplementation of glucose (Gailliot and Baumeister, 2007; Dvorak and Simons, 2009). This phenomenon has been frequently observed in laboratory settings where subjects are asked to consume a snack to help them restore their blood glucose to normal levels. The results usually report an increase in cognitive performance during real effort choice tasks following glucose supplementation (Gailliot et al., 2007; Masicampo and Baumeister, 2008). For example, Danziger et al. (2011) found that the percentage of favorable judicial rulings fluctuates in relation to the time in which judges take a food break. They attributed this effect to cognitive depletion. However, they were unable to identify whether these fluctuations were due to the replenishment of resources by eating, resting, or a combination of both.

An important research question that remains unanswered is whether cognitive resources can be replenished by the simple act of anticipating food intake, prior to actual food consumption. In fact, neurobiological evidence has shown that obese individuals are prone to a phenomenon known as “anticipatory food reward”, in which they exhibit greater activity in somatosensory and gustatory brain regions in response to anticipating food intake (Stice et al., 2008; Blumenthal and Gold, 2010; Volkow et al., 2011). These brain regions are responsible for encoding the sensory and hedonic aspects of food palatability (Stice et al., 2008), meaning that obese people derive more utility from the desire to eat food than from the actual act of eating. Importantly, neuroimaging studies suggest that greater activity in these brain areas might result in overeating and weight gain and provide evidence of an overlap between neural systems underlying drug addiction and food consumption (Grigson 2002). A key feature in the addiction literature relates to the dopamine reward system, which intensifies the “reward” in anticipation of the addictive action and not necessarily in the action itself (Dagher, 2009; Wang et al., 2009). Brain activation, especially in the insular cortex, in response to anticipation of food reward has been observed not only on the obese, but also in post-obese individuals (normal weight individuals with a history of severe obesity), which suggests that abnormal neural responses to food anticipation and consumption persist in groups at high risk of relapse (DelParigi et al. 2004).

In a laboratory experiment, we test for the presence of an “anticipatory food reward” effect by randomizing the order in which subjects perform a cognitive test and a food choice task. We hypothesize that subjects who perform the food choice task prior to a cognitive test will experience an anticipatory effect since they are aware that they will imminently consume a food snack. This is analogous to ordering food at a restaurant. Patrons know the food is coming soon and there is evidence that at that point, the digestive system starts to function (Power and Schulkin, 2008; Mattes, 1997). Based on the neuroscience literature, we expect an anticipation effect to be present for obese individuals only. The results show that overweight and obese subjects experience an anticipatory reward effect, which enhanced their cognitive capacity after merely choosing a food snack that would be readily available for them to eat after the experiment. In other words, overweight and obese subjects who completed the cognitive test before the food choice task performed significantly worse in the cognitive ability test than those who completed the food choice task first. This effect was not present in normal weight individuals, who performed similarly in the cognitive test regardless of the order of the tasks. This finding can help answer a very important question: How does the interaction between hunger and an anticipatory reward system affect the food choices of overweight and obese individuals? We show that the cognitive impairment induced by hunger only affected the food choices of obese individuals, who were more likely to select unhealthy food snacks. Furthermore, we use eye tracking to monitor participants' visual temptation to food-related pictures. Two metrics –total visit duration and pupil dilation– were used to examine the effects of an anticipatory food reward effect on the temptation and emotional arousal of individuals towards food while hungry. The findings suggest that in the absence of an anticipatory food reward effect, hungry obese individuals did not only exhibit more arousal towards food, but they were also more tempted towards unhealthy food snacks.

To our knowledge, this is the first study that combines the elements of food-related visual temptation, hunger state, body weight, and anticipation of food intake to examine whether food may constitute a form of addiction. Our findings provide behavioral support to the notion that food consumption potentially constitutes a form of addiction. While there is an ongoing debate as to whether addictions are a disease (Saletan, 2008) –which may be treatable and perhaps even covered by healthcare programs– our findings suggest that food consumption should be included in this conversation as a potential form of addiction.

3.2 Methodology

3.2.1 Participants

The sample consists of 182 students (91 males and 91 females) from Texas A&M University. Students were recruited as subjects since they are relatively homogeneous in terms of demographic and socio-economic characteristics (Cason and Wu, 2017), allowing us to make treatment comparisons across BMI categories.[2] Participants were recruited using bulk emails and received a show-up compensation fee of $20 for participating in the experiment. The experimental sessions were conducted at the Human Behavior Lab, one-person at a time during different times of the day (from 8:00 am to 8:00 pm) in order to control for time-of-the-day effects. Each session lasted around 60 minutes. To qualify for the study, subjects had to be at least 18 years old, must not have a history of psychiatric or eating disorders or corrective eye surgery (due to eye tracking calibration restrictions). Participants were instructed to refrain from eating for at least three hours prior to their assigned experimental session.[3] The three-hour food deprivation period was selected to mimic the hunger state that most people experience between meals and to ensure a similar state of hunger across participants.

3.2.2 Experimental Design and Procedure

Participants completed a cognitive performance test and a food choice task in randomized order. This generated the two conditions needed to test for the presence of an anticipatory food reward effect. In the first condition, known as the "*anticipatory effect*" condition, subjects completed the food choice task prior to the cognitive test, hence, they anticipated food intake. Subjects in the second condition, known as "*the control*" condition, performed the cognitive test first, thus, they

[2] We control for demographic and socio-economic characteristics in the regression models.
[3] There is no way to know for certain if subjects complied with the fasting requirement. However, because assignment to the treatments was random and did not depend on the fasting or hunger level, we were able to achieve balance across treatment with respect to subjects' hunger level.

could not anticipate food consumption while performing the cognitive task. This condition serves as the control.

The cognitive performance task included 24 problems from the Raven's Progressive Matrices test, which is a computer-based test that has been validated as a measure of fluid intelligence (cognitive function) independent of acquired knowledge (Raven, 2000; Engle et al., 1999). The Raven's problems were displayed individually in order of difficulty. For each test item, subjects were asked to analyze a geometric pattern and identify the missing element that completed the pattern of shapes (see Appendix B for an example). After going through an example, participants had 16 minutes to answer the 24 questions.

The food choice task presented subjects with 20 food snack pairs. Each decision started with a fixation point slide (2 seconds), followed by a stimulus (two food product images), a choice decision, and an inter-stimulus slide. For each choice set, subjects were asked to choose between a healthy and an unhealthy version of the same snack (e.g. original vs. light Yoplait vanilla yogurt). The healthy and unhealthy snacks were ready-to-eat snacks that were carefully selected to be similar in every aspect, except the number of calories (they were similar in terms of price, brand, packaging, and flavor). However, the food choices gave participants a menu of options to choose from in order to appeal to a variety of food snacks. In order to incentivize the food choice task, one of the 20 choice sets were randomly chosen at the end of the session as binding. Subjects had to eat the snack they chose in the binding choice set, after which they received their payment and were escorted out of the laboratory. The binding decision was randomly determined by the participant using a bingo cage that contained 20 balls numbered 1-20. At the end of the experiment, each participant withdrew a ball from the bingo cage to determine the binding choice set. The list of the products used in this task is available in Table B1 in Appendix B.

At the end of the experiment, participants filled out a demographic and behavioral survey. Since participants were required to fast for three hours prior to the experiment, they were asked to report the time at which they consumed their last meal that day. Moreover, they reported their level of hunger on a scale from 1 to 9 (1 = Not at all, and 9 = Extremely hungry) at the beginning of the session following Ashton (2015).[4] Finally, the actual weight and height of each participant were collected in order to accurately calculate their BMI. Appendix B provides details of the experimental procedures.

During the food choice task, eye movements were recorded with a Tobii TX300 desk-mounted eye tracker (Tobii 2014) at a sampling rate of 120 Hz. A nine-point calibration procedure was used to ensure the accuracy of the eye tracking metrics. Two eye tracking metrics, total visit duration and pupil dilation, were used to assess objective visual attention (temptation) and emotional arousal experienced by participants while performing the food choice task. Visual stimuli were presented using iMotions software platform (iMotions 2014).

3.3 Results

From the 182 participants in the experiment, about half the sample was male (49.4%), with an average age of 23.4 years, and an average family income of $40,275. On average, 34.8% identified themselves as White, 19.3% as Hispanic, and 45.9 % as non-White and non-Hispanic. Participants were classified according to their weight status using body mass index (BMI).[5] The average BMI of the sample was 24.7, which is indicative of normal-weight. Of the 182 participants, 116 were normal weight, 41 were overweight, and 25 subjects were obese. Due to random assignment of the

[4] Similar survey questions have been used in economic experiments to validate compliance with fasting requirements (Ashton, 2015). However, alternative methods such as using populations with specific characteristics might be useful to secure compliance with fasting requirements. For example, using Muslims who fast during Ramadan might assure full compliance with alimentary abstention as it is part of the ritual (Haruvy et al., 2018).

[5] Normal weight is defined as a BMI between 18.5 and 24.9 kg/m^2, overweight is defined as a BMI between 25 and 29.9 kg/m^2, and obese is defined as a BMI of 30 kg/m^2 or more (WHO 2000).

treatments, the distribution of weight status is balanced across treatments, with a larger number of normal weight individuals in both treatments (Table 3.1). Moreover, there is no difference in the proportion of male and White individuals between treatments. Recall that subjects were asked to fast for at least three hours prior to the experimental session (*M* = 4.91; *SD* = 3.20). Self-reported hunger levels were collected in the demographic/behavioral survey using a 9-point rating scale. The mean hunger level was 5.12, which indicates that subjects were facing a mild state of hunger at the beginning of the experiment. There were no differences in the reported level of hunger across weight categories ($P = 0.588$) and across conditions ($P = 0.745$), meaning that they experienced a similar state of hunger upon arrival to the lab.

Our main hypothesis states that subjects who performed the cognitive test prior to the food choice task will experience an anticipatory food reward effect. If this is the case, we expect a significant increase in cognitive performance (as measured by the Raven's test) of mildly hungry subjects in anticipation of food consumption.

Result 1: *An anticipatory food reward effect under a state of hunger, improved the cognitive performance of overweight and obese individuals.*

The cognitive performance in the Raven's test is plotted in Figure 3.1. Accuracy represents the proportion of correct answers in the Raven's test. The results show that normal weight individuals performance in the cognitive ability task did not change by the order in which the cognitive test and food choice task were presented ($P = 0.324$). This means that normal weight individuals did not exhibit a food reward anticipation effect. On the contrary, overweight and obese subjects who completed the cognitive test prior to the food choice task performed significantly worse than those who completed the tasks in the opposite order ($P = 0.005$; $P = 0.021$, respectively). This provides a clear indication of the presence of an anticipatory food reward effect for overweight and obese individuals. Recall that while being hungry, overweight and obese individuals were informed that they would be consuming a food snack. These results show that the expectation of the imminent food snack consumption helped enhance their mental resources and performance in the test. This conforms to biological evidence suggesting that digestive and metabolic responses are initiated when individuals are exposed to food-related cues or food intake anticipation (Power and Schulkin, 2008). Interestingly, we find this to be true only for overweight and obese participants. The results of our controlled experiment provide support to previous neurobiological evidence suggesting that obese individuals anticipate more reward from food intake compared to lean individuals (Volkow et al., 2011).

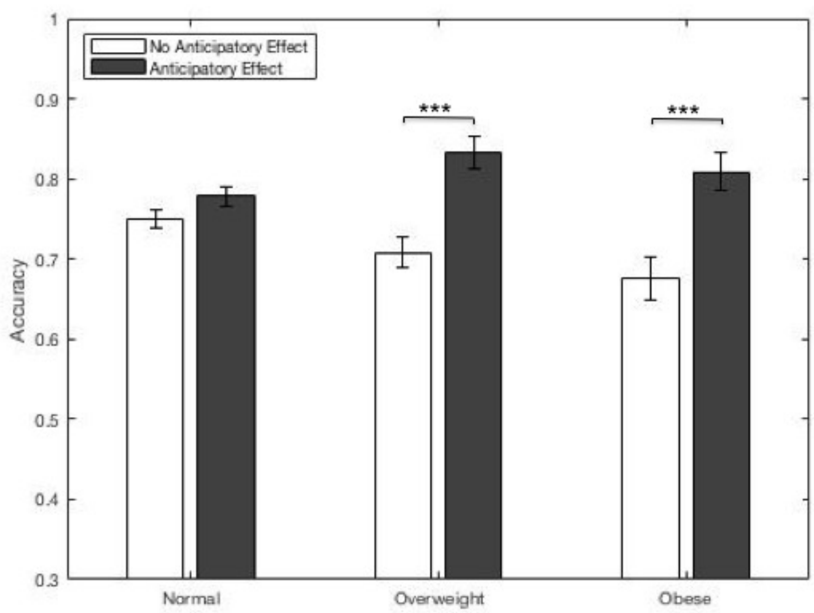

Figure 3.1. Accuracy on Raven’s test by treatment and BMI category.

