Consumers' Health-Related Food Choices and Behaviors

By

Yi Xie

A Dissertation Presented in Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy

Approved March 2018 by the
Graduate Supervisory Committee:

Timothy Richards, Chair
Carola Grebitus
Naomi Mandel

ARIZONA STATE UNIVERSITY

May 2018

ABSTRACT

This dissertation offers three essays that investigate consumers' health-related food choices and behaviors from three different, yet complementary, angles. The first essay uses an eye-tracking experiment to examine consumers' visual attention to the Nutrition Facts Panels for healthy and unhealthy products. In this essay, I focus on how involvement and familiarity affect consumers' attention toward the Nutrition Facts panel and how these two psychological factors interact with new label format changes in attracting consumers' attention. In the second essay, I demonstrate using individual-level scanner data that nutritional attributes interact with marketing mix elements to affect consumers' nutrition intake profiles and their intra-category substitution patterns. My findings suggest that marketing-mix sensitivities are correlated with consumers' preferences for nutrient attributes in ways that depend on the "healthiness" of the nutrient. For instance, featuring promotes is positively correlated with "healthy" nutritional characteristics such as high-protein, low-fat, or low-carbohydrates, whereas promotion and display are positively correlated with preferences for "unhealthy" characteristics such as high-fat, or high-carbohydrates. I use model simulations to show that some marketing-mix elements are able to induce consumers to purchase items with higher maximum-content levels than others. The fourth chapter shows that dieters are not all the same. I develop and validate a new scale that measures lay theories about abstinence vs. moderation. My findings from a series of experiments indicate that dieters' recovery from recalled vs. actual indulgences depend on whether they favor abstinence or moderation.

However, compensatory coping strategies provide paths for people with both lay theories to recover after an indulgence, in their own ways. The three essays provide insights into individual differences that determine approaches of purchase behaviors, and consumption patterns, and life style that people choose, and these insights have potential policy implications to aid in designing the food-related interventions and policies to improve the healthiness of consumers' consumption profiles and more general food well-being.

DEDICATION

To my Mother and Father

ACKNOWLEDGMENTS

I would like to take this opportunity to express my deep gratification to those who helped me complete this journey. The dissertation would never be completed without the support from my committee, my family, and my friends.

First and foremost, I owe a debt of gratitude to my advisor Dr. Timothy Richards, who guided me with his expertise, generosity, and patience. I benefited greatly from his advice and it was truly an honor to work with him. I would also like to express my sincere gratitude to the rest of my committee, Dr. Naomi Mandel and Dr. Carola Grebitus, for providing me the precious learning opportunities and generous help. I also appreciate the valuable comments from all other faculty members in the Morrison School of Agribusiness and the department of Marketing. I would like to thank my family and my mother in particular. My mother sacrificed much to help me get through the hard times. Further, I would like to thank my fellow graduate students: Claudia Dumitrescu, William Allender, Jake Wang, Di Fang, Sophie Winter, Karen Lewis, Simbarashe Pasirayi, Octavio Valdez, Iryna Printezis, Alwin Dsouza, Maria Luz Malabayabas, Kathy Ramirez, and Shijun Gao. I cherish our friendship and will never forget those up and down moments went though together. Moreover, I would like to express my deep gratitude to all my friends for their warmhearted support with a special thanks to Chen Xiang and Yingying Chen. Finally, I want to thank my daughter, Chelsea Wang, for her love and smiles, and giving me the faith to never give up.

TABLE OF CONTENTS

CHAPTER Page

APPENDIX Page

LIST OF TABLES

Table Page

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

The rising rate of obesity and overweight in the US has focused the attention of consumers, policymakers, and even food manufacturers on the choices consumers make among healthy and unhealthy foods. Better choices by consumers, more effective policies to modify consumer choices, and products that make it easier for consumers to manage their weight all depend on a better understanding of the consumer-choice dynamic. In this research, I consider three aspects of this choice environment, using three different analytical perspectives.

Fighting obesity is one of the most intractable issues facing US policy makers. Data from the National Center for Health Statistics show that two thirds of adults are either overweight (BMI over 85% percentile) or obese (BMI over 95% percentile) (Ogden et al. 2014, 2013). Although estimates indicate that the obesity rate has plateaued, and even shows a small downward trend among preschoolers in some states (CDC Report 2013), obesity is still one of the leading public health problems in the US. There are many factors that contribute to obesity, from lifestyle choices (i.e., physical activity, food intake, and sleep; Spruijt-Metz 2011), to the choice environment (i.e., access to quality food), and genetic predispositions (Shell 2002). In this dissertation, I focus on investigating consumers' food-intake related behaviors, especially their choice of healthy[1] food products. Specifically, I study three related questions on the nexus of

---

[1] There is no universally-accepted definition for "healthy" and "unhealthy" foods. Government agencies, private sectors, non-profit organizations and academic researchers define "healthy food" with different standards for particular policy applications (e.g., food labeling, food public settings, and food marketing)

marketing and nutrition. The first question concerns how, and whether, consumers pay attention to nutrition labeling on food products, while the second examines how marketing-mix elements affect consumers' nutrition- intake profiles, and the third considers how consumers moderate the intake of unhealthy items in their diet.

There is considerable evidence that consumers have become more health conscious (Prasad, Strijnev, and Zhang 2008; Leeflang and van Raaij 1995), and their concern is manifest in a higher demand for food products with attributes that are perceived to be healthier such as low fat, low calorie, or low-in-sugar (Sandrou and Arvanitoyannis 2000). However, obesity is a much more complicated problem that involves a host of behavioral and psychological issues. For example, some argue that one cause of obesity lies in the tendency for consumers to become addicted, in a "rational" sense, to specific nutrients (Cawley 1999; Richards, Patterson, and Tegene 2007). Second, acknowledging that obesity is a dynamic phenomenon in which errors in decision making accumulate over time, others maintain that present bias is a more important cause. Present bias (O'Donoghue and Rabin 1999), means that people prefer smaller and mediate instant gratification over future long-term but greater reward, so that a Twinkie today represents a higher increment to utility than the prospect of being fit in 10 years. Framing issues that concern how foods are presented, labeled, or packaged may also lead to overeating by decreasing feelings of guilt (Wansink & Chandon, 2006). This dissertation consists of

---

(Canada et al. 2009). Generally, "healthy" food contains less type and amount of negative nutrients such as fat, sodium, and cholesterol and more type and amount of positive nutrients such as vitamin A, vitamin C, calcium, iron, protein, and fiber. It is the opposite for "unhealthy" products. This study does not limit its focus on definite "healthy" or "unhealthy" food products, but rather considers alternatives within the same category as comparably "healthier" or "unhealthier" in a relative sense according to their differentiated nutritional profiles. For example, low-sugar jam can be considered relatively "healthier" than jam alternatives that have regular- or high-sugar levels. This study is interested in exploring the substitution pattern among these alternatives.

three main chapters that investigate consumers' health-related food choices and behaviors from three different, yet complementary angles.

One school of thought maintains that unhealthy diets result from a lack of information regarding the elements of a healthy diet, or one that is appropriate for the maintenance of an acceptable bodyweight (Jacoby and Chestnut 1977). Therefore, my substantive chapters begin with the second, in which I examine consumers' visual attention to Nutrition Facts Panel (NFP) for healthy and unhealthy products using an eye-tracking experiment. The use of the NFP is one of the most effective ways to promote healthy food consumption (Drichoutis, Lazaridis, and Nayga, 2006), but the actual use of the label is very low (Cowburn and Stockley 2005). In fact, consumers often ignore the information provided on the label, or simply do not understand it even if they do pay attention. Consumers' lack of attention to nutrition labels hinders their use of nutrition labels during grocery shopping (Bialkova and van Trijp 2010; van Trijp 2009).

The US Food and Drug Administration (FDA) in 2016 updated the NFP to help consumers better recognize and use the aid visual examination and label usage. In this study, I explore whether modifications to the NFP are likely to influence the amount of attention paid by consumers to the NFP, while accounting for other factors that may moderate their attention. Specifically, I measure the impact of consumer involvement and familiarity on visual attention. Involvement, in this context, refers to the level of importance consumers placed on certain product-related attributes (Rahtz and Moore 1989; Drichoutis, Lazaridis, and Jr 2007), while familiarity measures consumer's previous product-related experience, knowledge, or repeated exposure to the stimuli

(Alba and Hutchinson 1987; Pieters, Rosbergen, and Wedel, 1999). I expect that these factors will moderate the effect of modified label format on consumers' attention.

I test a range of hypotheses regarding the roles of involvement and familiarity on attention using a laboratory experiment with eye-tracking technology. Eye-tracking is able to measure differences in the amount of apparent attention paid by subjects to different versions of the NFP. In this experiment, if the new NFP is able to induce consumers to pay more attention to the label, then the change is more likely to be effective. However, even if it is not effective, I show that there is a range of moderating factors that may improve consumers' tendencies to better use NFP labeling.

The data from this experiment provides empirical evidence regarding the main and moderating effect of involvement on consumers' visual attention. Consumers who are less involved and less familiar with the NFP pay more attention to the newer version. At the same time, the newer label favors highly involved consumers who are able to find the necessary information more quickly. This chapter offers insights regarding the potential outcomes of the revised Nutrition Facts label, and how it may have heterogeneous effects on consumers' abilities to identify relevant nutrition information.

Stated preference data of the type gathered in chapter two, however, is often subject to the criticism that it lacks external validity, or the ability to explain and predict choices made in the real world. While my first essay considers consumers' attention to nutrition information, which can be important in forming consumers' purchase intentions, the second essay examines consumers' actual purchase behaviors toward healthy and unhealthy food products from revealed-preference data. In this chapter, I examine how health-related nutritional attributes, measured in terms of fat, protein, and carbohydrate content, affect consumers' choices among alternatives in the same category. I argue that different marketing strategies (i.e., price-promotion, non-price promotion, features, or displays) are likely to have different effects on preferences for healthy compared to unhealthy foods.

Why is this likely to be the case? In general, price-based strategies tend to appeal to consumers who are more prone to rational, calculating decision patterns and not the impulsive, reflexive decision making that is the primary behavioral mechanism that underlies featuring, displaying, or other merchandising strategies. A better understanding of the relationships between consumers' nutrient preference and their responsiveness to marketing strategies can potentially aid in creating marketing programs that that induce intra-category substitution. Substituting less-healthy for more-healthy choices can, in turn, lead to diets with better nutrient profiles.

Evidence of changing intra-category substitution patterns is typically revealed in household level scanner data. Figure 1.1 shows an example of intra-category competition among yogurt alternatives that vary in nutrient content. The data in this figure comparesthe sales of Yoplait yogurt subcategories from the IRI household panel data (IRI data, Bronnenberg, Kruger, and Mela 2008). Specifically, I compared the sales of Yoplait' "Light" subcategories with Yoplait "Original" and "Whips" products of the same flavor and same package size (6-ounce). Yoplait's Light Yogurt is fat free (0%) whereas the other two alternatives' fat contents are about 3% or 4% of the daily recommended intake. The lighter alternative also contains fewer calories and less sugar than the other two alternatives, while the Original and Whips alternatives have similar levels of fat, sugar, and calories. The three alternatives are the main options available for

6-ounce packages of Yoplait yogurt. Figure 1.1 shows that sales of Yoplait Light are increasing, whereas the other two alternatives' sales gradually decrease over my sample time period, and eventually fall below the Light alternative. The sales of the three alternatives in this example appear to reveal a type of zero-sum-game dynamic where sales lost by one are gained by the other. Clearly, the pattern of substitution among the alternatives may be affected by consumers' preferences for more than just nutritional attributes, but this pattern is deeply suggestive of a more general trend toward more healthy alternatives, at least in the yogurt category.

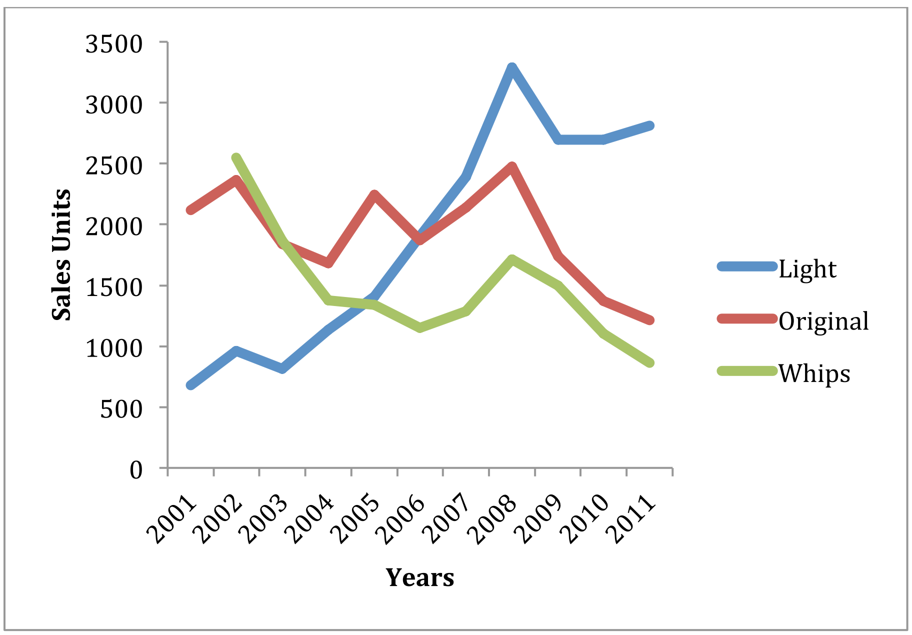


Figure 1.1 Yoplait Yogurt Products Sales in 2001-2012

In my second essay, I investigate how nutritional attributes interact with marketing instruments in affecting consumers' choices, and how these changes in demand affect nutritional outcomes. Previous evidence show that marketing strategies interact with product attributes in different ways (Singh, Hansen, and Gupta 2005; Ainslie and Rossi

1998; Richards 2017). These studies model the interdependence of product-attribute preferences within and across categories but do not address preference-correlations among nutritional attributes nor how these preferences are affected by different marketing strategies.

Empirically identifying changes in attribute preference in revealed-preference data is challenging, simply because nutrient-attributes do not change much over time. There is cross-sectional variation over product lines, but there are not enough product lines offered in most supermarkets to make this identification strategy viable. Therefore, I exploit the introduction of Greek yogurt to cleanly identify how changes in nutrient-attribute composition changed intra-category substitution patterns. The introduction of Greek yogurt serves as an excellent example of a transformational new-product introduction. Greek yogurt offered a fundamentally different combination of nutrients than incumbent offerings, and was immediately successful. Greek yogurt is much more protein-dense than existing yogurts, and arrived at a time when consumers were beginning to demand high-protein food products (Barreiro-Hurlé, Colombo, and Cantos-Villar 2008; Bimbo, Bonanno, and Viscecchia 2016). Because Greek yogurt grew quickly after its introduction, it not only serves as a means of identifying the effect of nutrient-variation on demand, but may have fundamentally altered the nutrient-consumption profiles of yogurt buyers. I use this example to examine how consumers' nutrition intake is influenced by the new product introduction, and how marketing strategies moderates this effect.

I first conduct a difference-in-difference (DID, Card and Kruger, 1994) analysis to provide some model-free evidence regarding household nutrient consumption before and after the introduction of Greek yogurt. Specifically, I follow Girma and Gorg (2007), Huang et al. (2012), and Kumar et al. (2016) and exploit a quasi-experimental approach that uses propensity score matching (PSM, Angrist and Krueger 1999; Rubin 2006) and DID analysis to reduce potential endogeneity biases in estimating the causal effect of Greek-yogurt's introduction on nutrient consumption patterns. I find that the introduction of Greek yogurt lead to changes in consumers' nutritient-consumption profiles, with decreased intake of fat, carbohydrates, and increased protein intake and overall calories. These findings show that the introduction of a product with an entirely different nutrient-composition can have a material impact on consumers' dietary quality.

This reduced-form analysis provides critical insight as to how variation in nutrient composition can influence consumption patterns but cannot address the question of how nutrient consumption is also influenced by marketing strategies. Therefore, in this essay, I also estimate a structural econometric model of yogurt demand in which the marginal value of each nutrient is influenced by marketing-mix elements. Specifically, I follow Train (1998), Brownstone and Train (1999), Petrin and Train (2010), and Richards (2017) and use a random-parameter logit (mixed logit) model that allows for correlation among nutrient and marketing-mix parameters. With this model, I examine substitution patterns among product lines by calculating the price, promotion, display and feature elasticities of demand.

I find that marketing-mix sensitivities are correlated with consumers' preferences for nutrient attributes in ways that depend on the "healthiness" of the nutrient. While display attracts attention with increasing exposures of the product and it may increase impulsive and hedonic food consumption, feature can use messages to express more product-related information such as nutritional characteristics. Therefore, featuring promotes the benefits of "healthy" nutritional characteristics so it is positively correlated with product characteristics that include high-protein, low-fat, or low-carbohydrate nutrient profiles. In comparison, promotion and display are positively correlated with preferences for "unhealthy" characteristics such as high-fat, or high-carbohydrates that likely provide greater taste benefits.

The estimated elasticities confirm that marketing-mix elements interact with nutrient-preferences in shaping substitution patterns among the subcategories. The elasticities also suggest that Light yogurts are strong competitors for Greek yogurts. However, Greek yogurts are not Light yogurts' strongest competitors. The same pattern occurs across different marketing-mix strategies.

Taken together, the findings of this essay imply that marketers have more power than previously thought in promoting products that have differing "healthiness" properties. This chapter also provides insight into how marketing-mix elements can impact overall nutrient-consumption patterns in ways that have not been previously considered.

While my second essay shows how marketing tools influence food choices, the implicit assumption throughout is that consumption can be inferred from purchasing patterns. Health outcomes, however, are determined by consumption behaviors, so my third essay delves deeper into understanding consumers' consumption behaviors. Specifically, my third essay focuses on consumers' dieting behavior and explores social psychological factors that lead people to adopt different diet patterns.

I argue that dieters are not all the same. Some dieters do not rule out specific food groups or have hard rules for eating, but instead pursue a balanced, overall eating goal

(Huber, Goldsmith, and Mogilner, 2008) or a food plan with planned indulgences (cf. Coelho do Vale et al. 2016). Others argue that it is very hard to get back on track after any indulgence and steer clear of goal-inconsistent eating to avoid falling off the wagon (Delistraty, 2016).

Gretchen Rubin first brought up the concepts of “abstainers” and “moderators” in her book *The Happiness Project* (Rubin, 2009). In Rubin’s definitions of these two types of dieters, “moderator” refers to people who are better off when they avoid absolute rules and instead moderate between indulgent and self-regulatory behaviors; by contrast, “abstainer” refers to those who are better off if they keep strict restraint from any indulging behaviors. Moderators and abstainers adopt different ways that best suit them to deal with temptation. According to Rubin's (2012) blog that discusses the same topic, a moderator usually needs an occasional indulgence to satisfy their hedonic needs and strengthen their resolve, and they are afraid of even thinking of the word never. But for abstainers, “never” is a simple and efficient strategy because it saves time and energy battling with indulgence, whereas moderating seems to require more self-control. There are similar examples in the case of alcohol consumption -- Alcoholics Anonymous (AA) maintains that alcoholics should never drink and the Atkins Diet involves avoiding carbohydrates, whereas Moderation Management (MM) supports alcoholics reducing (rather than eliminating) alcohol consumption. Studies with clinical trials outcomes have provide some evidence of the effectiveness of the MM program (Hester et al. 2009; Hester, Delaney, and Campbell 2011).

Traditional diet plans usually advocate that people reduce intake and avoid energy-dense food throughout the entire diet period. Proponents of abstinence-diet approaches argue for staying away from temptation and advocate complete avoidance of goal-inconsistent behavior. They believe it's very difficult to get back on track after a binge, thereby argue for adhering to a clean diet, and abstaining from any indulgence. For example, the Atkins Diet involves avoiding carbohydrates.

A new school of thinking argues that everything is okay in moderation, and some new diet plans even encourage dieters to regularly have a food indulgence during which delicious high-calorie foods are allowed. For example, Weight Watchers and calorie counting are diets that allow mediation with restrictions; the 12-week diet, 4-hour body, and exercise program Body for Life allows a "free day" every Sunday.