Table 3.1. Balance Test across Treatment Groups

Variable	Description	Mean (Std. Err.)	Mean (Std. Err.)	Tests
		No Anticipatory Effect	Anticipatory Effect	
BMI	Measured BMI, kg/m2	24.73 (0.46)	24.70 (0.58)	p-value= 0.83
Hunger	Hunger level, 1-9	5.14 (0.21)	5.08 (0.24)	p-value= 0.74
Age	Age in years, 18-40 years	22.72 (0.38)	24.32 (0.44)	p-value= 0.00
Male	DV = 1 if male, 0 otherwise	0.46 (0.05)	0.55 (0.06)	p-value= 0.27
White	DV = 1 if White, 0 otherwise	0.36 (0.05)	0.32 (0.05)	p-value= 0.60
Hispanic	DV = 1 if Hispanic, 0 otherwise	0.27 (0.04)	0.09 (0.03)	p-value= 0.00
Other	DV = 1 if race other than White or Hispanic, 0 otherwise	0.37 (0.05)	0.58 (0.06)	p-value= 0.00
Income	Yearly income	42618.84 (3943.32)	37077.68 (3566.02)	p-value= 0.93
N		105	77	

A primary function of decisions under scarce resources is drawing attentional focus to the task at hand. For example, food deprived individuals pay more attention to food-related cues on a computer screen compared to individuals who are not food deprived (Radel and Clément-Guillotin, 2012; Piech et al., 2010), while thirsty individuals attend more readily to water-related cues (Aarts et al., 2001). Similarly, alcoholics and restrained eaters are more likely to detect alcohol and food-related signals, respectively (Stetter et al., 1995). We use two eye tracking metrics –namely pupil dilation and total visit duration– to examine the effects of anticipatory food reward on visual temptation and emotional arousal towards food snacks under a state of hunger. These metrics were obtained by recording subjects' eye movements while they performed the food choice task.

Result 2: *An anticipatory food reward effect under a state of hunger shifted the temptation of overweight and obese individuals towards healthy food.*

We use the time difference in the visual attention of subjects between the healthy *versus* the unhealthy food snacks as a degree of temptation (Figure 3.2). That is, a negative value indicates more attention towards the unhealthy snacks, while a positive value implies the opposite. This difference, also known as gaze dwell time bias, has been previously used as an index of maintained attention on food-related stimuli (Werthmann et al., 2011; Castellanos et al., 2009). The results presented in Figure 3.2 show that hungry overweight and obese subjects in the *no anticipatory effect* control condition spent more time looking at the unhealthy snacks compared to normal weight individuals (P = 0.004 for overweight, and P = 0.008 for obese). This result supports the findings of Nijs et al. (2010) suggesting a higher level of automatic attention to food related stimuli in food deprived overweight and obese subjects compared to normal weight subjects. While hungry overweight and obese subjects exhibited more temptation towards unhealthy food in the *no anticipatory effect* condition, their attention shifted towards the healthy snacks after experiencing an anticipatory reward effect (P = 0.028 for overweight, and P = 0.085 for obese). For example, when people are hungry and decide to go to a restaurant, they experience a sense of relief immediately after placing their order. This is because individuals anticipate food consumption shortly after the order has been placed.

Pupil dilation, or changes in the pupil size, has been associated with emotional reactions and information processing (Kahneman and Beatty, 1966; Peavler, 1974). In the context of decision-making, pupillary activity has been found to be a reliable correlate of emotional engagement or arousal (Bradshaw, 1967; Hess and Polt, 1960), as the pupil dilates more when subjects exhibit higher approach towards the stimuli, regardless of their hedonic valence (Bradley et al., 2008). For example, Partala and Surakka (2003) found larger pupil diameter to both positive (baby laughing) and negative (baby crying) arousing auditory stimuli. Kimble et al. (2010)

reported increased arousal (larger pupils) in veterans with higher Post Traumatic Stress Disorder (PTSD) symptoms when exposed to threatening stimuli. The relationship between pupillary response and arousal has been found even in infants (i.e. younger than one year of age), whose pupil size increased as response to arousal exhibited when viewing novel stimulus (Jackson and Sirois, 2009) or unusual events (Gredebäck and Melinder, 2010). In the present study, average pupil size or changes in pupillary dilation, are used as indicative of emotional arousal exhibited by participants while looking at the snacks in the food choice task.

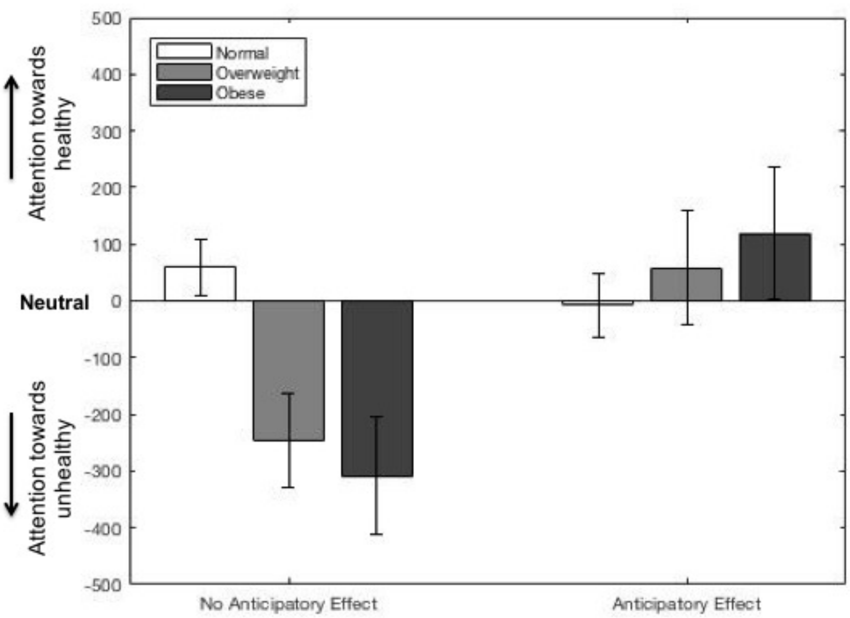

Figure 3.2. Attention level (temptation) towards food by treatment and BMI category.

Result 3: *An anticipatory food reward effect under a state of hunger, reduced emotional arousal towards food among obese individuals.*

The results for the average pupil size are displayed by treatment and BMI category in Figure 3.3. For normal weight and overweight individuals, no significant effects were found regarding their level of emotional arousal across treatments. However, there were significant differences among obese individuals. Specifically, the average pupil size was significantly lower for obese subjects who experienced an anticipatory food reward effect (P = 0.026), meaning that when the obese anticipated food intake, they exhibited lower arousal towards the food snacks. Conversely, under no anticipatory effect, the obese exhibited higher levels of arousal towards the snacks. This effect might be due to the scarcity state (i.e. hunger and cognitive impairment) obese individuals faced in the absence of a food anticipatory reward effect. A second possibility to the effect exhibited by obese subjects is that they might have experienced higher levels of anxiety due to the state of hunger they were facing during the food choice, effect that was vanished by the presence of an anticipatory food reward effect. In this regard, studies have shown that greater pupil dilation also occurs when individuals experience high levels of anxiety (Bernick and Oberlander, 1968; Simpson and Molloy, 1971); however, this should be carefully interpreted since these findings were developed in a context of anxiety related to apprehension about evaluation. The pupil dilation results are further supported by a second eye tracking metric, measured as the total time subjects spent looking at the snacks during the food choice task.

Overall, the observed pattern of attention allocation in this study indicates that in the absence of an anticipatory food reward effect, hungry obese individuals do not only exhibit more arousal towards food, but they also pay more attention and are more tempted by unhealthy rather than healthy snacks. These effects are attributed to the cognitive impairment subjects experienced while in a state of hunger. We show below how this temptation towards unhealthy food products exhibited by obese individuals translated to food choices.

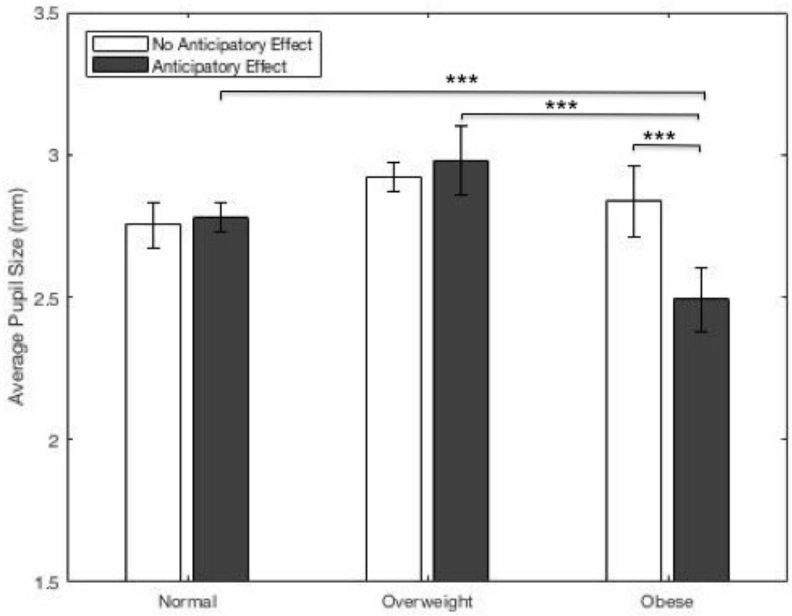

Figure 3.3. Average pupil size during food choice task by treatment and BMI category.

Result 4: *The hunger-induced impairment in the cognitive function of obese individuals had a negative impact on their food choices.*

The proportion of healthy food choices broken down by treatment and BMI category is displayed in Figure 3.4. The results show that the hunger-induced impairment in the cognitive capacity of overweight and obese individuals had a clear and significant effect only on the food choices of obese subjects. That is, when obese individuals are cognitively impaired, they make more unhealthy choices. This finding can be explained by the fact that obese individuals who performed the cognitive test prior to the food task (no anticipatory reward effect) demonstrated lower cognitive capacity. That is, their mental resources were depleted likely as a result of being hungry leaving them with fewer resources to make optimal food choices. Moreover, obese individuals drew more attention towards the unhealthy food snacks, meaning that they were unable to override their temptation towards unhealthy food. Interestingly, while overweight individuals exhibited the same pattern of temptation, they were able to override temptation and their food choices did not significantly change.

Although the descriptive analysis presented so far carries strong results, it fails to account for some individual and behavioral characteristics. Several Panel Logit regression specifications were estimated on cognitive ability using the treatments as the explanatory variables along with other socio-demographic and behavioral variables. As shown in Table 3.2, the specifications in the first two columns include the treatments (presence or absence of anticipatory food reward) and weight status as the only explanatory variables. The specification in column 3 included interactions between weight status and the treatments. Finally, the specifications in columns 4 and 5 controlled for socio-demographic and behavioral characteristics.