Indulgence may increase the chance of successful weight loss by comforting cravings ("Do cheat meals make diet sense? - NASM Blog" 2015). Food cravings may lead to negative mood states (Hill, Weaver, and Blundell 1991) and binge eating (Gendall et al. 1998; McManus and Waller 1995). Thus, moderately comforting food cravings may reduce the chance of impulsive eating or giving up. In addition, indulgences may help boost metabolism as metabolism studies show that short term overfeeding leads to significant increased thermic effect and increased releasing of thyroid hormone T3 and T4, which increases the metabolism rate (Poehlman et al. 1986). Thus, an indulgence may be, in theory, beneficial to achieving long-term dieting goals.

However, indulgences may also sometimes turn into a prolonged indulgence and lead to failure of the diet. For example, Polivy, Herman, and Deo (2010) show that, especially when restrained eaters are forced by someone else to have indulgences, they may exhibit the "what the hell effect" and just give in to bigger indulgences. Thus, it could be too risky to indulge for some dieters. Does occasional goal-inconsistent behavior help or hurt our pursuit of long-term goals? Findings from a series of experiments building on implicit self-theory indicate that the answer is different for dieters who hold different beliefs about themselves and self-control renewability, and the "what the hell effect" may not be true for every dieter.

These is no prior research that investigates differences among individual dieters. Meule, Papies, and Kübler (2012) briefly consider differences between successful and unsuccessful dieters regarding their perceived self-regulatory success, but do not analyze dieters' implicit beliefs regarding their self-regulatory resource. Job, Dweck and Walton (2010) recognize that people have different beliefs in willpower capacity and ego-depletion, but they do not identify people's beliefs about how willpower refills and whether having indulgences depletes or refill willpower. I take the first step in identifying critical individual differences in dieters' beliefs that lead dieters to behave differently, and respond to indulgences in differing ways.

In this study, I aim to investigate individual factors that affect dieters' beliefs towards goal-inconsistent behaviors, such as having food indulgences. I explore the two types of dieters: abstainers, who completely avoid temptations, and moderators, who occasionally break the rules. I compare the two types of dieters in many aspects, develop a measurement scale to identify these two different approaches to dieting behaviors, test how successful these two types of dieters are, and test how each type of dieter recovers from cheating on the diet. I show that lay beliefs about the renewability of self-control determines which approach people choose. My results suggest that there is no "best" strategy: Dieters are more successful when they follow their beliefs. My results also show that compensatory coping strategies provide paths for people with both implicit theories to recover from goal-inconsistent behavior in their own ways.

Taken together, my findings in the third essay suggest that eating recommendations are not one-size-fits all, but that individuals develop coping strategies consistent with their own self-theories, and that these strategies enable them to pursue their goals in the face of temptation.

The rest of this dissertation is organized as follows. In the first essay, I study the moderation role of consumers' involvement and familiarity in the effect of label format on consumers' attention towards the Nutrition Facts label. The second essay follows in which I examine how product introductions affect nutrient intake, and investigate correlations among nutrient preferences and responsiveness to marketing-mix strategies. Next, the third essay shows how self-beliefs regarding one's indulgence eating behaviors affect their actual consumption of unhealthy foods. I reserve my concluding and conclusion remarks for a final chapter.

CHAPTER 2

NUTRITION LABEL FORMAT AND CONSUMER ATTENTION: THE ROLE OF FAMILIARITY, INVOLVEMENT, AND PERCEIVED HEALTHINESS

Attention is a fundamental but limited cognitive processing resource (Anderson, 2005; Kahneman, 1973), leading consumers to process information selectively. This makes it necessary to understand factors that influence how and when consumers attend to a stimulus (Wedel 2014). Among factors that affect attention, consumers' involvement with stimuli plays a motivational role in their attention and even comprehension processes (Celsi and Olson 1988). Consumers spend more time attending to the relevant information when they are highly involved with the stimuli. At the same time, Pieters et al. (1996, 1999) show familiarity is negatively related to visual attention. When consumers become more familiar with stimuli, their attention may decline. For example, the amount of time (gaze duration) consumers attend to certain messages decreases when they repeatedly see the content. While existing research examined the separate effects of involvement or familiarity on attention (Cacioppo and Petty, 1986; Celsi and Olson, 1988; Drichoutis, Lazaridis, and Nayga Jr, 2007; Drichoutis, Lazaridis, and Nayga, 2006; Rahtz and Moore, 1989; Pieters et al., 1996; Pieters et al., 1999), there is little research regarding the joint effects of involvement and familiarity on information up-take.

In addition, since most of the literature focused on the domain of advertising, little is known regarding how involvement and familiarity affect consumers' attention towards other labels. For example, it's a commonly shared argument that people exert only minimum effort to read product labels (Folkes and Matta 2004; Balasubramanian and

Cole 2002; Cole and Balasubramanian 1993). In fact, lack of attention is one of the main barriers hindering the use of nutrition labels (Bialkova and van Trijp 2010; van Trijp 2009). Therefore, the objective of this research is to investigate the role of involvement and product familiarity on consumer attention.

To do so, I focus on the Nutrition Facts label. Given consumers' lack of attention towards the Nutrition Facts label, the Food and Drug Administration (FDA) announced a modified Nutrition Facts label in 2016—more than 20 years after the introduction of the Nutrition Labeling and Education Act (NLEA). FDA Policy advisors indicated that the goal of the modifications was to help consumers learn more about food products and make healthier choices. However, research has yet to test if the modified, new format of the Nutrition Facts label will indeed be effective in increasing consumers' attention towards the label, and subsequent usage. I aim to answer the question whether the modified label increases consumers' attention compared to the current label, and how this is affected by their involvement and familiarity with the Nutrition Facts label.

Studying attention towards the Nutrition Facts label is relevant since fighting obesity is one of the most intractable issues facing US policy makers. Data from the National Center for Health Statistics show that two-thirds of adults were either overweight (BMI over 85% percentile) or obese (BMI over 95% percentile) (Ogden et al. 2014, 2013). Using food labeling to alter food choices is one of the commonly used public policy interventions to reduce obesity. The Nutrition Labeling and Education Act (NLEA) of 1990 made the Nutrition Facts label mandatory for most food products in the U.S., and set clear regulations and guidelines on nutrition content claims and health claims (Burton, Biswas, and Netemeyer 1994). The disclosure of calorie and nutritional information makes nutrition information more accessible to consumers, and enables promotion of better purchasing behavior and healthier consumption (Drichoutis, Lazaridis, and Nayga, 2006). However, only few consumers look at the Nutrition Facts label when they are shopping in the grocery store (Wills et al. 2009; Grunert 2008) Also, consumers' actual usage of the nutrition labels is very low (Cowburn and Stockley 2005).

I aim to examine the mechanisms that influence consumers' attention to label information. In this study, I investigate the psychological factors involvement and familiarity, which are hypothesized to affect consumers' attention. I test what factors increase or decrease attention to the Nutrition Facts label. In order to account for the modifications to the Nutrition Facts label, I measure the impact of the determinants on attention towards the current and modified Nutrition Facts label. Since eye movements are a valid measure of visual attention (Wedel and Smith 2013), I conduct an eye tracking experiment with two conditions to investigate consumers' visual attention towards the current and the modified Nutrition Facts label while accounting for the role of involvement and familiarity on attention.

The results of this study contribute to the literature of visual attention to nutrition labels by providing insight into how different consumer segments (i.e., low- vs. high-involvement consumers) respond to format revision. My research provides empirical evidence regarding the separate and joint effects of involvement and product familiarity on consumers' visual attention towards the Nutrition Facts label. My results are relevant for policy makers and the food industry more generally, as they provide critical information regarding the outcomes of a revision of the Nutrition Facts label.

In the following sections, I describe the theoretical background of attention and visual attention, involvement, and familiarity. I then present the modified changes on the Nutrition Facts label and discuss previous related literature. Next, I explain my study design and econometric model. Last, I present my empirical results and finish with some concluding remarks.

Background on Nutrition Facts label

In 2016, the Food and Drug Administration (FDA) announced several changes to the Nutrition Facts label (see Figure 2.1), which has been used for more than 20 years. The modified label includes notable changes (listed in Table 2.1) that can be categorized into format and content changes. First, the modified label makes critical nutritional information more prominent. Specifically, the modified label highlights the calories and the number of servings per container by increasing the font larger and making it bolder; moved the daily value percentage of all nutrients to the left column to be more noticeable. Second, the modified label tailors the nutrient information provided in the Nutrition Facts label. In the macronutrients section, the new modified label added the "added sugar" information beneath the total carbohydrates since added sugar is a sub-set of carbohydrates, yet fundamentally different in its metabolic effects (often considered "empty calories" compared to complex carbohydrates). The micronutrients section replaced vitamins A and C with Vitamin D and Potassium since they are becoming the nutrients of public health concerns.

Figure 2.1
The Modified Nutrition Label (left) and the Current Nutrition Label (right)
Source: FDA federal register (March 2014)

I expect the modified Nutrition Facts label to draw more attention given that the design of the new label format was based on consumer studies regarding the label, as well as graphic design principles (FDA, 2014, see summary in Table 2.1). For example, increasing font size would capture consumers' attention and assist reading and understanding the critical information (Goldberg et al., 1999; Wogalter and Leonard, 1999; Wogalter and Vigilante, 2003). Popper and Murray (1989) showed that the increased type size could increase the recall of the information. Lando and Lo (2013) demonstrated that highlighted servings per container help consumers to understand that there is more than one serving in a package and to calculate the calories per container. Anchor lines help with attention landing, and thinner alignment lines help with information searching (Goldberg, Probart, and Zak 1999). An increased surface size and saliency of packaging elements, such as claims and labels, can boost the likelihood of being visually attended (Orquin, Scholderer, and Jeppesen, 2012). My research aims to test empirically whether the changes to the Nutrition Facts label indeed increase visual attention.

Table 2.1 Modifications to the Nutrition Facts Label Tested

Modified Formats
• Total calorie number- bigger, bold. • Serving per container - bigger, highlighted. • Percentage Daily Value (DV %) - Shifted to the left side.
Modified Contents
• Adding a line declaring “added sugar”. Replacing “Total Carbohydrate” with “Total Carbs”. • Replacing vitamins A and C with vitamins D and Potassium to the list of mandatory nutrients. • Changing the portion size from how much consumer “should” eat to the amount they “actually” eat. • Removing the current footnote regarding daily nutrition intake advice.

Source: FDA federal register (March 2014)

Conceptual Framework

I develop a conceptual framework to guide the empirical analysis of this study. I extend the previous literature by testing the effect of involvement and familiarity on consumers’ attention using the example of the current versus the modified Nutrition Facts label. First, I examine whether the modified changes to the Nutrition Facts label increase consumers’ attention. Then, I investigate how individuals react differently to the modified label, and whether the effect on attention holds or varies among different products. Specifically, I hypothesize consumers to have varying responses to the modified label due to individual differences in psychological factors, such as, involvement and familiarity.

Visual Attention

Attention is a selective mechanism which allocates processing capacity to a stimulus (Pashler 1998). Visual attention, as a physiological response, is a reliable and important measure of attention (Wedel 2014; Wedel and Pieters 2006; Krugman 1965). Visual attention is often conceptualized as a “window” or “spotlight” that controls the localized priority and speed of information processing (Deubel and Schneider 1993; Wedel 2014). Visual attention plays a vital role in monitoring consumers’ attention. People’s eye movements reflect their visual attention (Hoffman 1998), and are the operational definition of visual attention (Wedel 2014). When people gaze on a stimulus, attention is paid to the stimulus, and the key information is extracted from it (Kessels and Ruiter 2012; Wedel and Pieters 2000; Rayner 1998). In this study, I investigate the effect of consumers’ involvement and familiarity with the stimulus on visual attention.

Involvement

Involvement plays a motivational role in consumers’ attention in that a highly involved consumer is more motivated to attend to relevant information (Celsi and Olson 1988). As shown by Celsi and Olson (1988), involvement plays a motivational role in consumers’ attention in that a highly involved consumer is more motivated to attend to relevant information. The concept of “involvement” has many different definitions, but there is a common agreement that high involvement is equivalent to high personal relevance regarding a product (Petty and Cacioppo, 1986). The extent to which a product is personally relevant is the essence of measuring levels of involvement. A number of studies, , such as, Cacioppo and Petty (1986), Celsi and Olson (1988), Drichoutis, Lazaridis, and Nayga Jr (2007), Drichoutis, Lazaridis, and Nayga (2006) and Rahtz and Moore (1989), documented the importance of involvement on attention, information processing, comprehension, attitude, and food purchase..

In this study, I focus on consumers' involvement with the Nutrition Facts label, i.e., their personal relevance related to the Nutrition Facts label. This definition is akin to "product-class involvement" (Rahtz and Moore 1989; Drichoutis, Lazaridis, and Jr 2007), known as the level of importance consumers placed on certain product-related attributes, such as, price, nutrition, brand name, or taste.

Nutrition label information fall into two categories: intrinsic cues or extrinsic cues (Walters and Long 2012; Olson and Jacoby 1972). Intrinsic cues are product related internal attributes such as ingredients, nutrition content and physical characteristics that cannot be manipulated without changing the product's nature. Nutrient-specific information is considered more as intrinsic/central cues. Extrinsic/peripheral cues are environmental product-related information such as the formatting of the label. Processing intrinsic cues requires more cognitive effort than processing extrinsic cues. Compared to the current label, the modified Nutrition Facts label contains more prominent, large font information that is assumed to take less cognitive effort to process, and thus, is considered a heuristic cue[2]. I hypothesize that consumers' involvement with the Nutrition Facts label moderates consumers' visual attention towards the label. High-involvement consumers are hypothesized to pay more attention to the Nutrition Facts label in general because they are more motivated to examine the nutritional information than low-

[2] Heuristic, or peripheral cues refer to information that requires less cognitive effort in information processing and often lead individuals to use mental shortcuts. It is opposed to systematic/central cues, which focus on detailed message processing and require more cognitive effort (Chaiken 1980; R. E. Petty, Cacioppo, and Schumann 1983).

involvement consumers. Also, according to the Elaboration Likelihood Model of Persuasion (Petty and Cacioppo, 1986), high-involvement consumers focus on intrinsic information, their attention should not be affected by extrinsic cues, such as, the format of the label. In contrast, low-involvement individuals will use peripheral route processing and search for peripheral cues in information processing (Petty and Cacioppo, 1986; Petty, Cacioppo, and Schumann, 1983). Low-involvement consumers prefer and often read extrinsic cue, such as prominent formats, as they reduces the cognitive effort and simplifies the evaluation (Petty and Cacioppo, 1986). I hypothesize that low-involvement consumers are more likely to subject to extrinsic cues, and their attention will increase in response to formatting changes in Nutrition Facts label.

I hypothesize that motivational and experiential factors influence consumers' attention to the Nutrition Facts label as it relates to the modifications of the format. I expect these factors to interact with the modified label format in influencing consumers' attention, because consumers with heterogeneous preferences place importance on different attributes of the product, and product-class involvement subsequently influences the use of nutrition labels (Drichoutis et al., 2005; Drichoutis, Lazaridis, and Nayga Jr., 2007; Nayga, Lipinski, and Savur, 1998). For example, consumers who place more importance on price will be more likely to search and use price information than other information. In contrast, consumers who place a higher importance on nutrition will be more likely to examine the nutrition information on nutrition labels and be less likely to examine other attributes (Drichoutis, Lazaridis, and Nayga 2007). Hence, I expect that the modified format changes will be more likely to increase low-involvement consumers' attention to the Nutrition Facts label because low-involvement consumers tend to focus on heuristic/extrinsic cues such as formatting. High-involvement consumers, on the other hand, are motivated to prioritize information on the nutritional content of the product. Therefore, their attention to the Nutrition Facts label may remain the same because nutritional information on the modified label is almost identical to the current label. Their attention may even decrease because now the prominent label format makes it easier to search key nutrients information. In addition, Visschers, Hess, and Siegrist (2010) found that health motivations will stimulate deeper information processing of the nutritional information, thereby increasing duration and frequency of visual attention on nutrition information on food products.

Familiarity

While involvement takes on a motivational role towards attention, familiarity usually evokes a buffering effect in the sense that it reduces, i.e., negatively affects attention. Familiarity refers to a consumer’s previous product-related experience, knowledge, or repeated exposure to the stimuli. Familiarity is also defined as the “restored representation of an item” (Christie and Klein 1995), repeated exposures (Pieters, Rosbergen, and Hartog, 1996; Pieters, Rosbergen, and Wedel, 1999), or the number of consumers’ accumulated product-related experiences (Alba and Hutchinson 1987). Pieters et al. (1996, 1999) show that advertisement familiarity has a negative effect on visual attention towards the ad messages (Pieters et al., 1996; Pieters et al., 1999). Similarly, Graham, Orquin, and Visschers (2012) indicate that visual attention towards the Nutrition Facts label can be sensitive to familiarity because participants who are familiar with the product may retrieve memory content about the product information and be less likely to look at the nutritional information. To avoid dealing with the "familiarity problem," experiments tend to strip off the brand name or use unfamiliar products (e.g., foreign brands) in nutrition label studies. However, it is unrealistic to assume the absence of product familiarity when consumers look at the Nutrition Facts label of certain products while grocery shopping. I account for this with my experimental design, and test whether familiarity, per se, has a decreasing effect on attention towards the Nutrition Facts label.

Despite existing literature having the general agreement on the buffer role of familiarity, their inferences are based on the literature regarding the buffering effect of familiarity on consumers' attention towards advertisement. Little to no research has directly examined the effect of product familiarity in influencing consumers' visual attention to nutrition labels. I argue that this buffering effect may not apply to the Nutrition Facts label which has more numerical and detailed information that are not likely to be precisely stored in memory. Therefore, when consumers are examining products, even if they are very familiar with the product, they might not have a clear memory of the nutritional information. Hence, they are still motivated to check the Nutrition Facts label for the information they are interested in. As a result, I hypothesize that product familiarity, per se, does not decrease attention towards the Nutrition Facts label in general. However, as the modified Nutrition Facts label makes it easier to identify the key nutrition information, consumers with high product familiarity will be able to locate the information of interest faster on the modified label than on the current label. Therefore, I hypothesize that consumers with high product familiarity spend less time reading the modified Nutrition Facts label compared to the current label.

In addition, if familiarity indeed decreases consumers' visual attention, I need to examine how the buffering effect of familiarity influences low- and high- involvement consumers. As discussed above, high-involvement consumers focus on intrinsic information (i.e., nutritional facts). As a result, they are expected to pay less attention to the Nutrition Facts label as they are more familiar with the product, and the nutritional information can be easily retrieved from consumers' memory. In contrast, I expect low-involvement consumers to experience no buffering effect of familiarity because they are less motivated to search and scrutinize the intrinsic nutritional information in the first place. Instead, low-involvement consumers may pay more attention to the Nutrition Facts label when extrinsic cues, such as, format changes are present. Thus, I expect that low-involvement and high-involvement consumers experience different degrees of the buffering effect of familiarity. I test these effects on both the current and modified Nutrition Facts label.

Packaging Factors

I also consider packaging factors, such as location of the Nutrition Facts labels, the presence of Front-of-pack (FOP) labels, and the presence of nutrition content claims such as fat free claim, added omega-3 or fiber claim. On different food products, the location of the Nutrition Facts label varies on the package. Some nutrition facts labels locate at the upper left corner, and some are at the upper right corner, or on the side of the product. Graham and Jeffery (2011) show that nutritional information located at the top of the Nutrition Facts label are more likely to be viewed than those at the bottom, and Nutrition

Facts labels located at the center of the package attract more view time than the same label located at the sides.

I also test if the presence of additional front of pack labels may affect consumers' attention towards the nutrition facts label on the back. Front-of-pack (FOP) labeling has been used as complementary labels that simplify the information on key nutrients feature and the purpose is to help consumer make healthy food choices and can affect. The front of pack nutrition label may truncate consumers' attention to the Nutrition Facts label on the back (Roe et al. 1999). In addition, health claims may create halo effects that reduce consumers' likelihood to search further nutritional information (Williams 2005). Thus, I include these packaging factors as part of the determinants for the attention towards Nutrition Facts label.

Personal Factors

Finally, I also examine how personal factors such as BMI, physical activity, and perceived attractiveness affect consumers' attention. I test the effect of Body Mass Index (BMI) on attention paid towards the Nutrition Facts label, because exising research found that overweight people have higher likelihood to use nutrition label (Drichoutis et al. 2008). Exercising (Drichoutis et al. 2008) and low fat intake relates to label use (Neuhouser, Kristal, and Patterson 1999). Moreover, previous studies show that perceived attractiveness of the self bias people's visual attention (Roefs et al. 2008) and their self-schema (Wiederman and Hurst 1997).

Combining these elements, my conceptual framework (See Figure 2.2) shows how consumers' visual attention to the Nutrition Facts label is hypothesized to be influenced by label formatting, psychological factors, packaging factors, and personal factors. Specifically, I show that involvement, as a psychological factor, moderates the effect of label format on attention. The main purpose of explaining how involvement interacts with label format in formatting attention is not only to emphasize the importance of involvement. Rather, I show that the attention of people with various levels of involvement varies depending on the format changes of Nutrition Facts label. My conceptual framework also incorporates the packaging factors and personal factors as determinants of attention to form a comprehensive understanding of the attention allocation towards the Nutrition Facts label.

Product Factors

Previous research also shows that people are more sensitive to negative nutrition attributes than positive attributes (Worsley 1996; Balasubramanian and Cole 2002). Consumers may want to quickly identify the the information regarding content of nutrients commonly regarded as negative in the sense that they should be minimized, or at least not be excessive, in a diet designed to control weight. Once they recognize any negative nutrients information of the unhealthy product, they quickly switch their attention away from the Nutrition Facts label. As a result, they may spend less time looking at the Nutrition Facts label. Thus, I hypothesize consumers to have shorter attention duration (i.e., gaze time) on products that are rather unhealthy (which contain more negative nutrients attributes such as calories, fat, sugar, and sodium) than products that are high in protein, or complex carbohydrates. On the other hand, I expect consumers pay more attention to the Nutrition Facts label on their perceived healthy products, looking for potential negative information and trying to confirm their perception about the product healthiness. I test this hypothesis by using products that are more (bagged salad) or less (cookies) healthy.

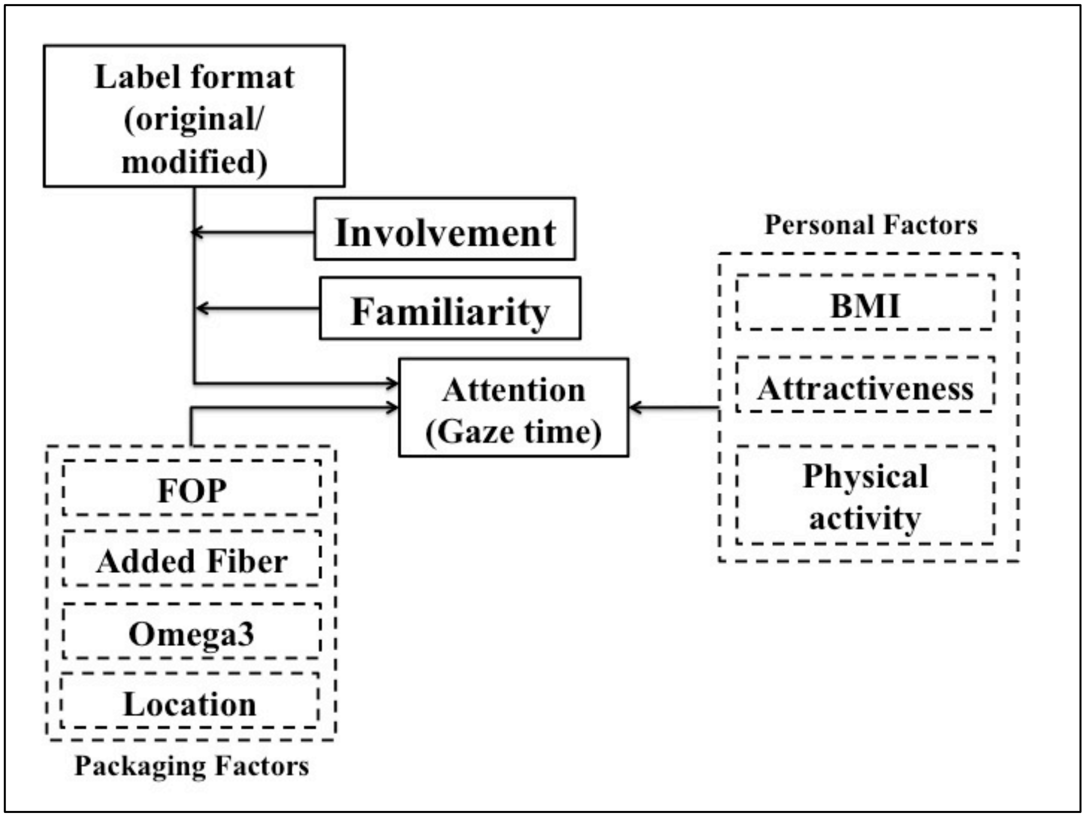


Figure 2.2
Conceptual Framework
Note: FOP=front of package label for macronutrients. Added fiber: front of pack added fiber claim. Omega 3: front of pack Omega 3 claim. BMI=body mass index.

Methodological Background

Eye Tracking

Eye tracking technology records participants' eye movements and gazes to examine visual attention. Eye movements consist of fixations during which the eye keeps relatively still and saccades where rapid movements occur. The eye fixation and gaze time captured in an area of interest (i.e., AOI) serve as measurements for consumers' visual attention. The measures in eye gaze data (e.g., the number of fixations, gaze time, first fixation) provide different information regarding visual attention (Rik Pieters and Warlop 1999; Rayner 1998). The number of fixations indicates the frequency of participants' gazes on a certain AOI. The total fixation duration (also called gaze time or gaze time) is the sum of all fixation durations. Gaze time measures the attention duration and often serves as an indicator of visual attention (Christianson et al. 1991). In this study, I focus on an important measure of visual attention: gaze time, also called gaze time. Gaze time serves as my dependent variable.

Design of The Study

In a laboratory experiment, I recorded participants' eye movements and gaze time to examine visual attention. The experiment consisted of two conditions: current label (current label) versus modified label (modified label). I used a between-subject design to compare the attention paid to the different labels (as measured in gaze time).

I included six different products in the experiment: Lay's chips, Fresh Express bagged salad, Yoplait Greek Yogurt, Kellogg's Raisin Bran cereal, Nilla wafer cookies, Healthy Choice frozen meal (See Appendix 2). I chose these food products for two reasons. First, it resembles a general grocery basket containing a variety of processed and packaged foods that carry the NFP, second, it allows us to test if there is a difference in attention towards the label according to healthiness, since for example, yogurt and salad are considered healthier than chips and cookies.

I displayed the front and back of each product to participants on a computer screen during eye tracking (see Figure 2.3).

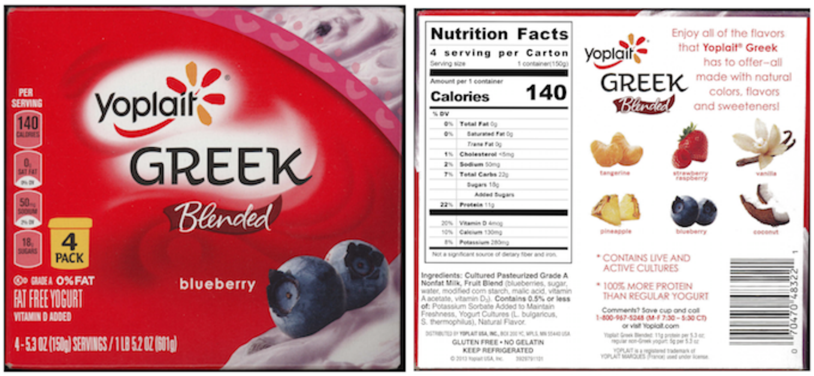


Figure 2.3
Experiment Product Image Front and Back for Yogurt

In condition 1, all packages carried the current label, in condition 2 all packages carried the modified label. I created modified label for each product using the graphic design principles modified by FDA (FDA 2014). See an example in Figure 2.4.

Current Label Modified Label

Figure 2.4
Back of Pack (Chips)

After the eye tracking, participants completed a supplementary questionnaire. To measure participants' involvement with the Nutrition Facts label, I used Zaichkowsky's (1985) personal involvement inventory (PII). The involvement scale contains 20 semantic differential items that measure needs, values, and interests towards the objective (i.e., Nutrition Facts label here) on a 7-point scale. The sum of the scores of all the items provides the measure for involvement and can range from 20 to 140. To explore the effect of familiarity on attention towards the Nutrition Facts label, I used branded products (e.g., chips and frozen meal) in this study, and measured consumers' familiarity with each product. I measured familiarity using a five-point Likert scale from 1 = Not at all familiar to 5 = Extremely familiar (Vagias, 2006).

In addition, the questionnaire contained general demographic questions regarding age, gender, household size, income, education, and the number of children in the household. Furthermore, I measured participants' BMI by including questions regarding weight and height. Physical activity was measured on a scale from 0 to 5 (see Appendix 3 for the complete physical activity scale categories), and whether participants were on a diet or not (0=no; 1=yes). Perceived attractiveness was measured using the self-rated attractiveness scale that ranges from 1= well below average to 7= well above average (following Wiederman and Hurst, 1997).

Descriptive Data Analysis

To analyze the data, I conducted descriptive analyses to test for significant differences between the modified label and the current label regarding gaze time. To test for moderating effects of involvement, I used the moderation analysis package PROCESS for SPSS developed by Hayes (2012).

Random Effects Panel Tobit Model

I also perform an econometric analysis to obtain estimates of the hypothesized effects. To estimate the impact of involvement with the Nutrition Facts label, product familiarity, and the modified label changes on consumers' visual attention towards the Nutrition Facts labeland whether the impact differs across products, I used a random effects Tobit model (Wooldridge 2002, 2003). Since there is a substantial amount of zeros in the eye tracking data (i.e., zero total fixation time where the consumer did not gaze at the Nutrition Facts label), the data was censored at zero. If there is a significant fraction of the observations that is censored at zero in the dependent variable, estimates produced by ordinary least squares (OLS) are biased (Henningsen 2010). Thus, a Tobit model is preferred as it provides a censored regression model that fits well with the censored sample. I used a panel Tobit model because each participant evaluated six different food products, which creates a panel. Following Greene (2003), the lower bound was set to zero to account for participants' none visual attending to the nutrition label.

Following Wooldridge (2002, 2003), in the random effects panel Tobit model, the latent dependent variable is expressed as:

$$y_{ij}^{*} = \alpha + \boldsymbol{\beta} x_{ij} + v_i + u_{\boldsymbol{it}} \qquad (1)$$

where x_{ij} is a vector of explanatory variables for individual i and product j, and $\boldsymbol{\beta}$ is the vector of parameters for x_{ij}. v_i represents the random effect that is i.i.d normally distributed with mean of zero and a variance of σ_v^2 (i.e., v_i ~ N(0, σ_v^2)). The error term $u_{\boldsymbol{it}}$ is i.i.d. N(0, σ_ε^2) independently of v_i. In a Tobit model (1958), the observed y_i is related to the latent variable y_i^* through the observation rule:

$$y_{ij} = \begin{cases} 0 \;\; if \;\; y_{ij}^{*} \leq 0 \\ y_{ij}^{*} \;\; if \;\; y_{ij}^{*} > 0 \end{cases} \qquad (2)$$

Following Wooldridge (2002, 2003), the likelihood function for the random-effect panel Tobit model for each observation is expressed as:

$$lnL\,(\beta, \sigma) = 1\big(y_{ij} = 0\big)\ \mathrm{ln}\ [1 - \Phi(\tfrac{x_{ij}\beta}{\sigma})] + 1(y_{ij} > 0)\{-ln\sigma + ln\Phi\left[\tfrac{(y_{ij} - x_{ij}\beta)}{\sigma}\right]\}$$

(3)

Where $\Phi(\cdot)$ is the standard normal probability distribution function. The estimation of $\boldsymbol{\beta}$ is obtained by maximizing the log-likelihood. An *xttobit* command in STATA is used to perform the estimation.

Expand equation (1) to incorporate the explanatory factors, the model specification takes the following form:

$$y_{ij}^{*} = \alpha + \beta_1 Chips_{ij} + \beta_2 Frozenmeal_{ij} + \beta_3 Cereal_{ij} + \beta_4 Cookie_{ij} + \beta_5 Salad_{ij} + \beta_6 Newlabel_{ij} + \beta_7 Involvement_{ij} + \beta_8 Familiarity_{ij} + \beta_9 BMI_{ij} + \beta_{10} Diet_{ij} + \beta_{11} Phys_{ij} + \beta_{12} Attract_{ij} + \beta_{13}\left(Newlabel_{ij} * familiarity_{ij}\right) + \beta_{14}\left(Newlabel_{ij} * Involvenment_{ij}\right) + \beta_{15}\left(Newlabel_{ij} * Familiarity_{ij}\right) + \beta_{16}\left(Familiarity_{ij} * Involvenment_{ij}\right) + \beta_{17}\left(Newlabel_{ij} * Familiarity_{ij} * Involvenment_{ij}\right) + v_i + u_{\boldsymbol{it}}$$

(4)

Where *Chips, Frozenmeal, Cereal, Cookies, Salad* are dummy variables for the particular food products. Yogurt was set as the base level and omitted in the regression. *Phys* is the frequency of physical activity; *Diet* is a binary variable that equals to one if the participant is currently on a diet; *BMI* equals to the value of body mass index calculated using height and weight; *Attract* is the level of self-rated attractiveness. I included the binary variable of *Newlabel* and the other two continues factors of interest – *Involvement* and *Familiarity*. I also included the interaction effects of *Newlabel* and involvement; *Newlabel* and familiarity; familiarity and involvement; and *Newlabel,* involvement and familiarity. $\beta_{13} \ldots \beta_{17}$ denote the interaction effects.

I conducted an additional model (model 2 below) to add packaging factors (i.e., label location, front-of-pack label, nutrients claims) and personal characteristics (i.e., BMI, attractiveness, physical activity). In model 2, I add the packing factors variables that are unique to each product, hence, product dummies are omitted to avoid collinearity.

Descriptive Results

Sample

In a laboratory experiment with n=115 participants, I recorded participants' visual attention via eye tracking. I recruited participants through flyers and email invitations. Each participant received $25 as compensation for his or her time. I use a threshold of 70% percent for accuracy in calibration. I excluded twelve participants from the analysis since they did not calibrate properly. The final panel contains 103 usable observations - the current label (current label) condition consists of 50 participants while the modified label (modified label) condition consists of 53 participants. I conducted a t-test and Chi-square test to compare the demographic characteristics between the two conditions. The current label and modified label conditions are not statistically different from one another regarding demographic background.

Involvement measures

In Table 2.2, the results for involvement towards the Nutrition Facts label are depicted. The average level of Nutrition Facts label involvement is above 100 (maximum total score = 140) in both conditions, suggesting a generally high motivation to read the nutrition information. A t-test shows that in both conditions, current label and modified label, participants' involvement levels were statistically the same.

Table 2.2 Involvement

Characteristics	Current Label (n=50)		Modified Label (n=53)	
	M	SD	M	SD
Nutrition label involvement	109.46	23.93	115.85	15.13

M=Mean, SD=Standard Deviation.

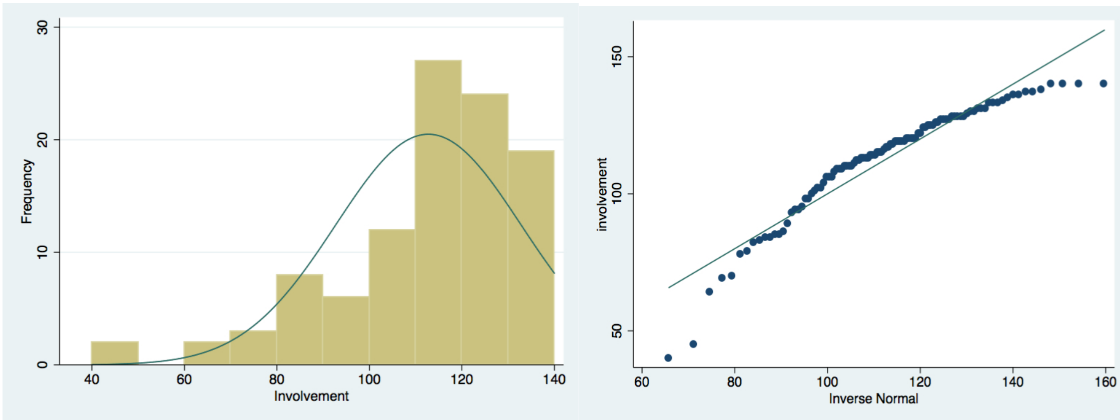


Figure 2.5
Distribution of Involvement

The distribution of Involvement plotted in Figure 2.5 show that involvement is slightly skewed to the left. The distribution suggests that there are more highly involved consumers than low-involved consumers.

Familiarity measures

Table 2.3 illustrates the results of participants' familiarity with each product. As determined by t-tests, the familiarity ratings are not statistically different between the two conditions. Among products, chips have the highest familiarity whereas bagged salad has the lowest familiarity. Between the medium familiarity products, participants are more familiar with cereal and yogurt than with cookies and frozen meal.

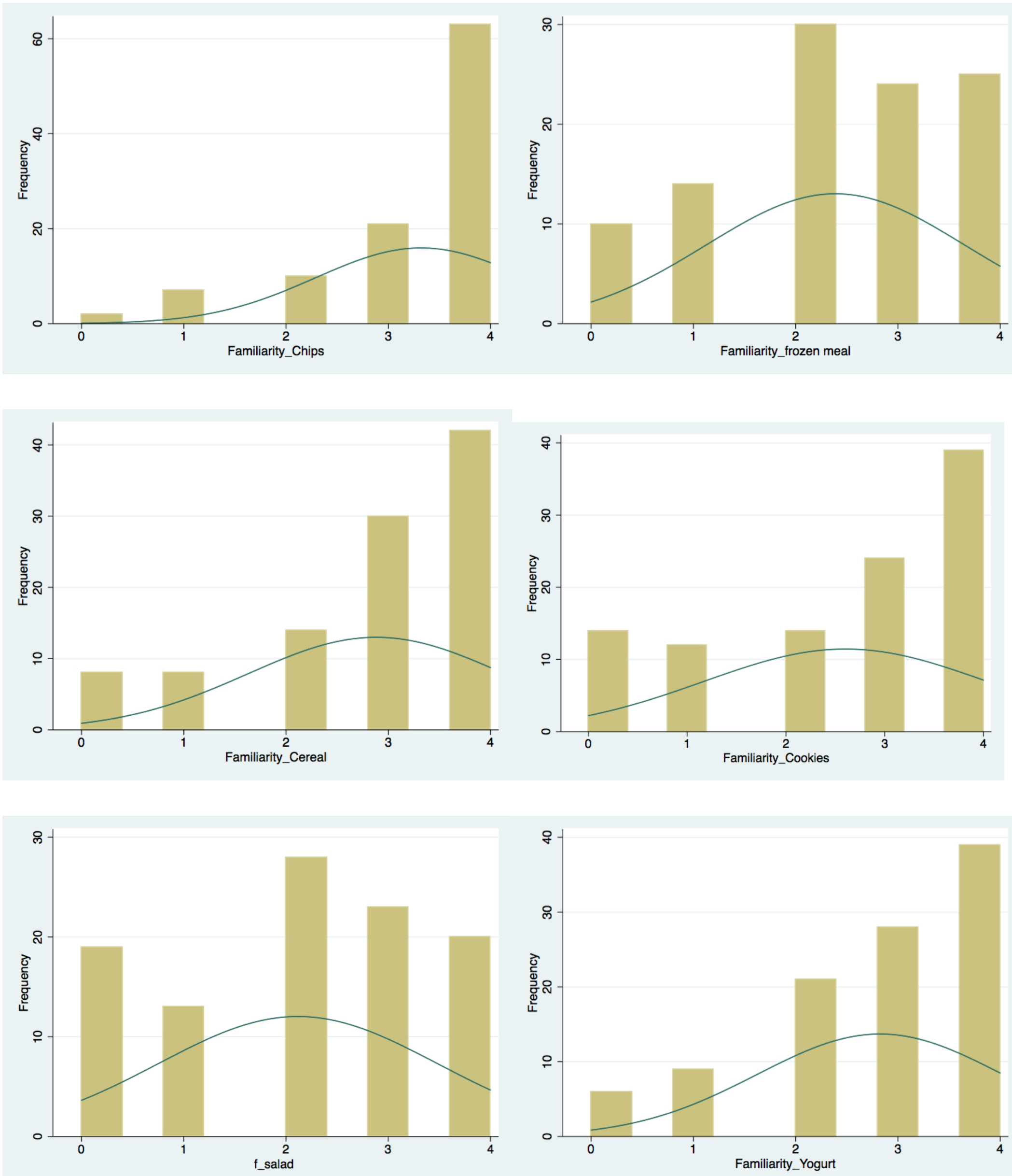


Figure 2.6
Distributions of Familiarity

Table 2.3 Familiarity with Products

Products	Current Label (N=50)		Modified Label (N=53)	
	M	SD	M	SD
Chips	3.32	1.06	3.32	1.01
Frozen Meal	2.32	1.22	2.45	1.31
Cereal	2.92	1.26	2.85	1.26
Cookies	2.34	1.56	2.85	1.28
Bagged salad	1.80	1.41	2.42	1.26
Yogurt	2.80	1.34	2.85	1.06

Figure 2.6 shows the distributions of consumers' familiarity with the six products. The distribution figures show that most consumers are very familiar with national branded products such as Yoplait yogurt, Lays chips, and Kellogg cereal. In comparison, consumers are less familiar with store-branded product such as salad.