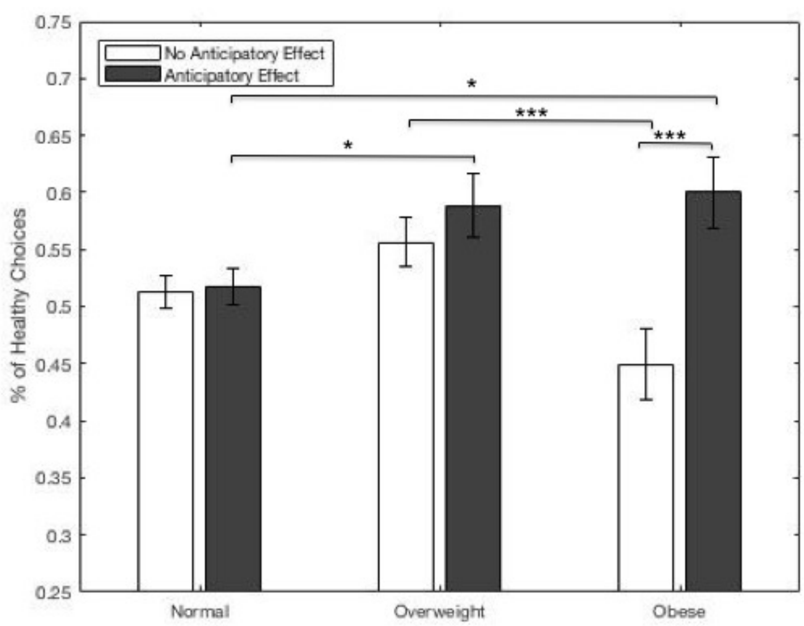

Figure 3.4. Healthy food choices by treatment and BMI category.

The estimation results support the main hypothesis of the presence of an anticipatory food reward effect for overweight and obese individuals. This effect is captured by the fact that the coefficients on the interaction between weight status (overweight and obese) and an anticipatory effect were positive and significant. This indicates that, in the presence of an anticipatory food reward effect, the cognitive capacity of hungry overweight and obese individuals was enhanced increasing their likelihood to perform better in the Raven's test. Regarding the effects of demographic characteristics, columns 4 and 5 show that the coefficient on age was the only variable with a significant effect.

Table 3.2. Panel Logit Regressions on Cognitive Ability

Variable	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)
	(1)	(2)	(3)	(4)	(5)
ANTICIPATORY EFFECT	0.361 ***	0.364 ***	0.158	0.306 ***	0.113
	(0.074)	(0.110)	(0.135)	(0.122)	(0.142)
Overweight		-0.010	-0.224	-0.017	-0.225
		(0.135)	(0.166)	(0.127)	(0.158)
Obese		-0.137	-0.384 *	-0.206	-0.447 **
		(0.155)	(0.227)	(0.159)	(0.232)
Overweight x Anticipatory Effect			0.596 **		0.571 **
			(0.277)		(0.264)
Obese x Anticipatory Effect			0.567 **		0.549 *
			(0.294)		(0.304)
Hunger				-0.049	-0.060
				(0.108)	(0.106)
Age				0.029 **	0.031 **
				(0.014)	(0.014)
Male				0.179	0.175
				(0.110)	(0.108)
Hispanic				0.193	0.199
				(0.146)	(0.143)
Other Race				0.185	0.154
				(0.121)	(0.121)
Income				0.000	0.000
				(0.000)	(0.000)
Constant	1.064 ***	1.083 ***	1.167 ***	0.224	0.289
	(0.074)	(0.085)	(0.094)	(0.366)	(0.345)
N	4,368	4,368	4,368	4,344	4,344
Log-Likelihood	-2372.34	-2371.96	-2368.75	-2354.67	-2351.57

3.4 Conclusions

The current research contributes to advancing the understanding of the effects of food anticipation on cognitive ability under the presence of hunger. The results of the experiment show that overweight and obese individuals exhibit an anticipatory food reward effect, which helped enhance their mental resources and improve their performance in a cognitive test. These behavioral findings are supported by eye tracking data, which reveal that temptation –in the form of visual attention and emotional arousal– is higher under low cognitive resources.

This study provides three important contributions. First, it adds to the exiting literature on resource scarcity and cognitive function (Banerjee and Duflo, 2007; Shah et al., 2012; Mani et al., 2013; Deck and Jahedi, 2015). While previous research on scarcity has been focused mainly on financial constraints (Carvalho et al., 2016), sleep deprivation (Castillo et al., 2017), and time mismanagement (Perlow, 1999), little has been done regarding food deprivation. The effect of hunger on non-hunger related decisions has been analyzed in terms of risk preferences and intertemporal decisions (Ashton, 2015; De Ridder et al., 2014; Briers et al., 2006). However, to our knowledge, the current research is one of the first to directly measure cognitive ability and food choices under a state of hunger. It not only provides evidence that hunger can compromise non-food related decisions, but it also offers a step towards understanding how resource scarcity may cause different behavioral responses in individuals with different health characteristics.

Second, the present research offers behavioral support to neuroscience evidence suggesting the presence of an anticipatory food reward effect among obese individuals (Stice et al., 2008; Volkow et al., 2011). Our findings show that an anticipatory food reward effect can help offsetting the cognitive cost associated with hunger by enhancing the mental resources of hungry overweight and obese individuals. Although alternative methods have proven useful in restoring mental resources –such as glucose supplementation, rest, and positive mood (Gailliot et al., 2007; Masicampo and Baumeister, 2008; Dvorak and Simons, 2009)– we find that the simple act of anticipating food consumption is also effective in this regard.

The current research offers implications for policy makers designing programs to promote the consumption of healthy foods. For example, in contexts where the anticipation of food reward is present, commitment devices should be incorporated in an effort to limit the available food options specifically to healthy foods. Results from our second experiment show that even anticipating the consumption of snacks with relatively low calories, can help restore the mental resources of overweight and obese individuals. Since an anticipatory food reward effect can only be achieved by imminently eating, committing to healthy snacks in advance (i.e. knowing exactly what you will be eating) might serve as a solution (Sadoff et al. 2015). This commitment might be as useful as getting rid of sugar and refined foods at home or creating grocery shopping lists to commit to healthy food in advance.

Third, this is the first study, to our knowledge, that uses eye tracking to examine the relationship between visual attention, hunger, and food-related decision making. The findings show that overweight and obese individuals seem to be particularly responsive to food stimuli when food deprived and cognitively impaired. While overweight and obese subjects drew more attention towards unhealthy food snacks, this temptation affected the food choices of the obese only. Specifically, obese individuals make poor food choices under food deprivation, possibly due to the depletion of their mental resources.

Further research can test whether anticipation of food reward would subsequently enhance not just cognitive ability, but also choice or consumption of healthier food among overweight and obese individuals. As mentioned above, future research is needed to extend the policy implications of this work by testing whether committing to healthy snacking can help replenish mental resources. Finally, it would be interesting to examine whether the negative impact of hunger on cognitive ability persists in the presence of financial incentives (i.e. when subjects are paid depending on the number of correct answers).

4. EPISODIC FUTURE INTERACTION: HOW DOES IT AFFECT CURRENT FOOD CONSUMPTION?

4.1 Introduction

It is commonly believed among economists and psychologists that an individual's sense –or lack thereof– of connection with his future self, plays a key role in driving myopic behavior today (Schelling, 1984; Thaler and Shefrin, 1981). Charles Dickens' depiction of Ebenezer Scrooge in "*A Christmas Carol"* serves as motivation for our work in the present paper. In the story, Scrooge is a cruel person who is given a chance to redeem himself through the intervention of ghosts from his past, present and future. The ghosts of the past and present make him melancholic, but ultimately do not succeed in changing his behavior. It is not until the visit of the Ghost of Christmas Yet-to-Come that Scrooge changes his present behavior. In the words of Scrooge:

> *"Ghost of the Future!" [exclaimed Scrooge], "I fear you more than any spectre I have seen. But as I know your purpose is to do me good, and as I hope to live to be another man from what I was, I am prepared to bear you company, and do it with a thankful heart."*
>
> *Charles Dickens (1843)*

Related to this story is the notion that the degree of connection of an individual with his self-image today, and possibly in the future, might affect his decisions in the present. Indeed, researchers believe in the existence of a gap or misunderstanding between how an individual may feel in the future and the discounted decisions taken in the present (Loewenstein et al., 2003). In this regard, Loewenstein (1996) argues that a more vivid visual imagery of the future consequences of today's actions might amplify the visceral emotions related to processing those actions. These heightened emotional states might help increase the saliency of future consequences associated with a present decision. For instance, extensive exposure of nutritionists to obesity and diabetes acts to charge their emotions against chronic disease, which in turn drives them towards healthier diets (Wardle et al., 2000).

Recently, researchers have taken interest in the relationship between evoking future event imagination or simulation and the associated response of memory processes and behavior. In these studies, participants are typically instructed to imagine realistic events into their own future, after which they are asked to make decisions in the present (Carvalho et al., 2016). For example, in a study conducted by Mani et al. (2013), subjects were induced to think about a hypothetical financial hardship situation. The authors found that inducing financial thoughts significantly decreased the cognitive capacity of the poor, but it had no significant effect on wealthy participants. They attributed this effect to the depletion of mental resources of the poor, which according to them, reduced their available resources for other unrelated tasks. While this literature mainly focuses on financial problems, little has been done regarding health and food consumption, which is the focus of the present study. To our knowledge, this is one of the first studies to investigate the effects of inducing future health-related thoughts in situations that require self-control exertion in food choices today (i.e., eating healthy vs. unhealthy food) (Dassen et al., 2016; Kuo et al., 2016; Daniel et al., 2015).

One issue that arises in the aforementioned literature is that individuals often fail to identify with their future selves due to lack of imagination (Schelling, 1984; Parfit, 1971), thus impairing the level of self-control exerted in subsequent decisions. In fact, several studies have shown that when individuals make decisions for their future self, they use similar processes as those used to make decisions on behalf of strangers (Pronin et al., 2008). It is almost as if the lack of connection between 'me-today' and 'me-in-the-future', drives people to see 'me-in-the-future' as a complete stranger. A strategy that has proven useful in helping individuals intensify the connection with their future and reduce the perceived distance between the future and the present is "Episodic Future Thinking" or "Episodic Prospection" (Atance and O'Neil, 2005). Episodic future thinking refers to the ability of an individual to project himself into the future in order to pre-experience an event (Atance and O'Neill, 2001). Pioneering work by Hershfield et al. (2011) shows that allowing people to interact with age-progressed renderings of themselves made them allocate more financial resources into the future. Similarly, Van Gelder et al. (2013), show that when people interact with realistic digital portraits of their future-self, they are less likely to cheat in a subsequent task. On that basis, we present subjects with altered digital images representing a "healthier" and an "unhealthier" version of themselves in order to facilitate the self-imagination "reward/punishment" and assess their food choices. The closest study to ours is Kuo et al. (2016) who allow participants to interact with a weight-reduced representation of themselves using a virtual environment. They find a significant effect of episodic prospection in reducing calorie consumption.

One of the research domains in which episodic prospection has been extensively utilized is delayed gratification. Immediate gratification refers to the discounting individuals place on larger future rewards in favor of smaller immediate rewards (Mischel and Ebbesen, 1970). In this regard, episodic prospection has proven to be a useful instrument for reducing the *present bias* by helping individuals consider the potential future rewards/punishment of their actions (Daniel et al., 2013; Benoit et al., 2011; Peters and Büchel, 2010). Although standard economic models are based under the assumption that individual preferences are stable over time (Stigler and Becker, 1977);

significant evidence proves that individual preferences vary over time and under different circumstances (Schildberg-Hörisch, 2018; Thaler, 1981). Potential factors causing variations in individual preferences include life cycle dynamics (Levin et al., 2007), exogenous shocks (Dohmen et al., 2016; Chuang and Schechter, 2015; Gerrans et al., 2015), physical conditions (Harrison et al., 2015), priming and framing (Benjamin et al., 2013), and emotions (Necker and Ziegelmeyer, 2016). For example, Castillo et al. (2017) identify changes in risk preferences due to a temporary manipulation of physical conditions (e.g. sleep deprivation), however, they prove that these changes can occur without loss of rationality.

Building on recent literature linking episodic prospection and temporal discounting, we investigate whether interacting with images of "healthier" and "unhealthier" potential future selves can serve as motivation for people to make better food choices in the present. The objectives of the present study are to 1) examine the effects of episodic prospection and inducing healthy thoughts on current food choices, 2) analyze how the treatments interact with food choices by BMI status, and 3) investigate the role of temporal discounting in the association between health-related thoughts inducement and food choices. To this end, we conducted a controlled laboratory experiment where participants were induced with health-related thoughts prior to performing a food choice task and a time preference (temporal discounting) task. The first treatment, referred to as the *immediate effects condition*, presented subjects with a two-minute video focusing on the immediate benefits of dieting and exercising along with the immediate costs of eating unhealthy foods. In the second treatment, known as the *episodic prospection condition*, subjects had the opportunity to interact with a "healthier" and an "unhealthier" version of themselves for two minutes. Subjects in the *control* condition received no information prior to performing the tasks and simply waited two minutes before proceeding to the next phase of the experiment.

We find that providing information about the immediate benefits/costs associated with healthy/unhealthy habits has a positive impact on the number of healthy food choices of overweight and obese individuals. However, when obese individuals are exposed to images of their potential future healthier and unhealthier selves, the opposite effect is uncovered. We argue that obese individuals look at the reward of becoming healthier as somewhat unreachable or as something difficult to achieve. The results from the time preference task further support this argument. Obese subjects displayed higher levels of impatience in both the *control* and the *episodic prospection conditions*, while the opposite effect was found in the *immediate effects condition*. Finally, our behavioral findings are supported by eye tracking data, which revealed that overweight and obese participants had higher levels of temptation and spent more time looking at unhealthy food snacks compared to normal weight individuals. We demonstrate how the temptation towards unhealthy snacks exhibited by overweight and obese subjects translated to their final food choices.

Our paper contributes to the behavioral economics literature focusing on policy interventions and food choices in a controlled decision-making environment. We highlight the importance of designing policy interventions that are tailored to the specific health characteristics of individuals for setting realistic health-related goals. Moreover, we evaluate the effectiveness of programs that focus on long-term rewards of healthy behavior, which if successful, can generate sustainable changes in future eating habits.

4.2 Methodology

4.2.1 Experimental Design

The experiment consisted of a between-subject design in which 182 students (91 males and 91 female) were randomly assigned to one of three experimental conditions, where inducing health-related thoughts was the manipulating factor: 1) *immediate effects condition,* 2) *"episodic* *prospection" condition*, and 3) *control condition*. Specifically, subjects in the *immediate effects condition* watched a two-minute video, which induced them with thoughts related to the immediate benefits of dieting and exercising along with the immediate costs of eating unhealthy food. Subjects in the *episodic prospection condition* were exposed to two digitally altered pictures of themselves for a period of two minutes: a weight-reduced image and a weight-increased image [1], and they were asked to retain their self-image representations for the remainder of the experiment. The order in which the two images were presented was randomized across subjects; that is, half of the subjects observed the weight-reduced image first, followed by the weight-increased image, and the other half observed the two images in the opposite order. We used a computer algorithm to alter the images to represent about a 15% change (increase/decrease) in BMI relative to the participant current BMI; the proportional change was mild in order to represent somewhat realistic goals comparable across participants. In the *control condition*, subjects received no information, and simply waited 2 minutes before starting the experiment to avoid differential incentive structures.

4.2.2 Experimental Procedure

The experimental sessions were conducted one person at a time throughout different times of the day. The participants were students from a large university in the United States who were recruited using bulk emails. A total of 182 subjects participated in the study in exchange for a $20 compensation. In addition, an incentivized time preference (described below) provided the opportunity for subjects to earn additional payments. Subjects were asked to fast for three hours prior to their assigned session. This food deprivation period was done in order to ensure that subjects experienced a similar state of hunger throughout the experiment.

[1] The images were modified using a computer algorithm available at: http://www0.modiface.com/weightmirror/.

Upon arriving to the lab, participants received a unique identification number and signed a written informed consent. After finishing the two-minute manipulation in their assigned treatment, they completed an incentivized food choice task and a time preference task. The food choice task was always performed before the time preference task. The food choice task consisted of 20 choice sets, where subjects were asked to choose between a healthy and an unhealthy version of the same snack in each food choice set (see experimental instructions in Appendix B). The time preference task was presented in a Multiple Price List (MPL) format (Andreoni et al., 2015; Andreoni and Sprenger, 2012; Hardisty et al., 2013; Andersen et al., 2008). The MPL consisted of 15 binary choices. For each decision, participants were required to choose between a lower immediate payment and a higher delayed payment to be delivered two weeks later (Table C1). In order to incentivize the time preference task, one of the choices was randomly selected using a bingo cage containing 15 balls. Subsequently, subjects were given a 10% chance (using a bingo cage with 100 balls) of being paid based on their choice in the binding decision). If the immediate reward was selected, the additional earnings were added to the $20 participation fee and participants received the total payment at the end of the session. If a delayed reward was selected, the additional amount was directly deposited to the subjects' bank account after the specified number of days had elapsed in order to minimize transaction costs. For delayed payments, we used the SurePay service from Wells Fargo Bank, which only requires the email of the participant to make the deposit.[2] A pilot test with 15 individuals confirmed the deposits would be made on time at the specified date. At the end of the session, participants filled out a demographic and behavioral survey and their actual weight and height were collected prior to payment.

[2] Subjects were provided with the PIs contact information as an assurance that they will receive the delayed payment. While this might raise trust issues, this method has been used and validated in previous economics experiments (see Andreoni and Sprenger (2012) for different methods to increase confidence about future payments). Moreover, considering that the sample was solely students it is safe to assume that there is a reasonable level of trust.

4.3 Theoretical Framework

A well-established literature consistently demonstrates that individuals are present-bias (Frederick et al., 2002). That is, for people with present-bias, the subjective value of a future reward is smaller than the same reward available immediately. Empirical evidence, mainly from economic experiments, suggests that individual preferences are constantly varying over time. The malleability of preferences has been attributed to different factors, including life-cycle dynamics, physical conditions, priming and framing, changes in self-control level, emotions and stress (see Schildberg-Hörisch (2018) for a review on preferences stability). For example, high levels of hunger, stress, and sadness are found to increase impatience (Ashton, 2015; Conelisse et al., 2013; Lerner et al., 2012). Intertemporal discounting has been highly associated with obesity outcomes since the rate at which future health benefits are discounted will directly affect today's food choices (Zhang and Rashad, 2008; Komlos et al., 2004). For instance, weight control methods require the individual to sacrifice the desire for overindulging in unhealthy foods in order to secure future health benefits. As Offer (2001) points out: "for weights to rise, it was necessary for people to prefer the immediate gratifications of eating, to the delayed ones of normative appearance". On this basis, we present a simple theoretical framework for the relationship between intertemporal discounting and food consumption.

In order to consider the role of time preferences in a utility maximization framework, assume that the utility function (*U*) is composed of current food consumption (*F*), expected physical appearance (*EA*), and expected healthcare costs related to overweight status and obesity (*EC*):

$$U = \gamma U(F, EA, EC) \tag{4.1}$$

where the discount factor, $0 \leq \gamma \leq 1$, represents the rate of decay of future utility or the impatience level of the individual (i.e., a higher value of γ implies lower future discounting or greater patience).[3] Food is a normal good with diminishing marginal utility, so that $U_F > 0$ and $U_{FF} < 0$; a better physical appearance gives the individual greater utility, implying that $U_{EA} > 0$; while medical spending due to weight-related illnesses creates disutility $U_{EC} < 0$. Physical appearance and healthcare costs are included as expectations since the individual does not know his future image or medical expenses with certainty. It is possible that future self-image may make healthcare costs more salient as the individual becomes aware of the increasing medical spending associated with weight gain. We assume that an individual recognizes the tradeoff between the satisfaction from eating today and the expected physical appearance and healthcare costs in the future, and chooses his path of consumption to maximize his utility.

As mentioned earlier, the bias towards immediate gratification (e.g., indulging in tempting food) is possibly affected by the individual's lack of self-imagination about his future self-image. In this regard, strategies involving future thinking have proven useful in reducing the immediate gratification bias by helping individuals consider the potential future rewards/punishment of their decisions. In our study, we conjecture that allowing individuals to interact with their potential future "healthier" and "unhealthier" self-images might cause them to increase the relative utility of the future reward of a better appearance and hence, change food choices. Additionally, future interaction may make the healthcare costs associated with overweight and obesity more salient and motivate individuals to choose healthier food. This brings us to the first hypothesis.

[3] The discount factor, γ, can be modeled following an exponential (Samuelson, 1937), hyperbolic (Thaler and Shefrin, 1981), or quasi-hyperbolic (Laibson, 1997) discounting function. We do not restrict γ to a specific form.

Hypothesis 1a: *Intervention programs inducing future self-image thoughts are effective in changing current food choices.*

Hypothesis *1a* is in line with research suggesting that episodic future thinking reduces discounting and calorie intake (Kuo et al., 2016; Daniel et al., 2013). We expect that this treatment will increase the value of delayed outcomes (make subjects more patient) since it allows individuals to pre-experience the reward of a future better appearance, which will steer them towards choices with long-term effects (e.g., lower caloric consumption in the present). That is, we expect them to put more weight on their expected future appearance relative to their satisfaction from current food consumption. Moreover, it is expected that future self-interaction will make individuals more aware of the medical care costs of obesity (higher probability of health illness as weight increases), reducing the present bias toward unhealthy food choices.

Hypothesis 1b: *Interventions focusing on the immediate consequences of healthy habits have a positive impact on food choices.*

We expect that inducing thoughts about the immediate benefits/costs of healthy/unhealthy dietary habits might make subjects more patient and decrease their temptation towards unhealthy food. The health-related video might motivate subjects to change their current dietary habits towards a healthier lifestyle. However, it is conceivable that thinking about the immediate consequences of unhealthy behaviors (e.g. stress, tiredness) might overwhelm them causing an opposite backfire effect (Hershfield et al., 2011). Moreover, we believe that this treatment effect might not be as strong as that from the episodic prospection condition since subjects might not feel connected with their future self-image, hindering them to act more future-oriented.

Hypothesis *1a* and *1b* relate to the value subjects place on the immediate satisfaction of eating *versus* the delayed reward of a better appearance and lower future health care costs of chronic-related illnesses. In our study, we directly measure participants' time preferences when making monetary decisions. This not only gives us a direct measure of the value subjects place in smaller immediate rewards *versus* larger future rewards but it also help us to understand the behavioral mechanisms underlying our results. In this regard, we expect to see a positive relationship between episodic prospection and patience when making monetary decisions. Our expected result is supported by previous research suggesting a positive impact of episodic future thinking on delayed gratification (Kuo et al., 2016; Daniel et al., 2013). This means that when the future is viewed in a more vivid and realistic way, people are more likely to align their choices today to benefit them at some point in the future (e.g. saving more money for retirement, as in Hershfield et al., 2011).

So far, the proposed mechanisms to decrease intertemporal discounting have focused on the assumption that there is no heterogeneity in results across individuals with different health characteristics. However, the general assumption of intervention programs that individuals with different BMI status behave similarly fails to capture the full impact of discounting on food consumption.

Hypothesis 2: *There are heterogeneous treatment effects on food choices by BMI.*

Although we do not know how the behavior across subjects with different BMI status will differ, we expect a negative relationship between food choices and BMI in the *control condition* since individuals with higher BMI are more likely to exhibit poorer eating habits (less fruit, vegetables, and nutrient intake) compared to normal weight individuals (Fan and Jin, 2013). That is, in the absence of a treatment, overweight and obese individuals may place a higher value in the immediate pleasure of eating unhealthy food compare to normal weight individuals. We do not have priors regarding the size or magnitude of the treatment effects by BMI category. To date, only two studies have addressed the effect of episodic prospection on delayed gratification differentiating individuals by BMI (Daniel et al., 2015, 2013); however, both studies differ from ours in terms of the sample and time preferences task used. Daniel et al., (2015) show that episodic prospection reduces discounting in overweight and obese children. Although the second study finds a positive effect of episodic prospection in reducing delayed discounting, this effect is similar for normal weight and overweight/obese women (Daniel et al., 2013).

Regarding the treatment effects on time preferences, we also expect differences across BMI categories. Specifically, when comparing the level of patience in the *control condition*, we expect a decrease with respect to the individual's BMI, meaning that patience decreases as BMI increases (de Oliveira et al., 2016; Epstein et al., 2014; Jarmolowicz et al., 2014; Sutter et al., 2013). On the contrary, we hypothesize that overweight and obese individuals will become more patient compared to normal-weight individuals after looking at their weight-modified images in the *episodic prospection condition*.