Personal characteristics

Table 2.4 displays the mean or percentage for the personal characteristics that serve as independent variables. In the current label group and the modified label group, participants' average level of BMI, physical activity frequency, nutrition label reading frequency, self-rated attractiveness are not statistically different from one another as determined by t-tests. There are more participants on a diet in the modified label condition than in the modified label condition. Table 2.4 also shows that the BMI of both conditions is around 25, which is approaching the overweight threshold, and indicates the pervasive obese issue. Another characteristic of the participants worth noticing is that the average self-rated body attractiveness in both conditions is over four (1=well below average… 4=average… 7=well above average), indicating that participants are on average confident about their appearance and attractiveness.

Table 2.4 Personal Characteristics

	Current Label (N=50)		Modified Label (N=53)	
	M	SD	M	SD
BMI (Mean)	24.8	5.11	25.29	5.1
On a diet *	0.06	0.24	0.24	0.43
Physical activity (Mean)	2.26	1.38	2.6	1.5
Self-rated attractiveness	4.54	1.13	4.26	1.2

* p<0.01.

Differences in attention between the current and modified Nutrition Facts label

Figure 2.6 shows a box-plot graph of the gaze time (in seconds) regarding the entire label for each product. I compare the visual attention towards the Nutrition Facts label in the two different formats. A longer gaze time (total fixation duration) indicates that more visual attention paid to the label.

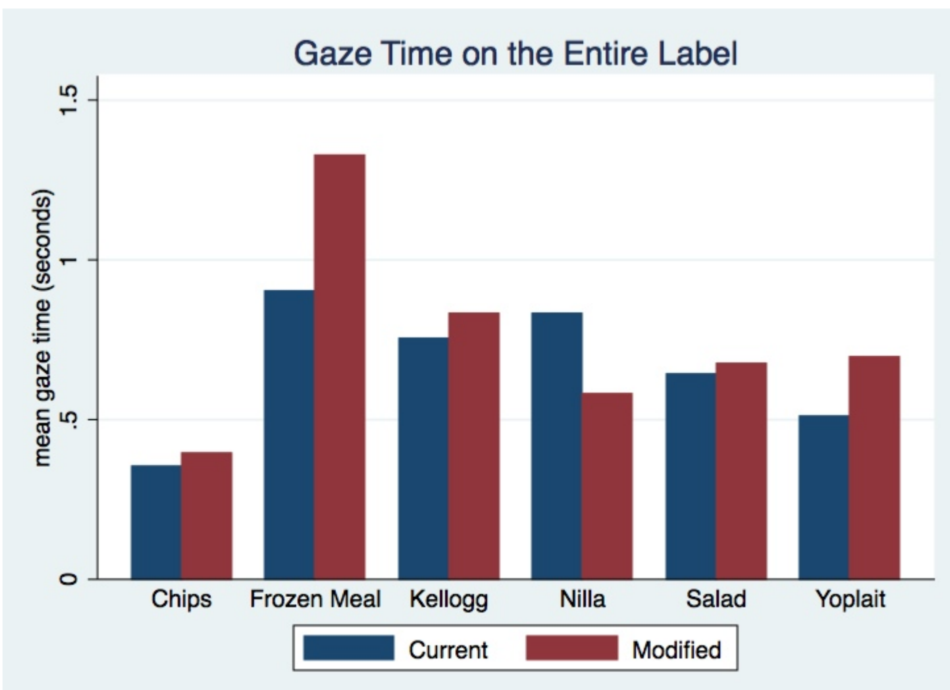


Figure 2.7
Box Plots for Gaze Time

Table 2.5 shows the mean of gaze time for the two label formats conditions. I observe that the modified label captured a longer gaze time for five food products (chips, frozen meals, cereal, yogurt, bagged salad) than current label. Only for cookies, current label captured a slightly longer gaze time (0.35 seconds compared to 0.40 seconds). However, although I observed eye movement differences between the two conditions, these differences are not statistically significant as determined by t-tests. There is no significant difference between the two label conditions based on gaze time.

Table 2.5 Gaze Time on Current Lable and Modified Lable (the entire label)

Attention measures	Products	Current Label (N=50)		Modified Label (N=53)	
		M	SD	M	SD
Gaze time	Chips	0.35	0.80	0.40	0.79
	Frozen Meal	0.90	1.44	1.33	2.34
	Cereal	0.75	1.28	0.83	1.41
	Cookies	0.83	1.36	0.58	0.87
	Bagged Salad	0.64	1.40	0.67	1.06
	Yogurt	0.51	0.92	0.70	0.99

* Significant different between current label and modified label based on t-test at 95% level.

Differences in Attention between Products in General

To test whether the attention paid to the nutrition label differs between products, I conducted a one-way ANOVA for the visual attention measure of gaze time in both conditions. I reject the null hypothesis that gaze time is the same across products for the label in the modified label condition (p=0.000), and the difference between products is not significant in the current label condition (p=0.212). Thus, consumers' total time attended towards the Nutrition Facts label does not differ between the products for the current version of the label but becomes significantly different when the current label is present.

Homogeneity of variances was tested using Levene's test. Levene's test is also used to analyze whether the sub-samples (i.e., different products) have equal variances. The

Levene's statistic rejects the null hypothesis that the variances equal across products for the modified label ($p= 0.00$ for both conditions). Similar to the findings of the ANOVA, the variances of gaze time among all the products in the current label condition is not significantly different for the current label ($p= 0.055$) but significantly different in the modified label condition ($p= 0.00$). T-test and ANOVA are both fairly robust to the violation of homogeneity when the sample sizes of the conditions are close.

Differences in attention between healthy and unhealthy products

Gaze time tells us how long one's eye stayed on a stimulus, whereas time to the first fixation mean how quickly the stimuli catches one's attention. In Figure 2.8 I compare time to the first fixation to the Nutrition Facts label of chips and salad, the least healthy product and the healthiest product, when consumers face the differently formatted labels (current vs. modified). I can see that time to the first fixation is very similar between chips and salad when the original label was present. In comparison, when the modified label was provided, consumers spent substantially more time looking at other information before gazing on the Nutrition Facts label of salad than that for chips.

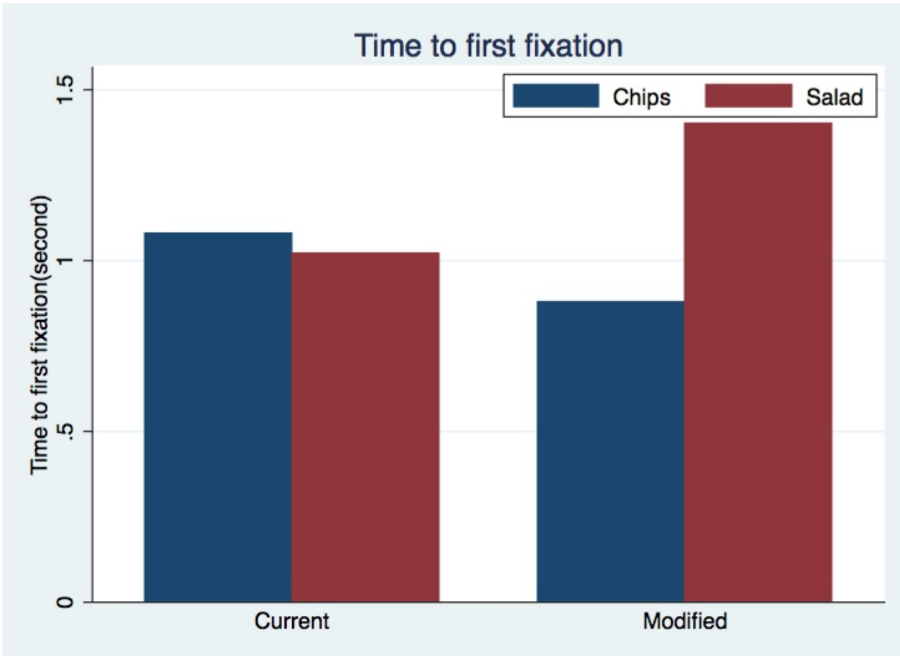
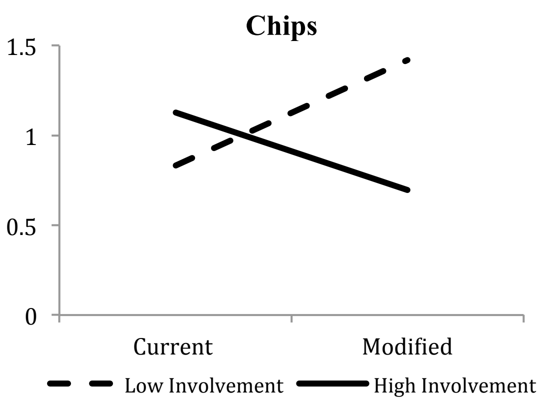


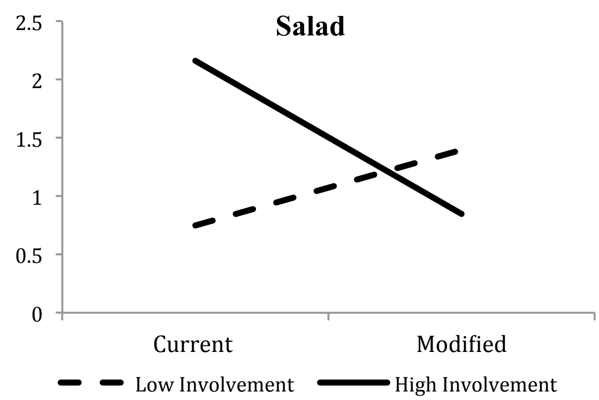
Figure 2.8
Time to First Fixation (Chips vs. Salad)

In Figures 2.9 I test the effect of involvement and familiarity on gaze time for both products. I find a significant interaction effect of involvement and label format on gaze time, showing that high involvement participants have a longer gaze time than low involvement participants towards the current label. For the modified label low involvement significantly increased their gaze time. On the contrary, both low and high involvement participants increase their gaze time for bagged salad when they see the modified label. Thus, the involvement level, the label format, as well as the healthiness of the product affect consumers' attention. Next, I will explore these effects more in detail.

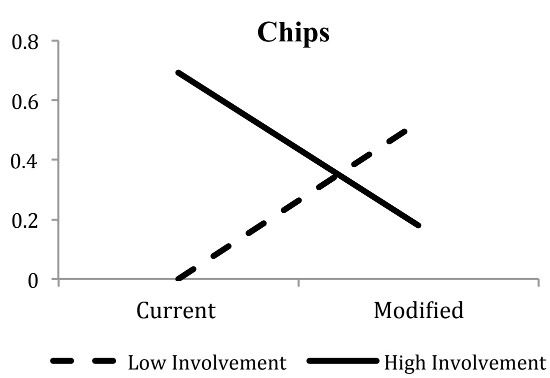
Involvement

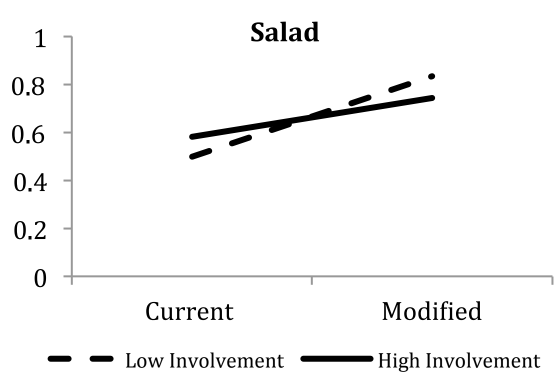
Dependent variable: Time to first fixation





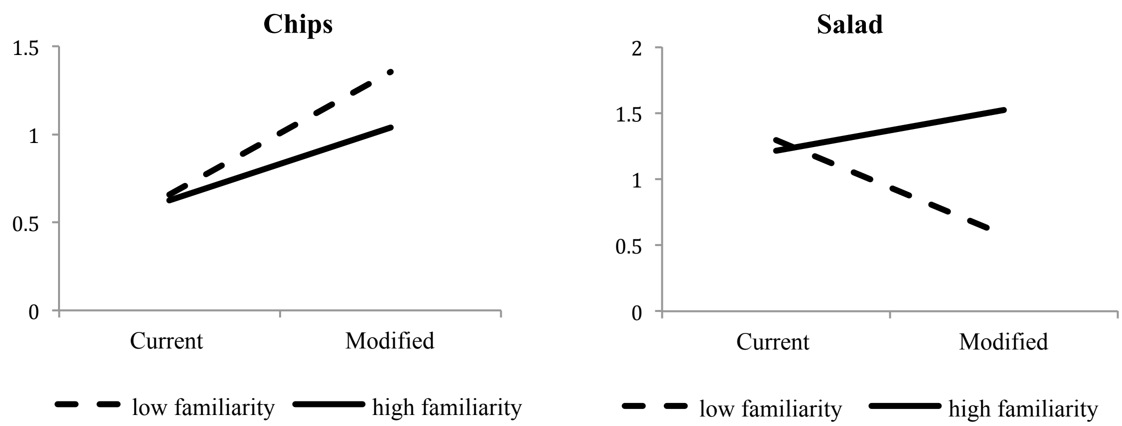
Dependent variable: Gaze time





Familiarity

Dependent variable: Time to first fixation



Dependent variable: Gaze time

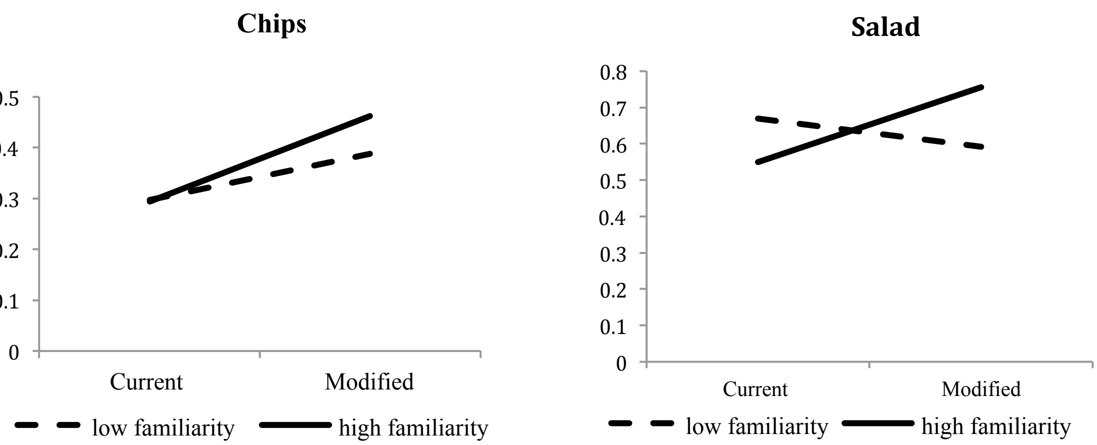


Figure 2.9
The role of involvement and familiarity on attention (chips vs. salad)

Moderation effect

To test the moderating role of involvement, I used the moderation analysis package PROCESS for SPSS developed by Hayes (2012). I selected Model 1 (one moderator analysis in PROCESS) with label format as the independent variable, attention as the dependent variable, and involvement as the moderator (see Figure 2.10 for the model and Table 2.6 for detailed results). The result supports my hypothesis that involvement moderates the effect of the modified label format on gaze time. Label format and involvement both have a positive main effect on the total gaze time. The negative moderation results indicate that participants with higher involvement decrease their attention paid to the new label format, whereas participants with lower involvement gaze longer on the modified label.

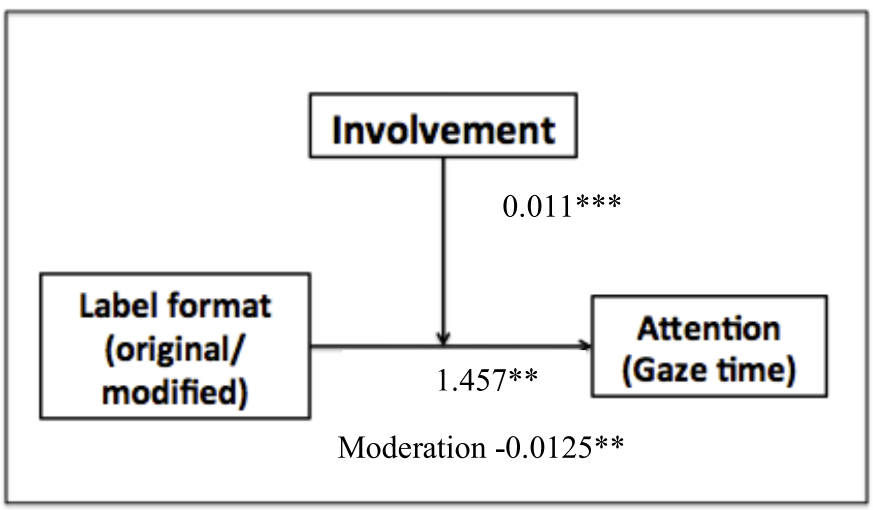


Figure 2.10
Involvement moderates the effect of label format on attention

Table 2.6 Involvement's Moderation Effect

Dep. variable: Gaze Time	Coef.		Std. Err.	z-value
Newlabel	1.458	**	1.575	1.65
Involvement	0.0116	***	0.007	2.59
Newlabel*Involvement	-0.0125	**	0.014	-1.63
Constant	-0.603	*	0.069	1.29
Model P-value	0.003			

*p < 0.1; ** p < 0.05; *** p < 0.01

Figure 2.11 visualizes the moderation effect, showing that low involved participants (negative SD) increase their gaze time on the modified nutrition label compared to when they look at the original label. Thus, the modified label benefits them by increasing their attention. In comparison, participants with high involvement (positive SD) decrease their gaze time on the modified nutrition label compared to when they look at the original label. This means that, they spend less time reading the modified nutrition label. For participants highly involved with the Nutrition Facts label, given that they already know the label well, shorter gaze time indicates that they only need to spend a short amount of time looking for the information of interest. Thus, the results support my hypothesis that the modified label format benefits participants with various levels of involvement in different ways. Econometric models are used next to validate these findings.

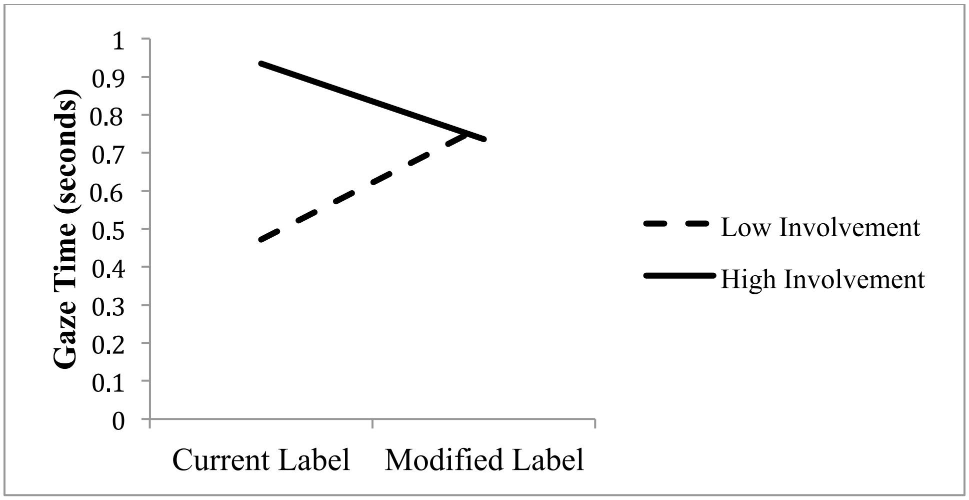


Figure 2.11
Moderation effect of involvement

Econometric results

The results above do not account for the cases where the information was ignored, in other words, when no gaze time occurred. To address this issue, I used a random effects panel Tobit model (see equation 4) to estimate the main effects and interaction effects of involvement, familiarity, the modified label format, and other consumer characteristics on consumers' visual attention. Table 2.7 displays the panel Tobit estimated for gaze time.