4.4 Results

4.4.1 Descriptive Analysis

Table 4.1 presents summary statistics of the demographic and behavioral characteristics by treatment. A balance check shows that the means for the proportion of males, White, and Hispanics were not significantly different across treatments. Importantly, the distribution of weight status was balanced across treatments, with a larger number of normal weight individuals in all treatments. Moreover, there were no differences in the reported level of hunger across weight categories ($P = 0.5931$) and across treatments ($P = 0.2635$), which indicates that all subjects faced a similar state of hunger upon arrival to the lab ($M = 5.119$).

In the food choice task, participants had to choose between a healthy and an unhealthy version of the same snack over 20 different choice sets. Hypothesis *1a* and *1b* state that the treatments will have a positive effect on healthy food choices. Although we expect the provision of information regarding the immediate benefits and costs of a healthy lifestyle to increase the number of healthy snacks chosen, based on hypothesis *1a* we argue that the representation of self-images in the future would have a stronger positive effect on the number of healthy snacks chosen.

Result 1: *Relative to the control condition, individuals in the immediate effects treatment made healthier food choices.*

The proportion of healthy snack choices by treatment is plotted in Figure 4.1. Participants in the *immediate effects condition* had a higher proportion of healthy choices compared to the control ($P = 0.0001$). Overall, there was no difference in the proportion of healthy choices between the *control* and the *episodic prospection condition* ($P = 0.4043$). Although the general sample results were not significant, as explained later, there are significant treatment effects for different BMI categories.

Result 2: *There are heterogeneous treatment effects on food choices by BMI categories.*

The results were broken down by BMI category as shown in Figure 4.2. In the *control condition*, the number of healthy choices is represented by a strictly decreasing function with respect to BMI. That is, individuals with higher BMI make less healthy choices. This result goes in line with the empirical literature, such as Fan and Jin (2013) who find that overweight and obese individuals have poor eating habits (eat less fruits and vegetables and more saturated fats) compared to normal weight individuals. After watching the health-related video in the *immediate effects condition*, subjects with the highest BMI respond to the treatment and choose more healthy products. This result suggests that inducing overweight and obese subjects with thoughts about the immediate consequences of healthy and unhealthy habits encourages them to choose healthier food snacks.

Table 4.1. Balance Test across Treatment Groups

Variable	Description	Mean (Std. Err.)	Mean (Std. Err.)	Mean (Std. Err.)	Tests
		Control	Immediate Effects	Episodic Prospection	
BMI	Measured BMI, kg/m2	24.37 (0.53)	25.09 (0.65)	24.71 (0.70)	*p* -value= 0.67
Hungry	Hunger level, 1-9	0.53 (0.06)	0.58 (0.06)	0.66 (0.06)	*p* -value= 0.39
Age	Age in years, 18-40 years	22.17 (0.43)	23.20 (0.49)	24.80 (0.56)	*p* -value= 0.00
Male	DV = 1 if male, 0 otherwise	0.43 (0.06)	0.51 (0.07)	0.54 (0.06)	*p* -value= 0.48
White	DV = 1 if White, 0 otherwise	0.45 (0.06)	0.30 (0.06)	0.29 (0.06)	*p* -value= 0.13
Hispanic	DV = 1 if Hispanic, 0 otherwise	0.25 (0.06)	0.18 (0.05)	0.15 (0.05)	*p* -value= 0.35
Other	DV = 1 if race other than White or Hispanic, 0 otherwise	0.30 (0.06)	0.52 (0.07)	0.56 (0.06)	*p* -value= 0.01
Income	Yearly income	52583.04 (5326.20)	34166.48 (4453.40)	34262.10 (4095.55)	*p* -value= 0.00
N		60	60	61	

Interestingly, the opposite effect was found in the *episodic prospection condition*, where the number of healthy choices increased only for overweight subjects and remained unchanged for normal weight and obese subjects. A potential explanation for this result is that overweight individuals look at the goal of becoming healthier (by losing weight) as something attainable in the short run. However, obese individuals might not be as motivated or excited about looking at self-images of their healthier version since they may perceive this goal to be out of reach or somewhat unattainable. This effect can also be explained by the discrepancy between weight-loss intentions and actual eating behavior found in among obese individuals (Fan and Jin, 2013).

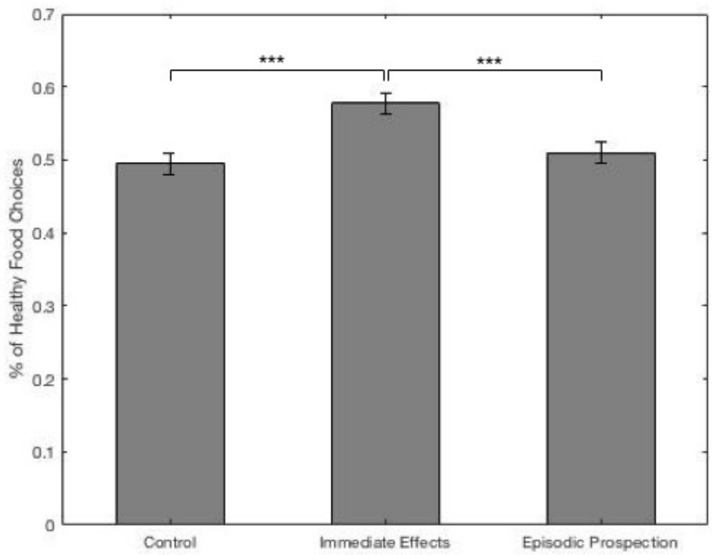

Figure 4.1. Proportion of healthy choices by treatment.

As mentioned above, when individuals choose what to eat, they have to trade off the immediate pleasure of flavorful food *versus* long-term health implications (e.g. weight loss, reduction of health illness) (Hall and Fong, 2007). In other words, people sacrifice the distal benefits of better health in favor of enjoying the immediate culinary pleasure. In this regard, research has shown that the tendency of obese individuals to discount the future is a good behavioral predictor of high energy-dense food intake and failure to keep up with weight loss programs (Best et al., 2012). The tendency to consistently choose immediate gratification while overlooking future rewards can manifest because of the lack of connection between actions today and their future consequences. In fact, when participants are allowed to interact with vivid renderings of their future selves they are more likely to save money (Hershfield et al., 2011), consume fewer calories (Kuo et al., 2016; Daniel et al., 2013), and less likely to engage in criminal behavior (Van Gelder et al., 2013). A potential explanation for this effect is that the vividness of interacting with the future self provides individuals with a clearer picture of the future consequences, thus helping them resist the temptation of immediate rewards.

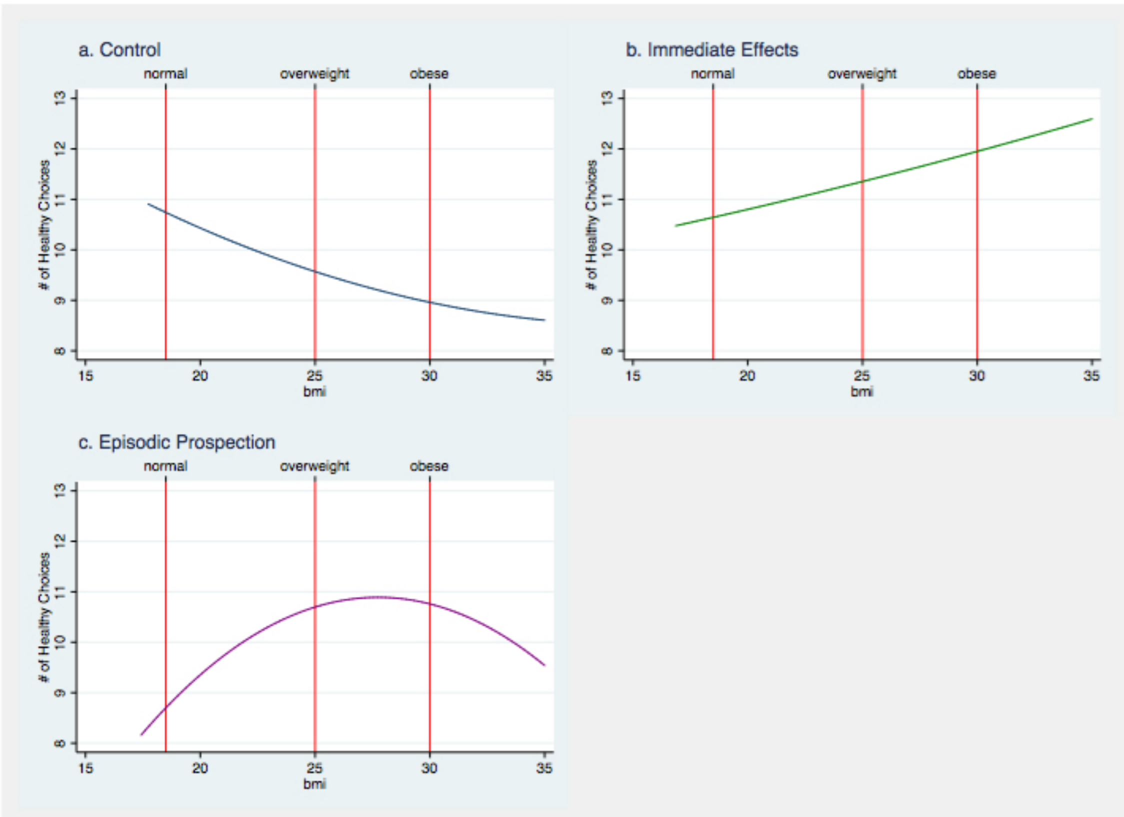

Figure 4.2. Number of healthy choices by BMI and treatment.

Result 3: *Episodic prospection reduces impatience.*

Our results show that when participants interact with representations of their possible future self-image, they made less immediate choices compared to those in the *control* ($P = 0.0261$) (Figure 4.3). That is, having a more future oriented outlook makes subjects more patient. No significant effect was found for the *immediate effects condition* compared to the *control*. Although our result goes in line with previous research (Kuo et al., 2016; Daniel et al., 2015; Hershfield et al., 2011), it is important to evaluate whether the positive effect of episodic prospection on time preferences is driven by individuals with specific health characteristics.

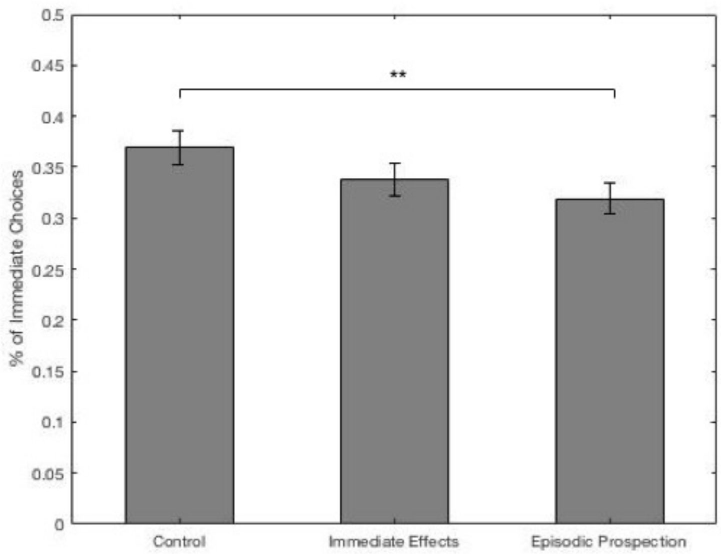

Figure 4.3. Proportion of immediate choices by treatment.

Result 4: *The treatment effects on temporal discounting differed by BMI.*

Figure 4.4 displays the number of immediate choices in the time preference task as a function of BMI. In the *control*, the number of immediate choices is represented by an increasing function with respect to BMI, meaning that subjects with higher BMI are more impatient. This goes in line with previous experimental research suggesting a positive relationship between BMI and impatience (de Oliveira et al., 2016; Epstein et al., 2014; Jarmolowicz et al., 2014; Sutter et al., 2013; Chabris et al., 2008). The opposite effect was found in the *immediate effects condition*, where overweight and obese participants are more patient. This result aligns well with the food choices made in this condition. Being exposed to the immediate benefits/costs of healthy/unhealthy habits not only made participants more patient, but it also helped them make healthier food choices. Interestingly, the opposite effect was found for individuals in the *episodic prospection condition*. While normal weight individuals became more patient after interacting with their future self-images, obese subjects displayed higher levels of impatience. This result provides support to the notion that episodic future interactions had no effect on obese individuals because they perceived the change in their image to be unrealistic or unattainable in the short-run. This result suggests that intervention programs targeting the obese may need to incorporate different goals requiring more tangible or plausible immediate outcomes.