Modified label (newlabel). The label format has a significant positive effect on gaze time ($p < 0.01$). Thus, the new format increases the visual attention duration towards the Nutrition Facts label.

Products. The dummy variable for Chips has a significant effect on gaze time with a negative sign, which supports my expectation that consumers quickly search for critical or negative nutritional information on the Nutrition Facts label of an unhealthy product, and then stop looking at the nutrition label once they find negative information that confirms their thoughts. The healthy frozen meal has significant positive effect on gaze time, suggesting that consumers perceive it as healthy and pay more attention to its Nutrition Facts label.

Involvement. The main effect of involvement ($p < 0.01$) on gaze time is significant and positive. Thus, this result supports the hypothesis that highly involved consumers pay more attention to the Nutrition Facts label, which is consistent with previous founding suggesting that involvement plays a motivational role on attention.

Familiarity. In contrast to previous research that suggests a negative effect of familiarity on attention (Pieters et al., 1996; Pieters et al., 1999), my results show that product familiarity does not affect attention to the Nutrition Facts label. This difference in findings may because previous research focused on advertisement messages, which are easy to be fully comprehended and stored in memory. However, this buffering effect may not apply to Nutrition Facts label, which contains much more information and numeric numbers that are less likely to be remembered and precisely recalled.

Interaction effects. As shown in Table 2.7, I find all interaction effects to be significant ($p < 0.01$), with the only exception for the marginally significant interaction effect between involvement and familiarity ($p < 0.1$). The negative interaction effect of the new label format and familiarity suggests that if the familiar product labeled with the modified format, people spend less time reading the modified Nutrition Facts label. This finding is intuitive because if consumers are familiar with the product, they may already have a vague memory about the nutritional information, therefore reading the Nutrition

Facts label is only to confirm the precise numbers. Once they found the information they need, they direct their attention towards other information.

The negative interaction effect of the new label format and involvement supports my hypothesis that low-involvement consumers will be more likely to be influenced by extrinsic cues (i.e., the new label format). Thus, their attention towards the Nutrition Facts label increases when the new label is present. When involvement is high, consumers focus more on intrinsic nutrition information. Therefore, their fixation duration on the Nutrition Facts label decreases because they are highly motivated to look for the information they want, and the prominent format makes that easier.

The non-significant interaction effect of involvement and familiarity does not support my hypothesis regarding the joint effect of involvement and familiarity. I expected high-involvement consumers to experience more if any buffering effect of familiarity than low-involvement consumers, because higher familiarity may foster the memory recall for high-involvement consumers but not the low-involvement consumers who lack motivation. The non-significant interaction, however, may indicate that low- and high- involvement consumers do not differ in their attention towards the Nutrition Facts label when they are highly familiar with the product. Thus, the effect of involvement may be stamped out by familiarity.

The three-way interaction between involvement, familiarity, and new label format is significant with a small positive coefficient (coefficient =0.011). This result shows that when an individual is highly involved with the Nutrition Facts label and highly familiar with the product, he or she may still have a slight increase in the attention when the modified new label is presented.

Packaging factors. My results of Model 2 show that, compared to the upper right corner, the upper left corner receives less attention for both the current and modified label. I tested the effects of the presence of front-of-pack nutrition label, health claim such as health heart claim, and nutrition content claims such as fat-free claim, added omega-3 or fiber claim. Model 2 results show that, when the FOP nutrition label is present, it does not truncate the attention to the nutrition facts label on the back. Instead, it can increase consumers' attention towards the back-of-pack nutrition facts label. Also, other types of FOP label such as added fiber and Omega3 labels are significant determinants of the gaze time towards the Nutrition Facts label. Interestingly, I find that added fiber label and Omaga3 label have opposite effects on gaze time: added fiber label decrease consumers' attention while Omega3 increases attention towards Nutrition Facts label.

Table 2.7 Random Effect Panel Tobit Model Estimates

	Model 1		Model 2	
Gaze Time	Coef.	SE	Coef.	SE
Chips	-0.582***	0.212	— —	—
Frozen meal	0.756***	0.197	— —	—
Cereal	0.271	0.199	— —	—
Cookies	0.117	0.2	— —	—
Salad	0.067	0.204	— —	—
Yogurt	— —	—	— —	—
New label	6.191***	2.292	2.708	1.654
Involvement	0.029**	0.012	0.019**	0.008
Familiarity	0.444	0.386	-0.024	0.014
BMI	-0.06**	0.029	-0.06*	0.031
Diet	0.12	0.38	0.126	0.408
Physical activity	0.218**	0.095	0.237**	0.101
Attractive	-0.297**	0.141	-0.355**	0.152
Newlabel*Fam.	-1.51**	0.681	— —	—
Newlabel*Involv.	-0.059***	0.02	— —	—
Familiarity*Involv.	-0.005	0.003	— —	—
Newlabel*Fam.*Inv.	0.015**	0.006	— —	—
Age	— —	—	-0.01	0.012
Gender	— —	—	0.118	0.297
Hh_size	— —	—	0	0.146
Children	— —	—	0.23	0.452
Education	— —	—	0.09	0.069
FOP	— —	—	0.542***	0.2
Fat free	— —	—	-0.056	0.289
Fiber_added	— —	—	-1.047***	0.292
Omega3	— —	—	0.593***	0.215
Up_left	— —	—	-0.714***	0.212
WTP	— —	—	0.082	0.057
Constant	— —	—	0.335	1.643
LR chi2(16)	71.34		66	
Prob > chi2	0		0	
Log Likelihood	-841.7		-835.1	

*p < 0.1; ** p < 0.05; *** p < 0.01

Personal characteristics. The higher the BMI, the lower the gaze time with regards to the Nutrition Facts label. Diet has no effect on gaze time, which indicates that people's attention towards the Nutrition Facts label is independent of restricted eating behaviors.

Physical activity frequency has a significant positive effect ($p < 0.05$) on gaze time. Thus, the more frequently an individual works out, the more time they spend reading the Nutrition Facts label. Finally, the more attractive the participant perceives her-/him-self, the less attention they pay to the Nutrition Facts label.

Conclusion and Discussion

In this chapter, I investigated the role of consumers' involvement and product familiarity on visual attention towards the current and modified Nutrition Facts labels. Also, I examined how these factors interact with each other in influencing consumers' attention. Applying an eye tracking experiment, I compared the gaze time for the current or the modified label. In the study, I included six different products to test whether attention differs between more and less healthy products. I used T-tests and ANOVAs to compare visual attention towards the two labels and between products. I performed a random effects panel Tobit model to estimate the potential effects of involvement, familiarity, and the modified label format on consumers' visual attention.

My results suggest that the modified Nutrition Facts label has a significant and positive main effect on consumers' attention. Its interaction effects with involvement and familiarity show that consumers have individual differences in their responses to the new label. The modified label leads low-involvement or less-familiar consumers to attend longer to the Nutrition Facts label.

Nutrition Facts label involvement has significant positive effects on consumers' total gaze time towards the Nutrition Facts label. Involvement moderates the effect of the modified label effect on consumers' attention towards the label. The interaction effect of the modified label and involvement has a significant negative effect on attention, indicating that low-involvement consumers have less motivation to search for nutrition information but they are more likely to be influenced by extrinsic cues such as formatting. Thus, their attention towards the Nutrition Facts label increases when the new label is presented. In contrast, high-involvement consumers are motivated to examine the intrinsic information (i.e., nutritional information). Thus, their gaze time decreases when the key nutritional information is more prominent on the modified label.

My results also suggest an insignificant effect of product familiarity on attention, which is different from the negative effect of familiarity found in previous research. In contrast to previous research that is mostly concerned with advertising, my study focuses on Nutrition Facts which have more numerical and detailed information that are not likely to be precisely stored in memory. Thus, when consumers look at the Nutrition Facts label, even if they are familiar with the product, they do not necessarily have a clear memory of the nutritional information. Thus, consumers seem to be still motivated to check the Nutrition Facts label for the information of interest. Therefore, product familiarity itself will not decrease attention towards the Nutrition Facts label. However, the interaction between familiarity and the new label format is significant and negative, suggesting that the buffering effect of familiarity occurs when there is a formatting change in the Nutrition Facts label. With the key nutritional information highlighted in the Nutrition Facts label, consumers' attention decreases when they become more familiar with the product because they have to hold more prior knowledge about the nutritional facts. The interaction between familiarity and involvement is not significant, indicating that familiarity weakened the involvement effect. The interaction of all three factors (i.e., familiarity, involvement, and the modified label format) is significant. To conclude, product familiarity per se does not influence consumers' attention towards the Nutrition Facts label, but its buffering effect occurs when combined with involvement and label formatting changes.

I also find that consumers' attention towards the Nutrition Facts label varies among products. For example, chips and the healthy frozen meal have an opposite significant impact on gaze time towards the Nutrition Facts label. This result indicates that product healthiness influences people's attention towards the Nutrition Facts label. Chips are usually considered unhealthy food products and frozen meals may be perceived as comparably healthy (considering that I presented a "healthy" frozen meal based on comparable frozen meal nutrition parameters). When the modified label is presented, it is easier for consumers to notice the negative nutrition information on the nutrition label of unhealthy products and thus, stop looking at the label after a short gaze time. For healthy products, consumers would spend more time exploring the modified Nutrition Facts label since it provides additional nutrition information.

CHAPTER 3

NUTRIENT DEMAND AND NEW PRODUCT INTRODUCTION: THE CASE OF GREEK YOGURT

Nutritional attributes play an important role in influencing the food choices made by consumers, but nutrients can only be purchased as components of complete foods. Consequently, nutritional outcomes are manifestations of consumers' preferences for foods with different ingredient formulations. For example, sales of low-calorie foods and beverages have been growing faster than high-calorie alternatives in U.S. supermarkets because consumers are more aware of the health impacts of eating foods that are too calorically dense (Hudson Institute report, 2015). Globally, the market value of low-calorie foods is expected to grow at a 5.9% compound annual growth rate (CAGR) between 2013 and 2019; from 7,400 million dollars to 10,400 million dollars (Persistence Market Research, 2014).

As new foods are introduced with nutrient profiles that reflect emerging preferences, intra-category substitution patterns reflect these preference-patterns. Indeed, as consumers become more health conscious (Leeflang and van Raaij, 1995; Prasad, Strijnev, and Zhang, 2008), their demand for more "healthy"[3] nutritional attributes drive

[3] There is no universally-accepted definition for "healthy" and "unhealthy" foods. Government agencies, private sectors, non-profit organizations, and academic researchers define "healthy food" with different standards for particular policy applications (e.g., food labeling, food public settings, and food marketing) (Canada et al., 2009). Generally, "healthy" food contains less types and amounts of negative nutrients such as fat, sodium, and cholesterol and more types and amounts of positive nutrients such as vitamin A, vitamin C, calcium, iron, protein, and fiber. It is the opposite of "unhealthy" products. This study does not limit its focus to definite "healthy" or "unhealthy" food products, but it considers alternatives within the same

them to substitute among food alternatives within the same category. In this chapter, I investigate how nutritional attributes influence consumers' intra-category substitution patterns and how new-product introductions can shape aggregate nutrient consumption profiles.

Consumers' switching behaviors are shaped by opportunities created by new-product introductions and by internal factors such as health concerns, or external reasons, such as promotions or stockouts (Hamilton et al., 2014). Consumer preferences for nutritional attributes serve as an important internal reason for intra-category substitution among alternatives that vary in their nutritional content. Previous empirical studies often focus on consumers' preferences and demand for low-fat or low-calorie products (Czyzewska and Graham, 2008; Sandrou and Arvanitoyannis, 2000), and consumers' perception and response to low-fat label claims (Wansink and Chandon, 2006). However, there is limited research on the substitution patterns among "healthier" and "unhealthier" alternatives and how intra-category substitution is affected by new product opportunities.

Consumers' preferences for a product and substitution behaviors are affected not only by the nutritional attributes of foods, but by how they interact with elements of the marketing-mix (Singh, Hansen, and Gupta, 2005). Perceived healthiness may increase the likelihood a particular item is purchased (Provencher, Polivy, and Herman 2009), but marketing strategies can influence perceptions. For example, health-conscious households are less price sensitive (Prasad, Strijnev, and Zhang 2008) so marketers set

---

category as comparably "healthier" or "unhealthier" in a relative sense based on their differentiated nutritional profiles. For example, low-sugar jam can be considered relatively "healthier" than jam alternatives that have regular- or high-sugar levels.

higher prices for products with healthier nutritional profiles. In promoting these healthy products, non-price promotion strategies can effectively increase the salience of healthiness and, consequently, increase sales. Liu, Steenburgh, and Gupta (2015) provide evidence that advertising and featuring are effective means of attracting new buyers into the yogurt category by informing and educating consumers on the potential health benefits of yogurt products. Therefore, marketing-mix elements, such as promotion, display, featuring or other merchandising activities, can be expected to have different effects depending on the relative healthiness of different foods. Therefore, it is important to understand how nutritional-attribute preferences interact with consumers' sensitivity to different types of marketing tools.

Voluntarily or being urged by government, some manufacturers have begun to make effort in improving the healthfulness of their consumers' diet and start to adopt policies of helping people eat better. For example, Campbell's Soup reduced the sodium content in their soup products, and Kelloggs reduced sugar of their products. However, these reformulations also come with risks of losing consumers due to the changes in taste (Moss 2010). My results inform manufacturers what they can do if they truly want their customers to eat more healthily - they can best achieve their goals through not only reformulation, but through marketing tools that direct consumers to make better choices.

The objective of this chapter is to estimate how nutritional attributes interact with marketing-mix elements to influence consumers' intra-category substitution patterns and how these changes in demand affect nutritional outcomes. But, empirically identifying the effect of nutritional attributes on demand patterns is difficult because attribute values rarely change within product categories. Due to the fact that nutritional attributes are stable characteristics of products, the only opportunity to study the effect of nutritional changes on demand arises from either new-product introductions, or reformulations. I use the introduction of Greek yogurt as a key identifying mechanism to empirically determine the effect of nutrient-profile variation on intra-category substitution patterns.

The positive effect of reformulations on improving nutrient intake is well documented (Spiteri and Soler 2017; Griffith, O'Connell, and Smith 2017). However, findings regarding new product introduction are ambiguous (Spiteri and Soler 2017; Griffith, O'Connell, and Smith 2017). These studies focus on whether new product introductions are effective in reducing the intake of "negative" nutrients such as sodium and sugar, but do not examine the role of new products in increasing "positive" nutrients such as protein. To fill this gap in the literature, I investigate how new products with differing nutritional attributes compete with other alternatives in the same category, and fundamentally re-orient the nutrient-consumption patterns of consumers.

The introduction of Greek yogurt is an excellent example of a new-product introduction in which the source of the novelty is largely nutrient-based. Greek yogurts are far more protein-dense than regular yogurts, and they were introduced at a time when consumers began to be more conscious of the protein content and functionality of their food (Barreiro-Hurlé, Colombo, and Cantos-Villar 2008; Bimbo, Bonanno, and Viscecchia 2016). Because the popularity of Greek yogurt grew rapidly after its introduction, it is possible that yogurt-consumers' diets were more protein-dense as a result. I use this example to examine how consumers' nutrition consumption is influenced by the introduction of a new product and how this effect is moderated by marketing-mix elements.

From an analytical perspective, the introduction of Greek yogurt created a discrete event that helps determine how product introductions influence nutrient demand. In this chapter, I first provide some model-free evidence that compares household macronutrient consumption before and after the introduction of Greek yogurt, and between households that bought Greek yogurt and those who did not buy. I follow Girma and Gorg (2007), Huang et al. (2012), and Kumar et al. (2016) and exploit a quasi-experimental approach that combines propensity score matching (PSM, Angrist and Krueger 1999; Rubin 2006) and difference-in-difference (DID, Card and Kruger, 1994) analysis to compare household macronutrient consumption before and after the introduction of Greek yogurt. Food-product manufacturers seldom introduce a product like Greek yogurt that fundamentally re-orders demand among existing products. However, because Greek-yogurt consumers likely gave up types of yogurt, the net effect on nutrient consumption remains an empirical question. The DID analysis shows that after the introduction of Greek yogurt, protein and total calorie intake were higher for Greek yogurt consumers, while the consumption of fat and carbohydrates were lower. These findings suggest that the introduction of Greek yogurt may have led to changes in the consumption of each macronutrient, and may have had substantial effects on the "healthiness" of consumers' yogurt-consumption habits.

Comparisons of nutrient-consumption patterns can provide insights into the aggregate impact of Greek-yogurt introduction, but simple, reduced-form analysis cannot control for demand-interactions among all products in a category, nor can it completely account for the potential moderating effect of marketing-mix variables. Therefore, I model demand heterogeneity in a way that is able to capture the effect of marketing-mix elements on consumers' tendencies to substitute among different items in the same category that differ in their nutritional composition. In fact, my econometric model is able to estimate how the marginal value of each nutrient is affected by marketing-mix elements, and allows me to estimate how the correlation between nutrient preferences and marketing-mix sensitivities affects the tendencies of consumers to substitute among yogurt product lines. In addition, I use this model to examine the competitive relationships among product lines by estimating price, promotion, and feature elasticities of demand.

I estimate this model using household-level purchase data from the IRI Academic Data set (Bronnenberg, Kruger, and Mela 2008). I assume that consumers consume all yogurt products they purchased and that enables me to infer nutrient intake from the analysis results of purchase data.

Summary evidence from this data shows that, after the introduction of Greek yogurt, households in the data set purchased yogurts consisting of significantly more protein and calories, and less fat and carbohydrates. In addition, consumers who bought Greek yogurt regularly consumed significantly more protein and calories, and significantly less fat and carbohydrates than those who did not buy Greek yogurt. My findings support the hypothesis that the introduction of Greek yogurt fundamentally changed nutrient-consumption profiles of consumers.

Estimates from the structural model of yogurt demand confirm the reduced-form findings regarding the change in nutrient consumption, and also support the overall hypothesis that marketing-mix sensitivities are correlated with consumers' preferences for nutrition attributes in ways that depend on the "healthiness" of the nutrient. Specifically, I find that featuring is more effective in increasing sales for products that have "healthy" nutritional characteristics such as high-protein, low-fat, or low-carbohydrates because features convey the health benefits of these characteristics; whereas promotion and display work better in promoting products that have "unhealthy" characteristics such as high-fat, or high-carbohydrates that likely provide greater taste benefits. For example, consumers' preferences for protein are positively correlated with feature-sensitivity, while they are negatively correlated with other marketing-mix elements. In comparison, preferences for "unhealthy" nutrients such as fat and carbohydrates have positive correlations with sensitivity to promotion and display.

The rest of the chapter is organized as follows: The next section provides some brief background on the nutrient-demand literature, and how marketing strategies influence nutrient demand. The third section provides a detailed description of the data, and the variables used in the subsequent modeling sections. A fourth section presents evidence from the PSM and DID analysis regarding apparent shifts in nutrient consumption that resulted from the introduction of Greek yogurt, while the fifth section describes the empirical model, and how we use the model to capture nutrients preference and marketing-mix sensitivities correlation. I present and discuss my estimation results in section six. In a final section, I conclude my findings and discuss limitations of this study, and offer some suggestion regarding future research extensions on nutrient attribute effects.

Background

Over the last two decades, the obesity epidemic has emerged as arguably the number one public health concern, as the rate of obesity reached an all-time high in the US in 2016-2016 (Larned 2018; Hales et al. 2017). Although the success of nutrient-based diets such as Atkins, South-Beach, and the Paleo movement is open for debate, it is true that they have re-focused consumers' concerns on the role of nutrients in maintaining a healthy weight. Research in economics and marketing has addressed many different dimensions of this issue, from the demand for nutrients, to the impact of labeling, nutrition knowledge, and addiction. There is little research, however, on the role of marketing and product development in re-ordering nutrient-consumption profiles. In this section, I demonstrate why a focus on marketing-mix elements and new-production introduction represents a novel, and interesting way to better understand consumers' nutrient preferences, and aggregate dietary outcomes.

Understanding consumers' nutrient-preferences is essential to predicting what foods they purchase. Considering the demand for products as an implicit demand for attributes, however, is not new (Lancaster 1966). The "characteristics theory" of demand encouraged economists to look at foods as a bundle of attributes, instead of commodities to be consumed solely independent of their composition (Drichoutis, Lazaridis, and Nayga 2007). Early studies on nutrient demand consider the demand for food as fundamentally a demand for nutrients, as opposed to the taste-characteristics of food (Silberberg 1985; Leung and Miklius 1997).

Observed consumer heterogeneity, as measured by socioeconomic status or demographic attributes, work together in shaping consumers' preferences, and affect nutrient intake. When income increases, changes in nutrient consumption are, in fact, small, as nutrient-expenditure elasticity tends to fluctuate around 0.3 (Huang 1996; and Huang and Lin 2000; Fousekis and Lazaridis 2005). Other socioeconomic and demographic factors such as age, education, gender, and household size (Nayga 1994; Adelaja, Nayga, and Lauderbach 1997; Fousekis and Lazaridis 2005), employment (Nayga, Lipinski, and Savur 1998), time spent grocery shopping (Adelaja, Nayga, and Lauderbach 1997) play important roles in determining nutrient intake in different ways. These factors serve as explanatory factors for consumers' decision to purchase Greek yogurt or not in my context. While these studies focus on households' internal factors that influence their nutrients intake, they do not address potentially critical influences from external factors such as nutrition labeling, food availability, and food policies.

Whether and how consumers distinguish between nutrients during the purchasing process is also important to nutrient intake. Consumers' use of the Nutrition Facts Panel (NFP) can promote healthy consumption (Drichoutis, Lazaridis, & Nayga, 2006), but the actual usage of nutrition labels during the food-purchase process is much lower than reported (Cowburn & Stockley, 2005). It is clear that people exert only minimum effort to read product labels (Dickson and Sawyer 1990) and tend to rely on simple heuristic cues in their search for nutrition information (Balasubramanian and Cole 2002). As evidence that consumers seek to minimize the amount of time spent reading labels, Roe et al. (1999) show that the availability of front-of-pack nutrition labeling reduces consumers' attention to the Nutrition Facts label on the back. Further, this lack of attention limits the use of nutrition labels overall (Bialkova and van Trijp 2010; van Trijp 2009). However, Keller et al. (1997) show that consumers still rely more on the Nutrition Facts Panel on the back. Health claims, on the other hand, may create halo effects that reduce the likelihood that consumers search for further nutritional information (Williams 2005). Consumers' knowledge about nutritional information (Park and Davis 2001), and use of nutrition labels significantly influence nutrient intake, but nutrient availability from specific foods could be another barrier to improving the quality of consumer diets.

Nutrient availability affects nutrient intake and, consequently, the nutritional status of household members (Basiotis et al. 1983; 1987). Therefore, government programs targeted toward availability should have substantial impacts on nutrient outcomes. Programs such as Food Stamps, now known as the Supplemental Nutrition Assistance Program (SNAP, Basiotis et al. 1983; 1987; Devaney and Moffitt 1991), the School Breakfast Program (Devaney and Fraker 1989), and the School Lunch Program (Akin, Guilkey, and Popkin 1983) are all key to the US government's food-access policy. Research on the nutritional impact of these programs finds that food assistance programs not only improve nutrient availability, but also the nutritional status of diets for low-income households. However, it is not possible for these food programs to provide customized food support plans that accommodate all households' nutrient preferences. That is, they are not intended to affect nutrient availability for all consumers, but only those in the programs. Food manufacturers, on the other hand, develop new products with the intent to sell to as many consumers as possible, thereby exhibiting a reach and influence that policymakers would only wish to have.

The popularity of successful new products may increase consumers' intake of certain nutrients, but over-consumption of nutrients may contribute to obesity. One explanation for the obesity epidemic lies in the notion that consumers can become addicted, in a "rational" sense, to specific nutrients, rather than simply consuming to satisfy physical needs (Cawley 1999; Richards, Patterson, and Tegene 2007). Building on Becker and Murphy's (1988) rational addiction model, Cawley (1999) suggests that the consumption of net calories could be addictive and, therefore, lead to obesity. Similarly, Richards, Patterson, and Tegene (2007) show that the obesity epidemic could be potentially explained by consumers' rational addiction to some specific nutrients, particularly carbohydrates, but not foods. Richards, Patterson, and Tegene (2007) show that consumers are indeed rationally addicted to macronutrients (i.e., fat, protein, carbohydrates) and the addiction to carbohydrates is stronger than others, particularly in the consumption of snack foods. Realizing that consumers may become addicted to nutrients instead of specific foods, they argue that consumers will switch among foods to find other sources of the addictive nutrient. Consequently, any "sin tax" policies should consider taxing specific nutrients. Their empirical analysis, however, does not include data from any instances in which taxing authorities actually levied nutrient-specific taxes.

Empirical studies that analyze nutrient-specific taxes, such as taxes on sugar and fat, show that they have larger effects on nutrient intake than product-specific taxes without causing larger consumer welfare losses (Jensen and Smed 2013; Falbe et al. 2015, 2016; Harding and Lovenheim 2017). Intuitively, because nutrient-specific taxes are broad-based, it is more difficult to substitute for other products that also contain the same nutrients (Harding and Lovenheim 2017). More importantly, nutrient-specific taxes can induce healthier nutritive bundles and support healthier diets. These nutrient-demand studies focus on price-based incentives to modify purchase behavior, but we know little about the correlation between nutrient demand and other marketing-mix elements. It is possible that non-price marketing strategies can have fundamentally different effects on nutrient-purchase patterns.

Marketing strategies interact with product attributes in different ways (Singh, Hansen, and Gupta 2005; Ainslie and Rossi 1998; Richards 2017). For example, Singh, Hansen, and Gupta (2005) demonstrate preference-correlations for product attributes such as brand name, low-fat or fat-free, and price sensitivities among household demand for salty snack categories. Richards (2017) investigates household preferences for private labels in the milk, egg, and cheese categories and shows that price sensitivities are positively correlated across private label categories. These studies modeled the interdependence of product-attribute preferences within and across categories but did not address preference-correlations among nutritional attributes nor marketing-mix elements. This essay extends this literature by focusing on how variations in nutritional attributes and marketing-mix elements across product lines affect the demand for individual items and the composition of consumers' diet.

Like taxes and other price-based tools, marketing strategies also influence consumers' choices and, consequently, nutrient consumption. In fact, the impact of price-promotion on the demand for low-calorie products may be fundamentally different from the impact of advertising, feature, and display (Chandon and Wansink 2012). While promotion may increase sales by generating switching behavior and accelerating product purchase (R. G. Walters 1991; V. Kumar and Leone 1988; Blattberg, Briesch, and Fox 1995; Nijs et al. 2001; Neslin, Henderson, and Quelch 1985), health-related advertising and featuring benefit the entire yogurt category by persuasion, and attracting sales from outside the category (Liu, Steenburgh, and Gupta 2015). At the same time, features or displays are effective means of increasing item sales by attracting the attention of consumers (Kumar and Leone 1988; Blattberg, Briesch, and Fox 1995). In other words, all marketing-mix tactics may be effective in altering consumption, but through different mechanisms.

Due to the unique nature of the marketing-mix elements, consumers' preference for certain nutrient correlates with the specific types of marketing-mix methods in different ways. Prior empirical evidence shows that health-conscious households are less price sensitive (Prasad, Strijnev, and Zhang 2008) and functional yogurts that claim to provide health benefits are less price elastic (Bonanno 2013). If a nutrient is perceived as "beneficial" or "good-for-health," I expect consumers who prefer the nutrient to be less sensitive to price changes. If a nutrient is instead considered "negative" or "unhealthy," higher levels are more likely to provide taste than health benefits, I expect the preferences for these nutrients to be positively correlated with sensitivity to price-cut. Promotion is more effective in increasing the likelihood of hedonic purchases than utilitarian products (Kivetz and Zheng 2017).

Hypothesis 1: Sensitivity to price and promotion are positively correlated with preferences for "unhealthy" characteristics such as fat, or carbohydrates that provide more taste benefits; they are negatively correlated with preference for "healthy" characteristic such as protein that provides more health benefits.

Non-price marketing mix elements display and feature are very similar mechanisms, but I expect them to have different correlations with "positive" and "negative" nutrients.

Display has variant types but they all attract attention with increasing exposures opportunity or exposure salience for the product. For example, the point-of-sale display place products near cash registers to catch consumers' eyes when they wait for checkout. Lobby and aisle display provide more space available for the product to attract consumers' attention. Displayed products are more visually appealing to consumers and it may increase impulsive and hedonic food consumption. Previous studies show that displaying enhance hedonic evaluations and acceptance of beverage products (Stein et al. 2003) and trigger impulse purchases of snack food (Thornton et al. 2012) through increased product exposure. Therefore, I expect display to be more effective in promoting "unhealthy" nutrients that enhance taste quality rather than health benefits.

Hypothesis 2: Display sensitivities are positively correlated with preferences for "unhealthy" characteristics such as fat, or carbohydrates that provide more taste benefits.

If a nutrient is perceived as "beneficial" or "good-for-health," I expect consumers who prefer the nutrient to be more sensitive to featuring or advertising that focuses on the health benefits that derive from its consumption. Health conscious consumers have higher levels of food involvement (Sarmugam and Worsley 2015), and high-involvement consumers focus more on intrinsic information such as nutrient-specific information (Olson and Jacoby 1972; Petty and Cacioppo, 1986; Walters and Long 2012). Feature refers to retailer feature advertising, which can be one line text small ad, or large size advertising. Features provide messages that convey product-related information, rather than merely increasing exposures. A survey study also shows that features in grocery store motivate consumers to make healthier food purchases (Moore, Pinard, and Yaroch 2016). Therefore, health-conscious households should be more sensitive to marketing-mix elements such as feature that emphasize health benefits as a selling point.

Hypothesis 3: Preferences for "healthy" nutritional characteristics such as high-protein, low-fat, or low-carbohydrates are likely to be positively correlated with featuring activity.

Studying these correlations provides insight into of how different marketing-mix elements promote or limit intake of a specific nutrient, but do not address the effect of how altering the nutrient mix itself changes purchase patterns. In this regard, introducing new products has the potential to lead to substantial changes in consumers' nutrient-consumption profiles. New products may affect consumers' nutrient intake either through their own success or by re-orienting the competitive landscape within the category. The existing literature on new product introduction focuses heavily on evaluating new product survival and success because new product failures are very common and expensive (Mason 1990; Griffin and Page 1993; Kekre and Srinivasan 1990; Meyer and Utterback 1995). Successful new products not only benefit their own brand but may also have a category-expanding effect. Mason (1990) and Dekimpe and Hanssens (1995) suggest that successful new-product introductions can increase demand for the entire category by increasing the overall attractiveness of the product category. Nijs et al. (2001) demonstrate that the category-expansion effect of widely adopted new-products can be permanent. While the existing product-introduction literature focuses on the effect of new products on category demand and consumer behavior, none of these studies directly examine how successful new product introductions can influence nutrient-consumption profiles.

The introduction of a new product has the potential to fundamentally re-order the demand for items within the same category, as each product is likely to differ in terms of its taste and nutrient characteristics. As a result, new products may cause broader changes in aggregate nutrient characteristics of entire categories, and in household nutrient profiles. Empirical evidence shows how new products can significantly change nutrient intake. For example, the significant increase in coffee consumption between 1999 and 2010 (Verster and Koenig 2017) coincided with the expansion of Starbucks, opening an average of two outlets daily (Bonander 2007). The introduction of instant noodles in Korea provides another example as consuming instant noodles also lead to excessive intake of calories, fat, and sodium (Park et al. 2011). Two recent studies (Griffith, O'Connell, and Smith 2017; Spiteri and Soler 2017) compare the effect of new product introduction relative to product reformulation on changing consumers' nutrient intake. Griffith, O'Connell, and Smith (2017) find that, in all food groups from which consumers obtained salt, product reformulations are more effective in reducing dietary sodium intake than new product introductions. USA and UK government both recommended regulation to reduce salt content of food and encourage the food industry to voluntarily reformulate food product so that the reformulations are aimed to improve diet quality in the first place (Griffith, O'Connell, and Smith 2017). However, for new product introduction, they find inconsistent effects of over time, with positive effects in some years, and negative in others. It's worth noticing that the new products in their study included not only new products with lower salt content but also saltier ones. The author concluded that the introduction of these saltier new products caused the rise in salt intake by inducing consumers' switching to higher-salt products (Griffith, O'Connell, and Smith 2017). Spiteri and Soler (2017) focus on fewer specific food groups and more nutrients (sugar, fat, saturated fats, fiber, and sodium), and find similar results as product reformulations have relatively strong effects on nutritional quality. Improvements in dietary quality from reformulation derive from reducing the intake of "negative" nutrients, whereas the effects of new product introductions are ambiguous. Spiteri and Soler (2017) explain that their findings as arising from the fact that product reformulation initiatives primarily aimed at improving the nutritional quality of the existing products by reducing "negative" nutrients without affecting taste. In contrast, new products seek to attract new consumers and thus often promote taste pleasure rather than health benefits.

My hypothesis is that successful new products that contain higher levels of positive nutrients (protein) can significantly increase the intake of the positive nutrient. If the new product contains a relatively large concentration of a positive nutrient, then its purchase can lead to higher intake of the nutrient in question.

Hypothesis 4: Successful introduction of a new product may lead to greater purchases of positive nutrient if the new product contains significant high levels of the positive nutrient.

Because higher intake of the positive nutrient will contribute more calories, it is possible that increases in the positive nutrient intakes could also lead to higher intake of energy. Greater purchase of positive nutrient may also lead to greater purchases of more energy-dense foods in general, because macro-nutrients differ in their energy content. Whether this effect is true in general, however, is an empirical question.

The introduction of Greek yogurt is an excellent example of the type of dynamic that I describe. First, however, it is necessary to better understand the context of its introduction, in the hyper-competitive yogurt market. For this reason, I provide some background on the yogurt market in general, and the Greek yogurt market more specifically in the next section.

Market Background

I test these hypotheses using the introduction of Greek yogurt as a case study. Fage, a company based in Greece, first introduced Greek yogurt to the U.S. market in the 1990s. However, Greek yogurt remained a niche product until influential retailers (Trader Joe's and Whole Foods) began to recognize the emerging preference for protein-based foods from their customers, and their willingness to fulfill this preference with yogurt (Mourdoukoutas, 2011). Nevertheless, Fage lost its first-mover advantage to another Greek yogurt company, Chobani, which entered the market after Fage, but on a larger scale[4]. Chobani purchased a former Kraft Food plant in New York and spent 18 months to come up with the Chobani product (Bhasin, 2012). When Chobani yogurt was introduced in 2007, it was a "perfect storm" in which the confluence of protein-demand, targeted-marketing, and the viral nature of social media came together to create an entirely new sub-category of yogurt around one firm's product (Bhasin, 2012). Chobani reached out to bloggers and used Facebook and Twitter to directly communicate with consumers when they did not have funds to run traditional marketing campaigns, and their social media marketing succeeded in spectacular fashion (Bhasin, 2012). When big chain retailers such as BJ's Wholesale Club and Costco started to carry Chobani in 2009, their sales skyrocketed. In fact, Chobani's sales rose from nearly zero in 2007 to $500 million by 2011 (Mourdoukoutas, 2011). With continuous, rapid expansion and another plant in Idaho (Durisin, 2013), it soon became the largest selling brand with nearly $2 billion in annual revenue by 2017 (Kell, 2017). But, the subsequent success of other Greek-yogurt brands suggests that the success was more due to the nature of the product than Chobani's particular variant of it.

Greek yogurt differs from more traditional yogurts. While it tends to be low-fat or non-fat like many "diet" yogurts, Greek yogurt tends to contain higher levels of protein,

[4] Fage relied on importing products from Greece for about ten years and finally decided to open its factory in New York. However, they built their factory in the same location as Chobani, which was on a larger scale. It was considered a big mistake Fage made (Bhasin, 2012).

and less sugar than the yogurt usually found in US stores. Protein has become generally regarded as an important, “functional” macronutrient (Marrapodi, 2014; Heitz, 2016 (Darmon and Drewnowski 2015) because it performs a vital role in maintaining a healthy immune system and metabolism (Wolowczuk et al. 2008). Protein-dense foods are believed to help control appetite, and reduce hunger by increasing a sense of fullness and delay subsequent eating relative to lower-protein foods (Douglas et al. 2013). Higher protein consumption also aids in weight loss and prevents weight regain (Leidy, Carnell, Mattes, and Campbell, 2007; Westerterp-Plantenga, Nieuwenhuizen, Tomé, Soenen, and Westerterp, 2009). These nutritional benefits have made Greek yogurt a viable choice not only as a breakfast food, but also as a snack; and it is also a substitute for other high-protein foods throughout the day.

Because Greek yogurt has a significantly different nutrition profile from traditional yogurts, and was immediately successful after its launch, its introduction provides an ideal natural experiment to study the effect of product-introduction on nutrient-purchase patterns. In this study, I use the discrete nature of the Greek-yogurt introduction to show how it was associated with changes in consumers’ nutrient consumption profiles. In the following section, I describe the data, and explain my identification strategy for testing the hypotheses proposed above.

Data

My empirical application uses data from the Information Resources, Inc. (IRI) Academic Data Set (Bronnenberg, Kruger, and Mela, 2008). I use household-panel data describing yogurt purchases of households for the years 2006 to 2011 for two

BehaviorScan markets, namely, Eau Claire, WI Wisconsin and Pittsfield, MA. The IRI data provides information on a household's food choices, including how much of what items they purchase, item prices, and other marketing variables, such as feature, display, and any other promotional activities. In addition, the data set provides product information regarding nutrient-attribute levels.

I include households that made over 100 purchases in the yogurt category over the six-year period from 2006 to 2011. For my empirical analysis, I use data only from 2006 to 2009, which covers the two years before (13,367 observations), and two years after the introduction of Greek yogurt (13,665 observations). As a result, the sample consists of 288 households, making 29,032 purchases over the entire sample period.

I define the date of introduction as the date on which Greek yogurts first appeared in the data. Although this is not likely to be the exact date of introduction, this assumption is necessary due to the limitations imposed by the data. With this assumption, the date at which Greek yogurt purchases were first observed was the last week of February in 2008.

Importantly, the IRI Academic Data Set provides product information regarding nutrient-attribute levels. Nutritional attributes for yogurt vary widely across product lines. I consider only fat, protein, and carbohydrates because these three are the major macronutrients in foods and are linearly related to calorie content[5].

There are too many specific UPCs in the yogurt category to analyze all of them in a tractable way, so I choose a representative set of items that capture the majority of the market. Specifically, I define the unit of analysis as the "product line," which consists of

[5] Carbohydrate and protein can each provide 4 calories per gram, while fat provides 9 calories per gram. This study implicitly ignores any interaction effects among the macronutrients that may be present.

all flavor variants within a sub-brand of yogurt, Yoplait Light, for instance. This assumption is necessary because there is no price variation at a sub-product-line level. I then rank the market shares of all product lines in the data, and select the top 31 product lines (summarized in Table 3.1). These product lines form 82.64% of the market, and provide sufficient variation to identify differences in demand that may be driven by differences in nutritional profile.

I consider four main sub-categories: Light, Regular, Thick, and Greek. Yogurt market segments are defined on the basis of product type, which includes regular yogurt and low-fat or fat-free segments (Futures Market Insights). Greek, Regular, and Light are the top three fast-growing segments (Neilson XAOC). I also include the Rich subcategory to provide more variation in the yogurt nutrient profile. These sub-categories assume a range of nutritional profiles and can be grouped into four primary yogurt subcategories based on their fat, protein, and calorie content levels (see Table 2.2). All other product-line purchases were defined as the outside option for econometric purposes. I follow Berry et al. (1995) and define the outside option as any purchase that does not involve any of the 31 product lines, and aggregate over all non-purchased product lines in assembling a complete picture of the yogurt market. The presence of the outside option allows the demand for the yogurt product lines to decline if there is a general price increase among all product lines, and thereby allows me to model the aggregate demand for the yogurt market more generally (Nevo 2000).

Table 3.2 also provides descriptive statistics for market share, price, promotion, feature, and display for each subcategory. Light products constitute a large part of the market, followed by Regular, Greek, and Rich. In comparison, high-calorie and high-fat products (i.e., the "Thick" subcategory) only account for a small part of the total market. These trends suggest that subcategories that contain "healthy" nutritional attributes such as high-protein and low-fat dominate the yogurt market.