4.4.2 Visual Attention and Arousal Towards Food

To aid in a more extensive analysis on the possible mechanisms underlying food decision-making, we utilize two eye tracking metrics, namely total visit duration and pupil dilation. These metrics allow us to examine whether individuals' visual attention and arousal towards the food snacks have an impact on their ultimate food choices. First, we measure the degree of temptation as the time difference (ms) in visual attention between the healthy and the unhealthy food snacks (Figure 4.5). A negative value indicates higher attention towards the unhealthy snacks, while a positive value implies the opposite. In the *control*, all subjects spent more time looking at the unhealthy snacks with no differences across BMI categories. The high levels of temptation towards unhealthy food snacks can be linked to individual preferences towards unhealthy food as they may be perceived to be tastier compared to healthy foods (Raghunathan et al., 2006). The health-related video in the *immediate effects condition* removed the temptation towards unhealthy snacks, shifting the attention of normal weight individuals towards healthy food. In the *episodic prospection condition*, overweight participants had the highest level of temptation towards the unhealthy products; however, we show below that they were able to override the temptation when making their food choices.

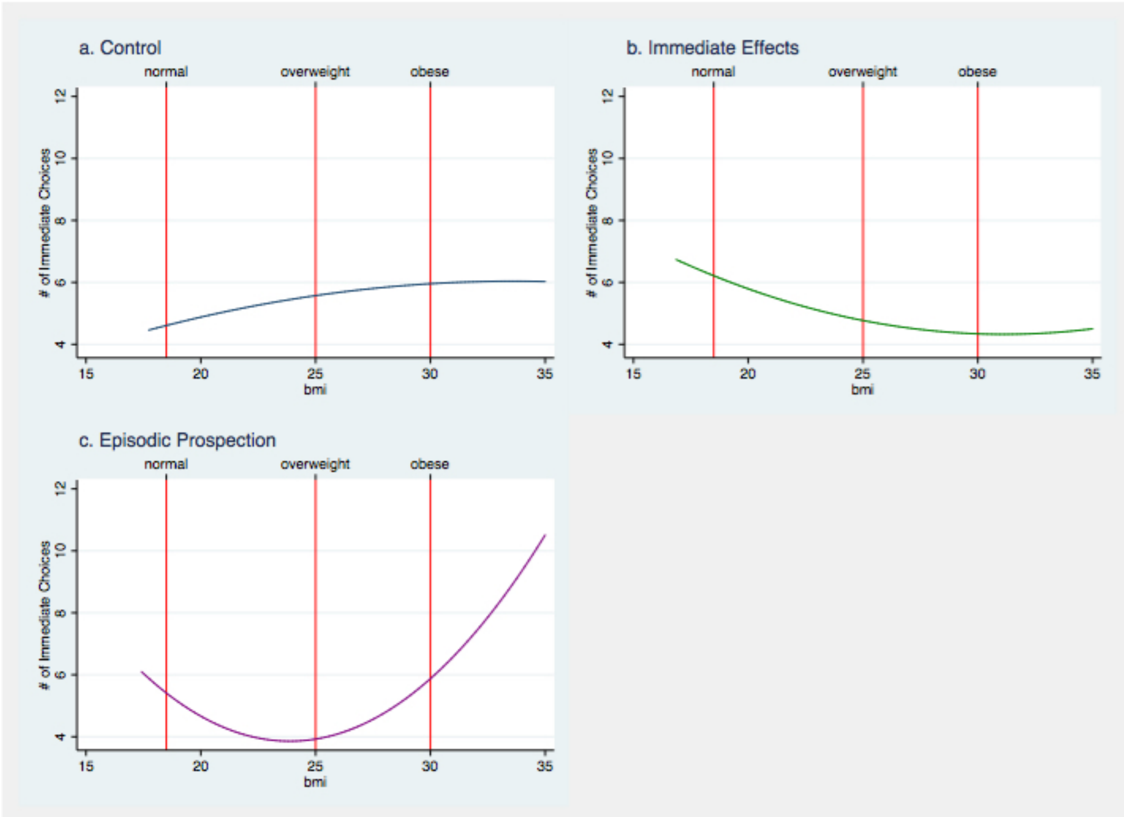

Figure 4.4. Number of immediate choices by BMI and treatment.

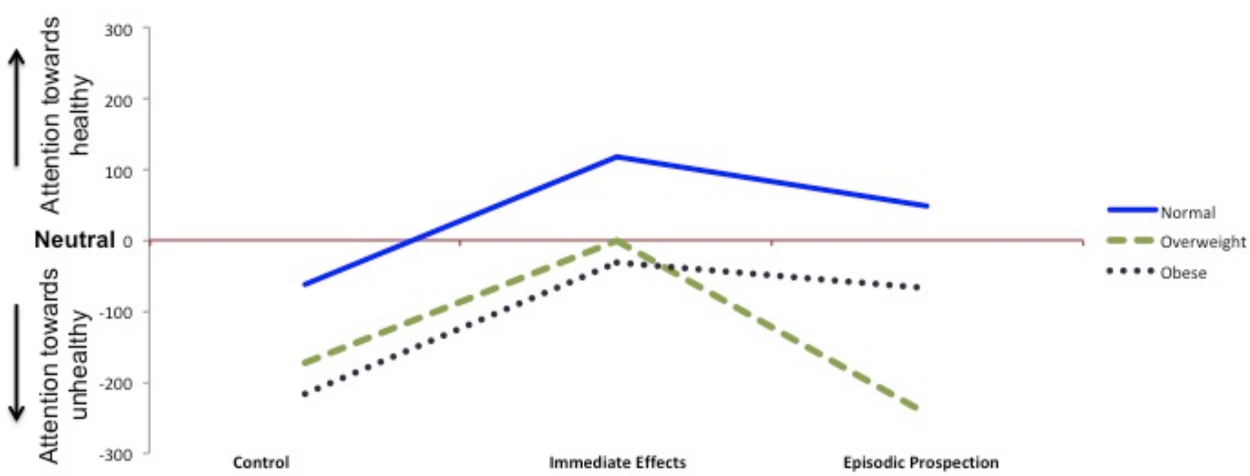

Figure 4.5. Temptation level, measured as the difference in total visit duration between healthy and unhealthy food products.

The second eye tracking metric we use to support our behavioral findings is pupil dilation. Pupil dilation has been linked to higher emotional engagement or arousal (Partala and Surakka, 2003), where an increase in pupil size is related to higher approach towards the stimuli, regardless of hedonic valence (Bradley et al., 2008). The average pupil size, which represents changes in pupillary dilation, is indicative of emotional arousal exhibited by participants while looking at the snacks in the food choice task. Looking at the results in Figure 4.6, it is clear that the average pupil size is significantly lower for subjects in the *immediate effects* and *episodic prospection conditions* compared to those in the *control* (P = 0.0000 for *control* vs. *immediate effects* and P = 0.0000 for *control* vs. *episodic prospection*). In other words, in the treatments participants exhibit lower engagement or arousal towards the food snacks. This result shows that inducing health related thoughts increases the self-control in food choices by decreasing the emotional reaction to food snacks. This result is further explored by treatment and by BMI category.

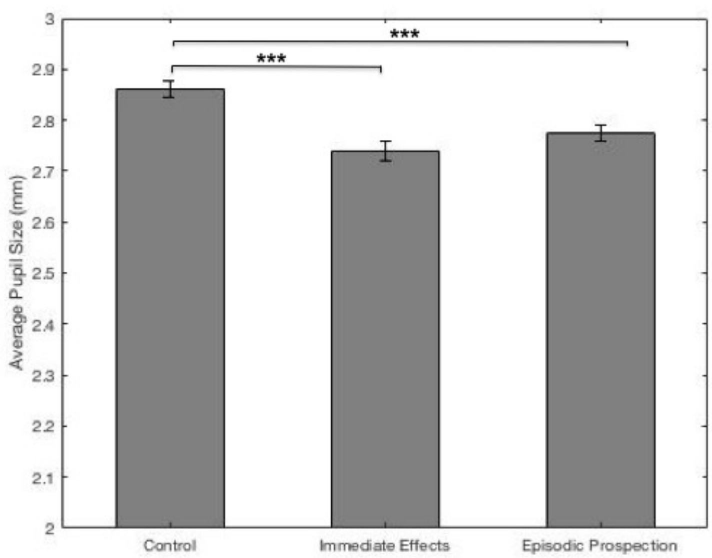

Figure 4.6. Average pupil size by treatment.

Figure 4.7 plots the average pupil size by treatment and BMI. For normal weight individuals, there was a significant decrease in the average pupil size in the *immediate effects* *condition* and in the *episodic prospection condition* compared to the *control* (P = 0.0000 and P = 0.0001, respectively). This result is indicative of an attentional shift from unhealthy to healthy food snacks after receiving the treatments. In the case of overweight individuals, the level of arousal towards food in the *episodic prospection condition* is significantly lower compared to that in the *control* (P = 0.0030) and the *immediate effects condition* (P = 0.0392). Finally, the results show that the obese exhibited lower levels of arousal towards food in the *immediate effects condition* compared to the *control* (P = 0.0001) and the *episodic prospection condition* (p= 0.0000). This result implies that being exposed to the immediate consequences of healthy habits not only removes the temptation of the obese towards unhealthy snacks, but it also decreases their overall emotional arousal towards food snacks. We show below how the behavior exhibited by the individuals translates to their final food choices.

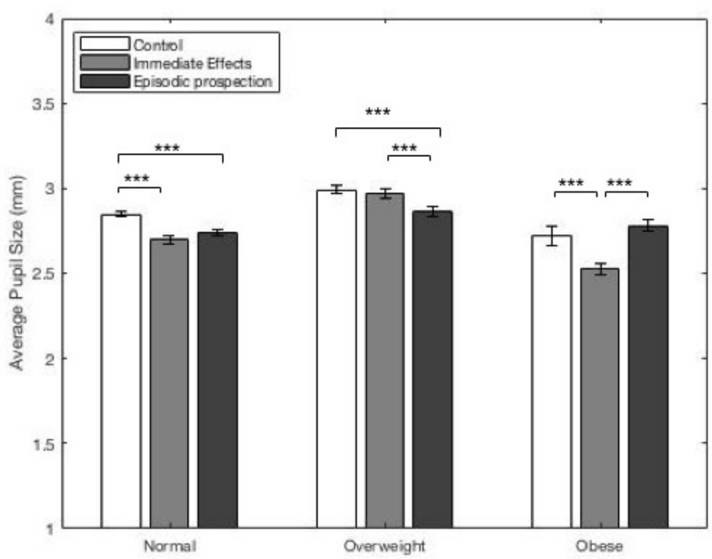

Figure 4.7. Average pupil size by BMI by treatment.

4.3 Controlling for Individual and Behavioral Characteristics

In this section, we estimate several panel Logit regression specifications by BMI category on the probability of choosing the healthy food alternative controlling for individual and behavioral characteristics. Following Train (2009), we assume that decision maker *n* faces a choice among *J* alternatives in each of S choice tasks. The utility that the decision maker obtains from each alternative j, is represented by:

$$U_{njs} = V_{njs} + \varepsilon_{njs} \; \forall \, j \, . \qquad (4.2)$$

where V_{njs} is a vector of explanatory variables, and ε_{njs} is an i.i.d error which follows a logistic distribution.

In the food choice task, subjects were asked to make twenty choices between two products differing only in the number of calories. Other than that, the products had identical attributes; hence there are no product specific covariates. The food choices were modeled as:

$$Y_{ns} = \beta_0 + \beta_1 Immediate_i + \beta_2 Episodic_i + \beta_3 X_n + \epsilon_{ns} \qquad (4.3)$$

where the dependent variable is an indicator variable of whether the individual chooses the healthy alternative. The variables $Immediate_i$ and $Episodic_i$ are treatment dummies ($Control_i$ is the excluded category); X_i is a vector of socio-demographic and behavioral characteristics, and ε_i is an error term i.i.d logistic distributed.