Because Greek yogurt's market share grew quickly after introduction, manufacturers of products in the incumbent subcategories appear to have reacted by adjusting their marketing strategies. Table 3.3 provides descriptive statistics that compare marketing-instrument values before and after the introduction of Greek yogurt. After the introduction of Greek yogurt, the Greek yogurt subcategory quickly drew market share from Thick yogurt and Regular yogurt products. Market shares of Light yogurt and the outside option remained relatively unchanged after the introduction.

Greek yogurt seems to have higher prices (about 2 dollars per 6-ounce cup on average) than other subcategories (about 1 dollars per 6-ounce cup on average), but is less-frequently promoted, featured, or displayed compared to the three main subcategories. This phenomenon is in line with Bonanno (2013) in that functional yogurts are less price elastic and have higher margins than conventional alternatives. As a result, Greek yogurts do not need to promote through price-based strategies as much as other subcategories. However, Greek yogurts are featured more frequently, only less frequently than the Light subcategory. This is consistent with my hypothesis that feature is expected to be more effective in marketing Greek yogurt that is high in "healthy" nutrients relative to products that contain more "unhealthy" nutrients.

Manufacturers of product lines in other categories actively responded to the introduction of Greek yogurt (see table 2.3). For example, Regular yogurt prices fell significantly after Greek yogurt entered the market, but manufacturers in the Regular yogurt subcategory significantly decreased the frequency of promotion, feature, and display. It is possible that manufacturers in the Regular yogurt subcategory realized that price cuts are far more effective in increasing demand for Regular yogurt than the other marketing-mix elements and thus adjusted their strategies. In comparison, Light and Rich yogurts' prices increase, but they had significantly more frequent promotions and non-price promotions such as feature and display. Manufacturers of yogurts in other subcategories appear to have changed their marketing strategies after the introduction of Greek yogurt, but whether these changes are caused by the new product introduction is not clear. I will further explore these relationships in the empirical exercise below.

My modeling approach assumes nutrient attributes, and the introduction of Greek yogurt itself are decisions taken by manufacturers in a prior, unmodeled stage of a larger strategic game being played among yogurt suppliers. Therefore, I focus only on the impact of marketing-mix elements, and their interactions with nutrient content, on demand. For my empirical model, nutritional attributes do not vary over the sample period, but the 31 product lines contain much different nutritional attribute levels (Table 3.1), which provide enough cross-sectional variation to identify the marginal values of each nutrient. Market share, retail prices, and marketing-mix elements vary across product lines and time, which easily identify the price and marketing-mix parameters. I also control for the endogeneity of price and marketing-mix elements with an instrumental variable (IV) estimator approach that I will describe in more detail below.

As is well understood in the empirical literature, observed prices in household-level scanner data are likely to be endogenous because of unobserved factors, such as shelf placement and in-store promotions that are unobservable in the data and may represent demand shocks that are correlated with the prices paid in the store (Villas-Boas and Winer 1999). Despite strong logical arguments for endogeneity, however, it is nonetheless necessary to formally examine the data before drawing a conclusion that results in using a more complicated, and perhaps also biased, estimation technique. Therefore, I tested the null hypothesis of exogeneity using a Wu-Hausman test. Intuitively, the Wu-Hausman test examines the null hypothesis that prices are exogenous by comparing the estimates of the model with instrumental variables to ordinary least squares (OLS) estimates (Wu 1974; Hausman 1978). An IV estimator will be consistent under either the null or alternative hypothesis, while the OLS estimator will be biased and inconsistent under the alternative, but efficient under the null. The Wu-Hausman test statistic value was is 409.551, and its p-value was less than .001, which suggests rejection of the null, and implies that prices are endogenous.

Appropriate instrumental variables should be correlated with prices but uncorrelated with the unobserved factors that may lead to changes in demand. Following Villas-Boas (2007), and Draganska and Klapper (2007), I use a set of instruments (see Table 2.4 for summary statistics) that include input prices such as milk price, sugar price, HFCS price, wages, utility, fuel oil, electricity, as well as a set of store and product line specific intercepts (Villas-Boas 2007). Yogurt production requires Class II milk as the main input material (Jesse and Cropp 2008). I use prices for Class II price provided by the USDA Agricultural Marketing Service. Sugar and high fructose corn syrup (HFCS) prices are from the USDA Economic Research Service database, and are originally from the Milling & Baking News. I obtained wage data from the Current Employment Statistics Survey of the U.S. Bureau of Labor Statistics (BLS) database, which provides hourly earnings of manufacturing workers. In addition, I use utility, electricity, and fuel oil prices from the BLS Consumer Price Index (CPI). These instrumental variables explain 28.71% of the total variation in prices, with an F-statistic of 2,562.75, suggesting that the instruments are not weak in the sense of Staiger and Stock (1997).

Because the introduction of Greek yogurt represents a discrete event that separates the data into natural pre- and post-introduction regimes, any impact on the structure of demand in the yogurt category should be apparent from casual observation of the data. In the next section, therefore, I examine the data for any model-free evidence of a longitudinal pattern of changes in the yogurt subcategories, and sales of brands that introduced their own Greek yogurt line.

Table 3.1 Yogurt Product Attributes and Market Shares

Product Lines	**Market Share**	**Fat Level**	**Fat (g)**	**Calorie**	**Protein (g)**	**Carbs (g)**	**Volume (oz)**
Yoplait Light	19.22%	Fat Free	0	90	5	16	6
Dannon Light N Fit	10.81%	Fat Free	0	80	5	14	6
Yoplait Original	13.18%	Low Fat	2	150	6	25	6
Yoplait Whips	4.33%	Low Fat	2.5	140	5	25	4
Dannon Fruit On The Bottom	4.72%	Low Fat	1.5	150	6	26	6
Chobani	0.50%	Fat Free	0	130	12	17	6
Yoplait Light Thick & Creamy	3.61%	Fat Free	0	100	5	21	6
Yoplait Thick And Creamy	3.77%	Low Fat	2.5	180	7	31	6
Stonyfield Farm	2.50%	Low Fat	2	100	4	12	6
Dannon Activia	1.03%	Low Fat	1.5	90	4	16	4
Wells Blue Bunny Lite 85	3.92%	Fat Free	0	85	6	14	6
Kemps Free	2.44%	Fat Free	0	80	3	19	6
Colombo Light	3.03%	Fat Free	0	90	6	16	6
Colombo Classic	3.06%	Fat Free	0	150	5	32	6
Weight Watchers	2.37%	Fat Free	0	100	7	17	6
Old Home 100 Calorie	1.13%	Fat Free	0	100	5	19	5
Yoplait Go Gurt	0.81%	Low Fat	0.5	60	2	10	2
Dannon Activia Light	0.33%	Fat Free	0	60	4	10	4
Breyers Yocrunch	0.07%	Low Fat	2	180	6	35	6
Yofarm Yocrunch	1.99%	Low Fat	3	130	4	23	6
Yoplait Trix	0.73%	Low Fat	0.5	100	3	20	4
Yoplait Grande	0.18%	Low Fat	1.5	200	7	39	32
Dannon Natural Flavors	0.54%	Low Fat	2.5	150	7	25	6
Old Home Gaymont	0.23%	Low Fat	2	220	10	40	8
Old Home	0.33%	Regular	8	190	12	17	8
Yoplait Greek	0.11%	Fat Free	0	160	12	26	6
Breyers Light	0.27%	Fat Free	0	80	6	12	6
Yoplait Yo Plus	0.12%	Low Fat	1.5	110	4	21	4
Kemps Nonfat 100 Calories	0.48%	Fat Free	0	100	5	22	5
Axelrod	0.53%	Fat Free	0	90	6	17	6
Dannon Oikos	0.05%	Fat Free	0	110	12	15	5.3
Outside Option	13.62%	Missing	2	130	6	21	6

Table 3.2 Attributes of Subcategories

Subcategory	Nutrition content	# of Product lines	Market Share	Price	Promotion	Feature	Display
Light	Non-Fat & Low Calorie	12	42.01%	1.00	0.37	0.25	0.12
Regular	Low Fat & Medium Calorie	14	31.06%	1.13	0.33	0.26	0.10
Thick	Higher Fat & Calorie	5	4.40%	0.89	0.27	0.20	0.03
Greek	High Protein & Low/Non Fat	3	5.17%	2.19	0.29	0.09	0.07
Outside option			17.36%	2.02	0.17	0.11	0.02

Note: Price is in $/unit. Promotion, Feature, and Display are in proportion of times.

Table 3.3 Descriptive Statistics for Yogurt Subcategories

	Market Share			Price			Promotion			Feature			Display		
Subcategories	Before	After		Before	After		Before	After		Before	After		Before	After	
Light	41.86%	42.09%		0.988	1.062	***	0.364	0.407	***	0.285	0.120	***	0.113	0.127	*
Regular	33.61%	29.61%	***	1.141	1.050	***	0.342	0.234	***	0.290	0.071	***	0.111	0.030	***
Thick	7.30%	2.76%	***	0.876	1.174	***	0.270	0.347		0.206	0.074	***	0.031	0.096	***
Greek	-	8.09%	-	-	2.191	-	-	0.286	-	-	0.093	-	-	0.074	-
Outside Option	17.23%	17.44%		2.010	2.201	***	0.314	0.340	**	0.110	0.031	***	0.019	0.028	**

Note: Price is in $/unit. Promotion, Feature, and Display are in proportion of times.
***, **, * => Difference is significance at 1%, 5%, 10% level

Table 3.4 Summary Statistics for the Instrumental Variables

Variable	Unit	Mean	Std. Dev.	Min	Max
Milk Price	$/Cwt	15.457	3.686	10.252	22.409
Sugar Price	$/Lb	214.478	68.347	125.400	355.800
HFCS	$/Lb	263.592	43.651	183.100	315.100
Wages	$/Hour	22.467	0.972	20.690	23.890
Utility	$/Therm	1.220	0.155	1.028	1.703
Fuel oil	$/Gallon	3.010	0.608	2.319	4.649
Electricity	$/KWH	0.123	0.007	0.108	0.135

Reduced-Form Evidence of the Impact of Greek Yogurt Introduction

I begin this section by offering a broad summary of the data on yogurt-consumption patterns before and after the introduction of Greek yogurt, and then follow with a detailed difference-in-difference (DiD) analysis of how the introduction caused changes in nutrient-consumption profiles. My findings in this section show the transformational nature of how successful new product introductions can change aggregate dietary quality.

The introduction of Greek yogurt completely changed the nature of the yogurt category. Figure 2.1 shows how the market shares of Light, Regular, Thick, and Greek yogurt subcategories changed between 2006 and 2011. Greek yogurt began to grow at an exponential rate after entering the market in 2008, while the market shares of Regular and Thick sub-categories declined rapidly after the introduction of Greek yogurt. From this summary data, it appears Greek yogurt rapidly assumed market share from the incumbent yogurt-types following its introduction in February of 2008. Greek yogurts, especially the early variants, usually contained moderately higher calories (over 100 calories per serving) whereas Light yogurts' calorie-content is usually around 80 to 90 calories. Therefore, consumers who have a strong preference for low-calories and Light yogurt may be reluctant to switch to Greek yogurt because of the obvious difference in energy content. Consequently, Figure 3.1 suggests that Greek yogurt drew mostly from Regular and Thick and not Light.

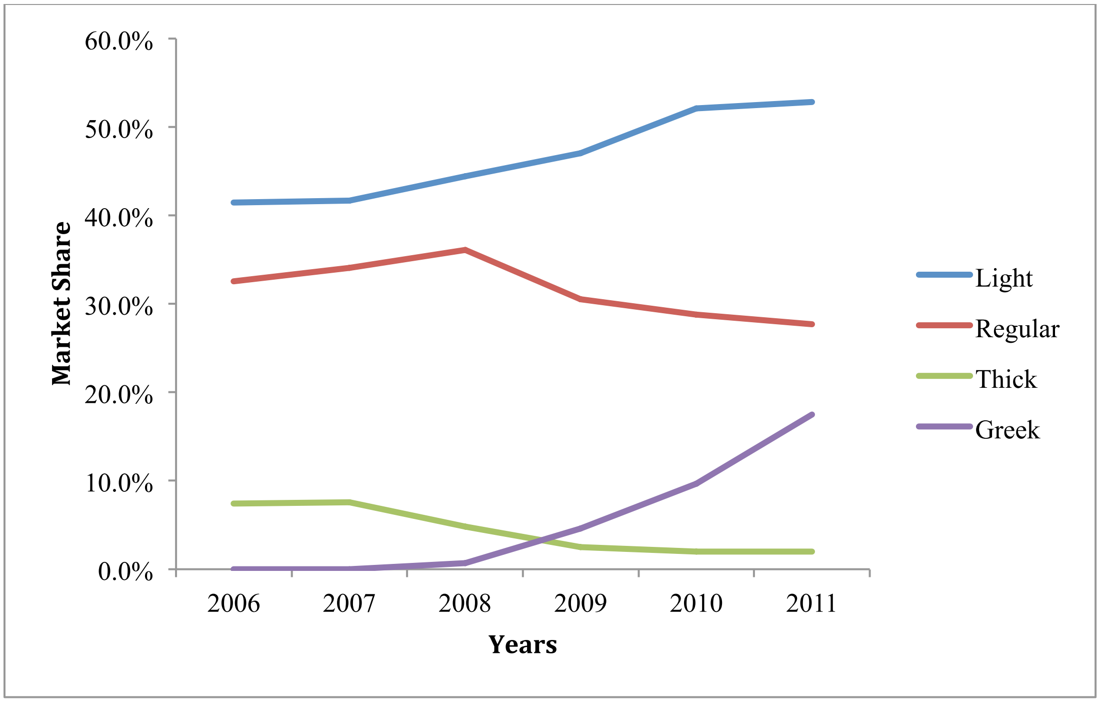


Figure 3.1
Main Subcategories Market Shares.

Success in the new Greek yogurt category does not appear to have been uniform as Chobani enjoyed a clear first-mover advantage. Chobani, Yoplait Greek, and Dannon Oikos were among the first products to appear on supermarket shelves, but Chobani, the most popular Greek yogurt brand, accounts for most of the Greek yogurt sub-category. Figure 3.2 shows that Chobani was largely responsible for much of the growth of the Greek yogurt segment. In comparison, Yoplait Greek and Oikos by Dannon were not as successful as Chobani because they entered the market late when Chobani established a beachhead in the subcategory (Kell 2017a). Other brands' market shares grew slowly and remained relatively small over the entire period of my data[6].

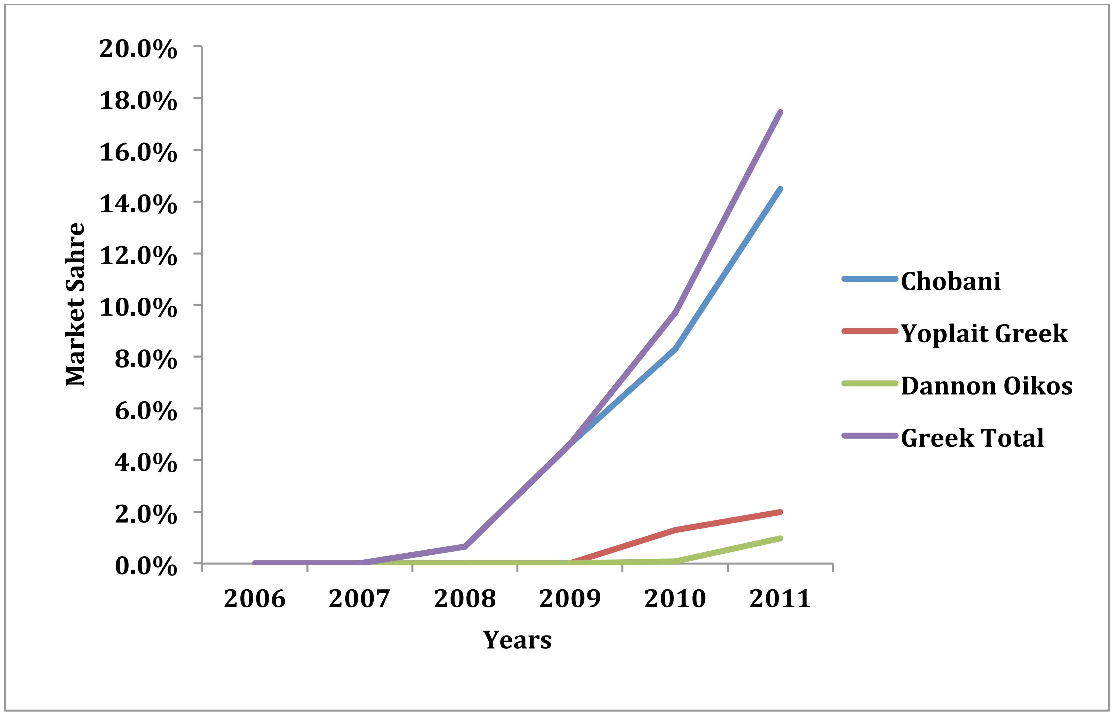


Figure 3.2 Greek Yogurt Growth

The rapid growth of Greek yogurt demand reveals consumers' acceptance of a new yogurt subcategory; however, the fact that Greek yogurt differs from other yogurts in nutritionally-important ways means that the implications go beyond simply business success. In fact, I argue that new products that target nutrient-specific demand trends can have a fundamental impact on aggregate, household-level nutrient-consumption patterns. In what follows, I examine this impact with a difference-in-difference analysis. I examine how the introduction of Greek yogurt influenced nutrient-purchasing patterns among

---

[6] Fage was mainly based on the New York market; therefore, samples from Eau Claire in Wisconsin and Pittsfield in Massachusetts did not provide purchase records of the Fage Greek yogurt.

yogurt buyers. Specifically, I measure the difference in nutrient intake within households (before introduction and after introduction), between households (Greek-yogurt consuming vs. non-Greek-yogurt consuming), and the combined difference (difference-in-difference) to show how the introduction of Greek yogurt affected the implied nutrient-purchase amounts of consumers that adopted Greek yogurt, and continue to purchase it regularly after introduction. I examine the changes induced by the introduction of Greek yogurt by employing a difference-in-difference (DID) analysis. A difference-in-difference (DID, Card and Kruger, 1994) framework is useful for examining treatment effects in a setting in which an exogenous shock divides the data into pre- and post- examination periods.

After the introduction of Greek yogurt in 2008, some households adopted Greek yogurt products, while others did not. Therefore, in this section, I define the change in nutrient consumption induced by the introduction of Greek yogurt in a conditional sense: If a household decided to purchase Greek yogurt, how did their nutrient consumption change? To examine the difference in macronutrient consumption between households that bought and households that did not buy Greek yogurt, I first examine how regularly a household bought Greek yogurt products by calculating the ratio of Greek yogurt purchases by the households to the total number of yogurt purchase occasions after the introduction of Greek yogurt. I perform a median split to classify consumers as regular buyers versus non-regular buyers[78]. Based on this split, the mean ratio of Greek yogurt to

[7] The use of a median split is a common method to dichotomize a continuous variable into a binary variable and is widely used for this purpose in consumer research, psychology and other fields (Iacobucci et al.

non-Greek yogurt for all non-zero purchase households is 9.07%. Next, I define regular Greek yogurt buyers as those households with a purchase ratio greater than the mean, and a non-regular buyer as one with the ratio less than the mean (there are no households that have a ratio exactly equal to the mean). I compare the difference in the nutrient profiles between households that consume Greek yogurt regularly (referred as regular buyers below) with those who do not consume Greek regularly (referred as non-regular buyers below).

To conduct both a within-household and between-household comparison, I created a binary variable that represents the discrete date upon which Greek yogurt was introduced. While I do not know the specific date of introduction, I create a binary indicator by inferring the date of introduction from my data as described above. I use these two indicators for the difference-in-difference estimation.

A primary benefit of using a DiD approach is that the results of the DiD estimator are intuitive and easy to interpret. However, two issues need to be addressed before conducting a DID analysis: First, for the treatment effects to be valid, the underlying trends in both the pre- and post- data must be the same, or at least taken into account. This is known as the "parallel trend assumption" (Abadie 2005). The parallel trend assumption means that the treatment and control group should have a similar trend in their behavior before the intervention. In my context, it means that all yogurt eaters should have the same nutrient-intake trends over time. For this assumption to hold, I need

2015b). Median split is acceptable and valid to use as long as the independent variables are uncorrelated (Iacobucci et al. 2015a).