Table 4.2 presents the results for each BMI category. Column 1 represents the specification for normal weight individuals, column 2 for overweight individuals, and column 3 for obese individuals. The three specifications control for demographic and behavioral characteristics. The results of the panel regressions support the general findings described above. The treatment effects differ depending on the health characteristics (BMI status) of the participants. First, the *immediate effects condition* has a positive and significant effect for overweight and obese individuals, meaning that after watching the video regarding the immediate consequences of healthy habits, their probability of choosing the healthy snack increased. Second, the estimates of the *episodic prospection condition* show that the probability of choosing the healthy alternative significantly increased only for overweight individuals and had no effect on the obese. We argue that this effect may be due to lack of motivation of the obese to attain the goal of becoming healthier as it might require high levels of effort with low immediate rewards. This result was supported by the behavioral data from eye tracking. In the case of normal weight individuals, none of the treatments had an effect on their food choices. This result highlights the importance of setting achievable and realistic health-related goals customized for specific health characteristics, such as BMI.

4.4 Conclusions

Given the alarming increase in obesity rates, many policy interventions have been implemented in order to promote healthy diets and increase physical activity. In this paper, we highlight the importance of creating customized programs and interventions targeting particular groups according to their specific health characteristics for setting achievable and realistic health-related goals. We conclude that a one-size fits all approach for weight-loss intervention programs may not be effective for all individuals. In fact, our results suggest that the potential benefits for the most vulnerable BMI groups may be very small if the programs fail to account for prompt observable outcomes. Realistic and immediate tangible gains can be useful in producing significant increases in the motivation and engagement for individuals to keep up with the intervention program. In this regard, fitness-tracking applications are now designed to provide participants with immediate feedback about their progress in terms of caloric consumption, weight loss (changes in BMI and

% of body fat), exercising, and sleeping habits. Importantly, individuals are able to set their own (realistic) goals and share their progress with other participants, which might help increase their motivation towards the goal.

Table 4.2. Panel Logit Regressions on Healthy Food Choices

Variables	Normal[a]		Overweight[b]		Obese[c]	
IMMEDIATE EFFECTS	0.132		0.763	***	0.532	**
	(0.146)		(0.141)		(0.243)	
EPISODIC PROSPECTION	-0.092		0.506	***	0.130	
	(0.137)		(0.193)		(0.274)	
Hunger	0.017		0.023		-0.058	
	(0.118)		(0.157)		(0.279)	
Age	0.012		0.007		0.044	**
	(0.015)		(0.017)		(0.018)	
Male	-0.178		-0.182		-0.370	
	(0.111)		(0.133)		(0.294)	
Race2 (Hispanic)	-0.086		-0.179		0.185	
	(0.151)		(0.185)		(0.313)	
Race3 (Other)	-0.127	**	0.072		0.807	***
	(0.146)		(0.164)		(0.271)	
Income	0.000		0.000		0.000	
	(0.000)		(0.000)		(0.000)	
Constant	-0.034		-0.313		-1.525	***
	(0.357)		(0.443)		(0.489)	
Log-Likelihood	-1567.56		-551.06		-335.45	
Observations	2280		820		500	

Note: Standard errors are reported in parentheses.
[a]Normal category corresponds to a bmi<= 24.99
[b]Overweight category corresponds to bmi>=25 and bmi<=29.99
[c]Obese category corresonds to a bmi>=30

In our study, we utilize behavioral economics and biometric tools (i.e., eye tracking) to analyze whether inducing health-related thoughts and self-image representations influence the eating behavior of normal weight, overweight, and obese individuals. We find that the provision of information about the immediate benefits of eating healthy and exercising had a positive impact on the food choices of overweight and obese individuals. However, exposing the obese to images representing healthier and unhealthier versions of themselves, results in the opposite of the intended effects. We attribute this effect to the possibility that the obese look at the reward of becoming healthier difficult to achieve or somewhat unreachable. The self-consciousness of their appearance may play a role in their motivation (or lack thereof) for having healthy lifestyles.

The results found here can serve as recommendations for obesity intervention programs. So far, health-related policy has focused on interventions highlighting the immediate consequences of eating habits. In this paper, we evaluate the effectiveness of programs that focus on the long-term rewards of healthy behavior, which if successful, are believed to generate a more sustainable change in future eating habits. Furthermore, by customizing programs to the individuals' specific health characteristics, programs can appeal to different priorities and goal setting. Tailoring realistic targets can keep individuals engaged and translate into better outcomes. For instance, while using education about the immediate consequences of healthy habits works well for overweight and obese individuals, based on the results of the episodic prospection treatment, we believe that long-term rewards work poorly for obese subjects, who might require more tangible or plausible immediate results. This speaks to the efficacy of the "immediate effects" intervention program in achieving sustainable improvement in the healthy behavior of obese individuals. Future studies should assess how long the "immediate effects" intervention effects last in relation to healthy food choice behavior.

5. CONCLUSIONS, LIMITATIONS, AND FURTHER RESEARCH

5.1 Conclusions

This dissertation examined food-related individual behavior using hypothetical and non-hypothetical economic methods in combination with eye tracking data. Several controlled laboratory experiments were implemented to examine:

- The consistency of stated preferences for food products in repeated choice experiments, and the use of econometric models in WTP space that allow for more flexible mixing distributions.
- The effect of food anticipation on the cognitive ability of normal weight, overweight, and obese individuals while facing a state of hunger.
- The impact of thoughts inducement and episodic future thinking on the food choices and time preferences of normal weight, overweight, and obese individuals.

Specifically, Essay 1 evaluates the consistency of preferences for food products as using the same experimental design of DCEs and changing only the position or order of the choice set. The empirical results indicate that after changing the position of the same alternatives in the choice set, participants were consistent with their choices 69% of the time. Furthermore, after reverting back to the identical original positions of the alternatives but randomizing the order of the choice sets, individuals' choices were consistent 67% of the time. These results were supported by using random parameters models with flexible mixing distributions to estimate WTP for food attributes. Consistency in choices resulted in similar WTP estimates across choice experiments. It was also found that none of the attributes followed a normal distribution, which highlights the importance of considering more flexible forms such as polynomials when estimating the distribution of random parameters.

Essay 2 reported the results of a laboratory experiment in which the hunger level of participants was manipulated before evaluating their cognitive performance and food choices. An anticipatory food reward effects was found for overweight and obese individuals, which helped enhanced their mental resources and performed better in a cognitive test. Moreover, eye tracking data revealed that temptation, in the form of visual attention and emotional arousal, was higher under low cognitive resources.

Finally, in Essay 3 participants were induced with health-related thoughts and self-image representations prior to performing a food choice task and a time preference task. The findings suggest that the provision of information about the immediate consequences of healthy/unhealthy habits had a positive impact on the food choices of overweight and obese individuals. However, exposing obese subjects to images representing healthier and unhealthier versions of themselves, results in the opposite of the intended effects. This last result is attributed to the possibility that the obese look at the reward of becoming healthier difficult to achieve or somewhat unreachable. These findings are supporting by eye tracking data showing how visual attention and arousal towards the food products have an impact on the ultimate choices of obese individuals only.

5.2 Limitations

This dissertation contains a number of limitations, which include:

- The hypothetical nature of the laboratory experiment in Essay 1 may have affected the way participants evaluated the product attributes and stated their preferences; thus, it must be recognized as a potential source of bias in valuations. Specifically, participants may pay little attention to the price of the products as there were no real monetary transactions involved.

- The sample used in the experiments in Essays 2 and 3 is unbalanced in terms of BMI, with a significantly lower number of obese individuals compared to overweight and normal weight individuals. Although several recruiting methods were implemented, there were persistent difficulties in recruiting obese subjects. A potential solution is to use in-person recruiting with an obese experimenter approaching potential participants. This might create a more comfortable environment for obese subjects, which in turn might increase their participation rate.

5.3 Directions for future research

There are several directions for further research. In particular, an extension to Essay 2 would be to directly measure the effect of hunger on individuals' cognitive ability. While there is evidence that hunger compromises non-hunger related decisions (Ashton, 2015; De Ridder et al., 2014), the direct impact of food deprivation on cognitive function has not been investigated. This can be done by conducting laboratory experiments where participants' hunger level is manipulated by varying the number of required fasting hours prior to the experimental sessions. Furthermore, it would be interesting to use individuals with different weight status as participants to test whether the hunger effect is ubiquitous or specific to certain types of individuals. On another note, while the cognitive test used in Essay 2 was hypothetical, it might be worthwhile to measure cognitive ability using an incentivized task to determine whether the presence of real rewards can affect the performance of hungry individuals.

Concerning Essay 3, additional research could test the use of more real environments, such as virtual reality, to induce future health-related thoughts in situations that require self-control exertion. To date, only one study has utilized virtual reality to test whether allowing subjects to interact with weight-reduced representations of themselves affect their calorie consumption and time preferences (Kuo et al., 2016). However, this method has not been previously used in incentivized economic experiments.

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APPENDIX A

A.1 Experimental Instructions

[*Screen 1*]

WELCOME!

Thank you for participating in today's session. The experiment will proceed in several stages.

Stage 1: First choice task

Stage 2: Short quiz

Stage 3: Second choice task

Stage 4: Demographic survey

Stage 6: Third choice task

Stage 6: Receive Product and Payment

Let us know when you are ready to continue

[*Screen 2*]

We will begin with a review of the definitions of the artichoke products you will be evaluating.

If you have any questions during the instructions, please do not hesitate to ask.

Please let us know when you are ready to continue.

[*Screen 3*]

There are five attributes to consider:

1. Price:

   In US Dollars, how much would you pay for one unit of the described artichoke product.

2. Size:

Small – golf sized (1.5-1.75” diameter)

Medium – tennis ball sized (2.5-2.75” diameter)

Large – baseball sized (2.75-3.0” diameter)

3. Color:

   Green, purple or a mix of purple and green

   Please let us know when you are ready to continue

[*Screen 4*]

4. Presentation:

   Fresh, brined in glass containers or brined in cans

5. Production method:

   Certified organic, pesticide free, conventional productions

   If you have any questions please do not hesitate to ask. Otherwise, please let us know when we can begin.

[*Screen 5*]

We will begin the first set of decision tasks now.

Please review the options presented to you and select one. When you have selected, please tell us which one and click it.

The mouse click will take you to the next selection.

From this point onward, please remember to keep your eyes on the screen while making your decisions.

[*Screen 6*]

This concludes the first choice task.

You will now complete a short quiz.

When you are done with the quiz click the escape key in the keyboard to continue with the study.

When you are ready to begin click the mouse.

[*Screen 7*]

We will now begin the second decision task.

Please remember to keep your eyes on the screen at all times.

Click the mouse when you are ready.

[*Screen 8*]

This concludes the second choice task.

You will now fill out a survey.

When you are done with the survey click the F10 key in the keyboard to continue with the experiment.

If you are ready to begin, click the mouse.

[*Screen 9*]

We will now begin the third decision task.

Please review the options presented to you and select one. When you have selected please tell us which one and click on it.

The mouse click will take you to the next section.

Please remember to keep your eyes on the screen at all times.

Click the mouse when you are ready.

[*Screen 10*]

This concludes today's experiment! We will now prepare your payment.

Thank you very much for your participation!

A.2 Random Parameter Models with Normal Distributions

Table A1. Parameter Estimates of WTP Space Models with Normal Distributions

	Baseline Control			Position Change Treatment			Baseline Treatment		
				WTP Means					
	Coefficient		SE	Coefficient		SE	Coefficient		SE
Green	1.1749	***	0.2255	1.2158	***	0.1720	0.6370	***	0.1333
Mixed	0.7454	***	0.2050	1.0617	***	0.1846	0.6978	***	0.1375
Fresh	3.6049	***	0.4059	2.7876	***	0.3182	2.7716	***	0.2564
Glassed	2.0499	***	0.3319	1.5566	***	0.2360	1.3194	***	0.2042
Small	-1.6688	***	0.2685	-1.4049	***	0.2540	-1.0304	***	0.1635
Large	0.6516	***	0.1857	0.6878	***	0.2040	0.7767	***	0.1184
Organic	1.8541	***	0.3284	2.0799	***	0.2954	1.2757	***	0.1833
Pest-free	1.8714	***	0.3392	1.3468	***	0.2724	0.8458	***	0.1714
No-prod	-0.9170	**	0.4219	0.1008		0.1329	-1.0407	***	0.2669
Price	-0.7767	***	0.1002	-0.7378	***	0.0639	-1.2884	***	0.1633
				WTP Standard Deviations					
Green	0.9756	***	0.2355	-0.6530	***	0.2602	0.4421	***	0.1400
Mixed	0.6201	***	0.2626	-0.0312		0.2637	-0.2807	**	0.1379
Fresh	2.2675	***	0.3233	2.2472	***	0.3219	1.9428	***	0.2248
Glassed	-0.8939	***	0.2605	1.0784	***	0.2839	-0.8747	***	0.1499
Small	1.3791	***	0.2758	1.4510	***	0.2570	0.8701	***	0.1532
Large	0.7085	***	0.2482	1.2565	***	0.2174	-0.4199	**	0.1924
Organic	1.2451	***	0.2709	2.3331	***	0.3183	-0.1423		0.2263
Pest-free	0.7283	***	0.2534	2.0724	***	0.2929	0.6377	***	0.1515
No-prod	4.1154	***	0.6851	-0.4224	***	0.1634	1.8813	***	0.2873
Price	0.3590	***	0.1067	0.0373		0.0914	0.7931	***	0.2418
NOBS			4848			4848			4848
Log Likelihood			-1172.93			-1211.78			-1176.73

Note: *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

APPENDIX B

B.1 Experimental Instructions for Experiment 1

[*Screen 1*]

WELCOME!

Thank you for participating in our study. The session will proceed in several stages.

Stage 1: Cognitive Test

Stage 2: Survey

Stage 3: Receive Payment

[*Screen 2*]

Cognitive Test

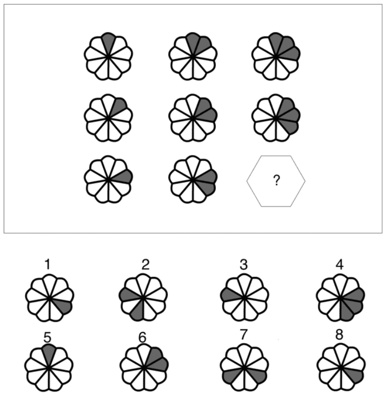
This stage will proceed as follows:

1. You will be asked 24 questions.
2. In each question, you will be asked to analyze a geometric pattern and identify the missing part to complete the series.
3. The test takes approximately 16 minutes. Once the 16 minutes have elapsed, you will proceed to the next stage.

[*Screen 3*]

First, consider the following example:

The objective is to identify the missing element that completes the pattern of shapes.



Here, the fourth alternative is the most appropriate match among the eight available options.

[*Screen 4*]

This concludes this stage of the experiment.

Now we will proceed to the Survey.

[*Screen 5*]

Please answer the following survey questions.

How often do you exercise? (Include only periods of exercise longer than 20 minutes).

a) Never
b) Once a month
c) Once a week
d) 2-3 times per week
e) 4-6 times per week
f) Once a day
g) More than once a day

Do you currently smoke cigarettes?

How many hours did you sleep last night?

How many days per week do you eat breakfast?

a) 0 days
b) 1 day
c) 2 days
d) 3 days
e) 4 days
f) 5 days
g) 6 days
h) 7 days

At what time did you consume your last meal today?

[*Screen 6*]

Rate on the scale from 1 to 9, how hungry were you feeling at the beginning of the session (1= Not at all; 9= Extremely hungry).

Rate on the scale from 1 to 5, how strongly do you agree with the following two statements (1= Strongly disagree; 5= Strongly agree)

a) Things that are good for me rarely taste good
b) There is no way to make food healthier without sacrificing taste.

[*Screen 7*]

Do you currently have a serious health issue?

Please indicate your age in years.

Please indicate your Major by Department.

Please indicate your current academic year.

a) Freshman
b) Sophomore
c) Junior
d) Senior

Please indicate your gender.

a) Male
b) Female

[*Screen 8*]

Please indicate your race.

a) Asian/Pacific Islander
b) African American
c) Caucasian/White
d) Native America/Indigenous
e) Hispanic
f) Other (Please list below)

Please indicate your household yearly income for 2018. (Include all forms of income, including salary, interest and dividend payments, tips, scholarship support, student loans, parental support, and allowance)

a) Less than $30,000
b) $30,000 - $39,999

c) $40,000 - $49,999
d) $50,000 - $59,999
e) $60,000 - $69,999
f) $70,000 - $79,999
g) $80,000 - $89,999
h) $90,000 - $99,999
i) 100,000 - $149,999
j) $150,000 or more

[*Screen 9*]

This concludes today's experiment!

You will now receive your payment.

Thank you very much for your participation.

B.2 Experimental Instructions for Experiment 2

[*Screen 1*]

WELCOME!

Thank you for participating in our study. The session will proceed in several stages.

Stage 1: Cognitive Test

Stage 2: Food Choice Task

Stage 3: Survey

Stage 4: Receive Product and Payment

Press <Enter> to continue…

[*Screen 2*]

Cognitive Test

This stage will proceed as follows:

4. You will be asked 24 questions.

5. In each question, you will be asked to analyze a geometric pattern and identify the missing part to complete the series.
6. The test takes approximately 16 minutes.

Press <Enter> to continue…

[*Screen 3*]

This concludes this stage of the experiment.

Now we will proceed to the Food Choice Task.

Press <Enter> to continue…

[*Screen 4*]

Food Choice Task

This stage will proceed as follows:

1. This stage consists of 20 choice situations.
2. In each trial, you will be presented with two food products.
3. You need to choose which of the products you would prefer to eat.

Press <Enter> to continue…

[*Screen 5*]

4. Your decisions are real. At the conclusion of the experiment, one decision will be randomly selected to be binding.
5. You will receive one single unit of the food product you chose and will have to eat it at the end of today's session.

Press <Enter> to continue…

[*Screen 6*]

Please answer the following survey questions.

How often do you exercise? (Include only periods of exercise longer than 20 minutes).

a) Never
b) Once a month
c) Once a week
d) 2-3 times per week
e) 4-6 times per week
f) Once a day
g) More than once a day

Do you currently smoke cigarettes?

Do you consume alcohol?

How many hours did you sleep last night?

How many days per week do you eat breakfast?

a) 0 days
b) 1 day
c) 2 days
d) 3 days
e) 4 days
f) 5 days
g) 6 days
h) 7 days

At what time did you consume your last meal today?

Rate on the scale from 1 to 9, how hungry were you feeling at the beginning of the session (1= Not at all; 9= Extremely hungry).

Do you currently have a serious health issue?

Please indicate your age in years.

Please indicate your Major by Department.

Please indicate your current academic year.

a) Freshman
b) Sophomore
c) Junior
d) Senior

Please indicate your gender.

a) Male
b) Female

Please indicate your race.

a) Asian/Pacific Islander

b) African American
c) Caucasian/White
d) Native America/Indigenous
e) Hispanic
f) Other (Please list below)

Please indicate your household yearly income for 2016. (Include all forms of income, including salary, interest and dividend payments, tips, scholarship support, student loans, parental support, and allowance)

a) Less than $30,000
b) $30,000 - $39,999
c) $40,000 - $49,999
d) $50,000 - $59,999
e) $60,000 - $69,999
f) $70,000 - $79,999
g) $80,000 - $89,999
h) $90,000 - $99,999
i) 100,000 - $149,999
j) $150,000 or more

[*Screen 6*]

This concludes today's experiment!

You will now draw the decision in the food choice task that will be realized.

You will have to consume the chosen food product before leaving the lab.

Finally, you will receive your payment.

Thank you very much for your participation!

Figure B1. Example of products displayed in food choice task.

Table B1. List of Food Products Used in Food Choice Task

Unhealthy Snacks	**Healthy Snacks**
Classic Lays potato chips (160 cal.)	Oven-baked Lays potato chips (120 cal.)
Original Fiber One chewy bar (140 cal.)	90 – Calorie Fiber One chewy bar (90 cal.)
Original Jell-O gelatin (70 cal.)	Low calorie Jell-O gelatin (10 cal.)
Original Sargento string cheese (80 cal.)	Reduced fat Sargento string cheese (50 cal.)
Original Pringles potato chips (150 cal.)	Fat free Pringles potato chips (70 cal.)
Original Yoplait yogurt (150 cal.)	Light Yoplait yogurt (90 cal.)
Original Snack Pack pudding (110 cal.)	Sugar free Snack Pack pudding (70 cal.)
Traditional Oikos Greek yogurt (150 cal.)	Non-fat Oikos Greek yogurt (120 cal.)
Original Cheez-It baked crackers (150 cal.)	Reduced fat Cheez-It baked crackers (130 cal.)
Original Jif peanut butter (250 cal.)	Reduced fat Jif peanut butter (250 cal.)
Original Gatorade beverage (80 cal.)	Low calorie Gatorade beverage (30 cal.)
Original Quaker chewy bar (140 cal.)	Low fat Quaker chewy bar (90 cal.)
Original Ritz crackers (80 cal.)	Whole wheat Ritz crackers (70 cal.)
Traditional Lipton green tea (100 cal.)	Diet Lipton green tea (0 cal.)
Original Great Value ice cream sandwich (160 cal.)	97% fat free Great Value ice cream sandwich (110 cal.)
Xtreme butter ACI II popcorn (160 cal.)	94% fat free ACI II popcorn (130 cal.)
Original BelVita biscuits (230 cal.)	Soft baked BelVita biscuits (190 cal.)
Original Jell-O swirls pudding (110 cal.)	Reduced calorie Jell-O swirls pudding (60 cal.)
Original Dole peaches (70 cal.)	No sugar added Dole peaches (25 cal.)
Classic coca cola can (90 cal.)	Zero calorie coca cola can (0 cal.)

APPENDIX C

C.1 Experimental Instructions

Notes: Prior to completing the tasks, subjects in the treatments receive the respective manipulation. Subjects in the control simply waited two minutes and started the experiment.

[*Screen 1*]

WELCOME!

Thank you for participating in our study. The session will proceed in several stages.

Stage 1: Food Choice Task

Stage 2: Time Preference Task

Stage 3: Receive Product and Payment

Press <Enter> to continue…

[*Screen 2*]

Food Choice Task

This stage will proceed as follows:

6. This stage consists of 20 choice situations.
7. In each trial, you will be presented with two food products.
8. You need to choose which of the products you would prefer to eat.

Press <Enter> to continue…

[*Screen 3*]

9. Your decisions are real. At the conclusion of the experiment, one decision will be randomly selected to be binding.

10. You will receive one single unit of the food product you chose and will have to eat it at the end of today's session.

Press <Enter> to continue…

[*Screen 4*]

This concludes this stage of the experiment.

Now we will proceed to the Time Preference Task.

Press <Enter> to continue…

[*Screen 5*]

Time Preference Task

This stage will proceed as follows:

7. You will be presented with 15 alternatives that include economic decisions.
8. Each alternative involves a choice between two payment Options.
9. Please choose your preferred payment option for each alternative.

Press <Enter> to continue…

[*Screen 6]*

10. At the end of the experiment, one alternative will be chosen, and you will be paid according to the payment option you chose for this alternative.
11. To facilitate the delivery of the payment, the experimenter will get your email address and transfer the payment to your bank account.
12. The payment amount and delivery date will depend on the option chosen by you in the binding alternative.

Press <Enter> to continue…

[*Screen 7*]

This concludes today's experiment!

You will now draw the decisions in the food choice task and time preference task that will be realized.

You will have to consume the chosen food product before leaving the lab.

Finally, you will receive your payment.

Thank you very much for your participation!

Table C1. Time Preference Survey

Payoff Alternative	Payment Option A (Pays **today**)	Payment Option B (Pays in **2 weeks**)	Preferred Payment Write A or B
1	$10.00	$10.50	
2	$10.00	$11.00	
3	$10.00	$11.50	
4	$10.00	$12.00	
5	$10.00	$12.50	
6	$10.00	$13.00	
7	$10.00	$13.50	
8	$10.00	$14.00	
9	$10.00	$14.50	
10	$10.00	$15.00	
11	$10.00	$15.50	
12	$10.00	$16.00	
13	$10.00	$16.50	
14	$10.00	$17.00	
15	$10.00	$17.50	