[8] I also test the same treatment effect analyses with different thresholds (i.e., the ratio being greater than zero, 20%, 30%, 40%, and 50%) and find consistent patterns of changes, with only few exceptions of changes in significance (See results presented and discussed in Appendix B).

to assume that all other potential covariates are held constant, which is nearly never met. Alternatively, I can use matching methods to ensure that the two groups' trends substantially overlap. Second, consumer-specific variables, such as nutrient intake preferences, may simultaneously influence consumers' nutrient intake profiles and their decision to purchase Greek yogurt. In other words, the decision to purchase Greek yogurt is not randomly assigned across the sample, so the DiD estimates are likely to be biased and inconsistent unless endogeneity is otherwise taken into account.

Matching and instrumental variables (IV) are two commonly used techniques to address the endogeneity issue (Angrist and Krueger 1999). Instrumental variables are not feasible in this context because it is difficult to identify good instrumental variables that are correlated with households' Greek yogurt purchase behaviors, but are uncorrelated with households' nutrient intakes. However, matching methods mimic a randomized experiment by using covariates to pair the treatment group and control group (Rubin 2006). Therefore, I adopt a propensity-score matching (PSM) method to ensure that the decision to adopt is as close to being randomly assigned as possible across my sample households.

Exact matching and propensity score matching (PSM) are two commonly used matching methods. Exact matching is not appropriate here because it requires all the matching variables to have exactly the same values, thereby limiting the number of matching variables, and potentially introducing more selection bias by excluding subjects that do not have available data for some matching variables (Stuart 2010; Burden et al. 2017). PSM reduces the dimensionality of the matching problem and (Rubin 2006) and increases the randomness of the sample by conditioning on a propensity score (Rosenbaum and Rubin 1983). Therefore, PSM is preferred over exact matching in my sample.

The PSM technique pairs subjects in the treatment group and control group on the basis of propensity score similarity (Gensler, Leeflang, and Skiera 2012). Propensity scores are defined as the probability of being assigned to the treatment group conditional on observed characteristics (Austin 2011). Scores can be obtained by calculating the predicted probability implied by regressing the likelihood of the treatment assignment on covariates that explains the propensity of receiving the intervention or treatment. In the current context, I obtain propensity scores by regression whether a household purchases Greek yogurt regularly on households' demographic attributes.

The combination of PSM and DiD produces a plausible quasi-experiment between the treatment and control groups that address endogeneity, and satisfies the parallel-trends assumption of DiD. A number of recent studies use this approach to examine treatment effects in a variety of settings, from the effect of technology efficiency and acquisition scale on productivity after multinational acquisition (Girma and Gorg 2007) to the impact of Wal-Mart entry on supplier profits (Huang et al. 2012), and the influence of firm-generated content in social media on consumer behavior (Kumar et al. 2016). Each of these studies uses PSM to match similar subjects in the treatment and control group, to satisfy the parallel trend assumption, and to correct for self-selection bias. Although consumers did not decide when Greek yogurt was introduced, they do decide whether or not to consume Greek yogurt.

My context is similar to Kumar et al. (2016) in which the firm-generated content in social media is exogenous to consumers, but consumers' participation in the social media page is endogenous to the outcome variable of interest – consumers' transaction and purchase behaviors. Similarly, in Huang et al. (2012), the entry decision is endogenous to suppliers' profit because Wal-Mart strategically chooses the markets in which it decides to open new stores, and this decision may involve evaluating suppliers. Using the PSM method, they address this likely source of endogeneity prior to applying a DID analysis.

In my study, I employ the PSM method to match households that bought Greek yogurt regularly and non-regularly on the basis of propensity score similarity (Gensler, Leeflang, and Skiera 2012). To obtain propensity scores, I model whether a household purchases Greek yogurt regularly using a logistic function of households' demographic attributes. I examine different sets of demographics as covariates and choose the set that minimizes bias. These variables include the education level of the household head, the age of the household head, language, and IRI geography number (1=Pittsfield, 3= Eau Claire). The logistic regression results are reported in Table 3.5. These results are used to produce a common index or "score" for each household, and households are then matched on the basis of score similarity.

Table 3.5 Logit Model of Regular Greek Buyer

Matching Variable	Estimates	SE	Z
Education_Household Head	0.0121***	0.0037	3.23
Age_Household Head	-0.2047***	0.0133	-15.34
Language	-0.0036***	0.0004	-8.44
IRI_Geography_Number	-1.0763***	0.0231	-46.46
Constant	0.7997***	0.0687	11.64

Note: ***, **, * => Significance at 1%, 5%, 10% level

Follow Huang et al. (2012), and Kumar et al. (2016), I use the 1:1 nearest neighbor matching method (Rosenbaum and Rubin 1985) to create matched samples. This matching technique is commonly used because it is simple and very useful in reducing bias (Rosenbaum and Rubin 1985; Stuart 2010).

After households are matched according to their propensity score, I assess the quality of matching by checking whether the covariates (i.e., the matching variables) are well balanced between the regular- buyer group and the non-regular buyer group. Balance checking tests the equality of means in the two groups, both before and after matching. If the sample is well balanced, the standardized differences between the treatment and control groups should be insignificant and the percentage of bias of all matching variables should be less than 5% after matching. Table 3.6 shows the standardized differences between the two groups on the matching variables before and after matches, and the bias reduction percentages after matching. The results presented in Table 3.6 indicate that, while most of the standardized differences between the variables are significant before matching, the differences are not significant after the matching process. The absolute bias percentages are all below 5% after matching. Therefore, PSM successfully achieves a statistical balance between the two groups (Rishika et al. 2013).

Table 3.6 Covariance Balance Before and After Matching

Panel A. Separate Balance Test for Each Matching Variable

	Before Matching	%bias	After Matching	%bias	Bias Reduction (%)
Matching Variable					
Education_Household Head	-0.0138	-0.4	0.0078	0.2	43.3
Age_Household Head	-0.2969***	-29.6	0.0000	0.0	100.0
Language	-2.125***	-6.4	0.0440	0.1	97.9
IRI_Geography_Number	-0.7215***	-89.4	0.0000	0.0	100.0

Panel B. Balance Test

Before Matching			After Matching		
Combined Baseline Difference	df	p-value	Combined Baseline Difference	df	p-value
31.4	4	0.0000	0.1	4	0.998

Note: ***, **, * => Significance at 1%, 5%, 10% level

Checking for common support is another way to evaluate the quality of matching. Common support is also called “overlap condition” and it means that there is substantial overlap of the propensity score distribution in the treatment group and control group (Stuart 2010). Common support ensures that observations in the treatment group have comparison control group observations “nearby” in the propensity score distribution (Heckman, Lalonde, and Smith 1999). To minimize estimation bias, it is critical to ensure that the distributions of propensity scores for the treatment and control group share a common support (Busse, Silva-Risso, and Zettelmeyer 2006; Kumar et al. 2016). I examine the common support by visually analyzing a histogram plot of the distribution of propensity scores before and after the matching process to see if the distribution overlaps after matching (Guo and Fraser 2010). The plots indicate that the propensity score distributions of the two groups are nearly identical (see Figure 2.3) after matching. This provides evidence of common support between the distributions of the matched groups.

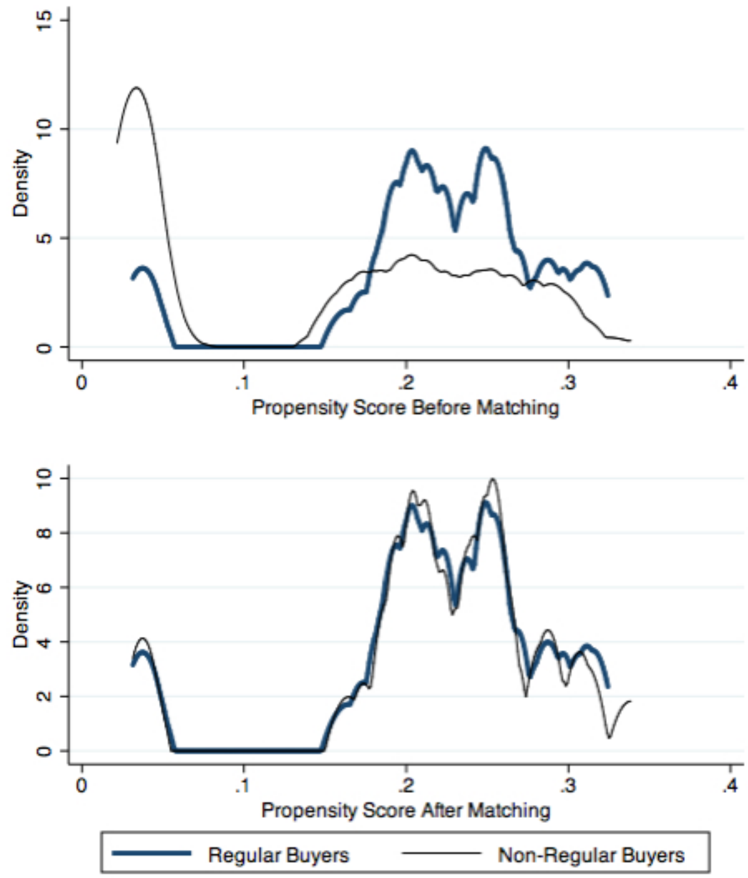


Figure 3.3 Distributions of Propensity Score before and after PSM.

After finding a successful match, I conduct a DiD analysis on the matched samples to examine the effect of Greek yogurt purchases on households' nutrient purchases. Following the difference-in-difference approach proposed by Card and Kruger (1994), I assume the dependent variable y, nutrient intake, for household i at time t and treatment g is:

$$y_{igt} = \alpha + \gamma G_{im} + \lambda T_t + \delta(G_{im} * T_t) + \varepsilon_{igt} \tag{1}$$

where G_{im} is a dummy variable that captures the difference between households i that buy Greek yogurt regularly (G_{im}=1) in a matched pair m and households that do not

(G_{im}=0). T_t is a binaryvariable for the time period after (T_t=1) the introduction of Greek yogurt and before (T_t=0). As G_{im} and T_t take the value of either 0 or 1, the DiD estimator δ can be expressed as:

$$\hat{\delta} = (y_{22} - y_{21}) - (y_{12} - y_{11}) \quad (2)$$

The expression shows that DiD estimator is essentially the testing the difference, between the regular Greek yogurt buyers and non-regular Greek buyers, of the changes in the nutrient intake that occurred before and after the introduction of Greek yogurts.

The variables of interest for the difference-in-difference analysis are the weekly intake of each macronutrient (i.e., protein, fat, and carbohydrates). Specifically, I calculated each household's total protein purchase amount (from yogurt) by summing up the protein content in all purchased yogurt products by week, and weighing the sum by the total volume purchased.[9] I created the same measures for fat, calories, and total carbohydrates to test whether the introduction of Greek yogurt was associated with a general shift in nutrient consumption. I look at both nutrient density and total nutrient intake to see if the effect holds in different magnitudes.

The DiD estimation results are presented in Table 3.7 and Table 3.8. The results in table 3.7 show that, after the introduction of Greek yogurt, protein and calorie intake per ounce, which is a measure of nutrient density, for regular Greek yogurt buyers rose significantly, whereas fat and carbohydrate intake fell significantly relative to the pre-introduction period. More importantly, I find that while non-regular Greek buyers have no significant change in caloric intake, regular buyers consumed significantly more

[9] I assume that consumers have consumed all yogurt products they purchased.

calories. Changes in nutrient intake among adopting households are likely due to the fact that Greek yogurts contain high levels of protein and lower levels of fat, but Greek yogurts do not necessarily have lower calories. In general, the DiD analysis shows that the introduction of Greek yogurt may have led to a decrease in the intake of some nutrients, but an increase in others, even after controlling for the endogeneity of the adoption decision.

The DiD analysis reveals other insights into the effect of Greek-yogurt introduction that are important to the broader picture of how consumers' nutrient consumption patterns may have been affected. First, Table 3.7 shows that the calories of non-regular buyers fell after the introduction of Greek yogurt. Intuition would suggest that non-buyers should be unaffected, so this finding is somewhat surprising. This observation could be due to the fact that consumers are becoming more health conscious, so are consuming more Light yogurts in general. However, my approach controls for any common trends among the treatment and control groups. Because manufacturers responded to the introduction of Greek yogurt by reducing prices, it is more likely that non-buyers were induced to increase their consumption as a result of lower prices, which is an important, yet indirect, effect of the introduction of Greek yogurt. In addition, I find that regular Greek buyers consumed more fat than non-regular buyers before the introduction of Greek yogurt; but regular Greek buyers started to consume less fat than non-regular buyers when they started buying Greek yogurt regularly after the introduction. It is possible that most of the Greek yogurt regular buyers were consuming Regular yogurt, or even Rich yogurt, before began consuming the new product, and switched to regularly consuming Greek yogurt after. Therefore, their consumption of fat fell more sharply after the introduction of Greek yogurt.

In addition to investigating the effect of introduction on the density of nutrient intake, I also examine changes in total nutrient consumption to test if the cumulative effect remains the same. Table 3.8 reports the DiD results for the total consumption of each nutrient before and after the introduction of Greek yogurt. The data in this table show roughly the same pattern as the density case. Namely, nutrient intake per ounce (Table 3.7) and total nutrient intake (Table 3.8) show a consistent pattern of changes in protein, fat, and calorie intake. Total protein and calorie intake for regular Greek yogurt buyers increase significantly, whereas total fat intake decreases. Although Greek yogurt is often referred as a healthy alternative to other yogurts, the idea of “more is better” may not be true for eating Greek yogurts.

Table 3.7 The impact of Greek yogurt introduction on the PER OUNCE nutrient intake due to yogurt consumption

		Protein		**Fat**		**Carbohydrates**		**Calorie**	
Before	Non-Regular Buyer(C)	0.942		0.181		3.506		20.145	
	Regular Buyer (T)	0.904		0.220		3.435		20.153	
	Diff (T-C)	-0.038	***	0.039	***	-0.071	***	0.008	
After	Non-Regular Buyer(C)	0.947		0.170		3.390		19.640	
	Regular Buyer (T)	1.294		0.153		3.254		20.950	
	Diff (T-C)	0.348	***	-0.018	***	-0.135	***	1.310	***
Diff-in-Diff		0.386	***	-0.057	***	-0.064	**	1.302	***
R-square		0.241		0.020		0.006		0.019	

***, **, * => Significance at 1%, 5%, 10% level
T - treatment group, C - control group

Table 3.8 The impact of Greek yogurt introduction on the TOTAL nutrient intake due to yogurt consumption

		Protein		Fat		Carbohydrates		Calorie	
Before	Non-Regular Buyer(C)	24.207		4.496		89.927		515.888	
	Regular Buyer (T)	22.143		5.242		83.744		492.510	
	Diff (T-C)	-2.064	***	0.746	***	-6.183	***	-23.378	***
After	Non-Regular Buyer(C)	24.983		4.213		88.773		513.830	
	Regular Buyer (T)	32.728		3.691		82.383		528.583	
	Diff (T-C)	7.745	***	-0.522	***	-6.391	***	14.753	***
Diff-in-Diff		9.809	***	-1.268	***	-0.208		38.130	***
R-square		0.055		0.014		0.002		0.008	

***, **, * => Significance at 1%, 5%, 10% level

T - treatment group, C - control group

I conduct a sensitivity analysis to check if the result of the PSM+DID analysis is robust against the "hidden bias", which means biases that arise from unobserved variables that simultaneously affect the treatment assignment (i.e., being regular Greek buyers) and the nutrient consumption outcome variables (Rosenbaum 2002a, 2002b; DiPrete and Gangl 2004). Follow DiPrete and Gangl (2004), I calculate the Rosenbaum bounds (the upper and lower bound estimates of significance level if there is a given level of hidden bias, which is set to be 0.95 in my analysis, Rosenbaum 2002a, 2002b) for average treatment effects in the presence of hidden bias between the matched treatment and control cases.

The sensitivity analysis test the null hyporthesis that no treatement effect exist with different levels of sensitivity parameter (Γ). The sensitivity parameter Gamma (Γ) is a hypothetical odds ratio that one buyer, in a matched pair, being Γ times more likely to be assinged to the treatment group than another due to the unobserved bias, and therefore it measures the degree of the insensitivity when hidden bias is present. For example, for a sensitivity paramter that is greater than 1 ($\Gamma \geq 1$), if the estimated Rosenaum bounds p-values are above the 0.05 level, which rejects the null hypothesis that there is no treatment effect, it means that the result become sensitive due to the hidden bias. However, the sensitivity analysis result does not suggest that the hidden bias exists and there is no treatmet effect, it only suggests that the confidence interval for the treatment effect would include zero if the potential hidden bias caused the odds ratio of the differential assignment between the two groups to increase by Γ (Becker and Caliendo 2007). My sensitivity analysis shows that the result is not sensitive to hidden bias before

Γ reaches the value of 1.5, which means that the results of DID+PSM anslysis are not affected by potential hidden bias before the hidden bias is powerful enough to cause one subject in the matched pair to be 1.5 times as likely as another to become a regular Greek yogurt buyger.

In summary, the introduction of Greek yogurt is associated with changes in nutrient consumption by yogurt consumers. Protein and total calorie intake were higher for Greek yogurt consumers, while the consumption of fat and carbohydrates were lower, relative to non-regular Greek yogurt consumers. Clearly, the introduction of Greek yogurt appears to have changed the nutrient profile of yogurt purchases more generally. However, this summary analysis considers only the introduction, but not the strategic responses of other yogurt sellers, or the subsequent reactions by consumers. That is, changes in nutrient consumption within each household after the introduction of Greek yogurt may have been driven as much by changes in price and marketing activity as it was driven by the mere introduction of Greek yogurt. I examine this question in the next section.

Table 3.9. Sensitivity Analysis Results.

Γ	sig+	sig-
1	0.0000	0.0000
1.05	0.0000	0.0000
1.1	0.0000	0.0000
1.15	0.0000	0.0000
1.2	0.0000	0.0000
1.25	0.0000	0.0000
1.3	0.0000	0.0000
1.35	0.0000	0.0000
1.4	0.0000	0.0005
1.45	0.0000	0.0176
1.5	0.0000	0.1678
1.55	0.0000	0.5571
1.6	0.0000	0.8878

Gamma Γ - log odds of differential assignment due to unobserved factors
sig+ - upper bound significance level
sig- - lower bound significance level

Empirical Model of Intra-Category Substitution

The model-free analysis above provides indirect evidence on the effect of introducing Greek yogurt on consumers' nutrient intake patterns. However, the descriptive statistics comparing marketing-mix values before and after the introduction of Greek yogurt also shows that the introduction of Greek yogurt was accompanied by sharp changes in marketing strategy by the other firms. In this section, I examine the potentially-moderating effect of changes in marketing strategy by yogurt manufacturers.

I use a structural econometric model for this purpose. An econometric model is necessary to estimate how the marginal value of each nutrient is affected by marketing activities, and how these interactions affect the tendencies of consumers to substitute among yogurt product lines. I assume that the utility obtained from consuming yogurt from each product line is dependent upon both the embodied nutritional attributes and marketing-mix elements, including prices. Further, the interaction between nutrient preferences and marketing responsiveness is likely to produce a pattern of correlation in demand across yogurt product lines.

Within the class of demand models that are able to capture this interaction, a discrete-choice model of differentiated-product demand, with preference-heterogeneity over nutrient attributes, is the most suitable for my objectives. That is, I use an attribute-based model of demand because the intrinsic utility of a product is a function of underlying attributes (Berry 1994; Nevo 2000; Hansen, and Gupta 2005), and of marketing activities that may differentially-affect items of different nutrient composition. In other words, consumers purchase products only as a means of obtaining the underlying attributes (Lancaster 1966), so marketing tactics are likely to work differently across products with different attributes. My model allows for a deeper parameterization that permits the marginal values of the attributes themselves to be functions of marketing-mix elements. Namely, I used a mixed-logit model with a flexible specification for unobserved heterogeneity in nutrient preference.

A simple logit model is not appropriate because it assumes a very strict substitution pattern and is subject to the Independence of Irrelevant Alternatives property (IIA). The IIA property implies that the relative preference between two alternatives remain constant, and do not depend on the utility obtained from other alternatives. The primary implication of the IIA property is that it implies that changes in marketing-mix elements for one yogurt will not affect the rate of substitution between two other, related products. Clearly, this is inconsistent with my objective of estimating the impacts of marketing-mix values, and changes in nutritional attributes.

A mixed logit model is preferred because it relaxes the IIA property by allowing for heterogeneity in utility beyond the preference heterogeneity captured by the logit error terms. Within the general class of discrete choice models, I follow Train (1998), Brownstone and Train (1999), Petrin and Train (2010), and Richards (2017) and use a random-parameter logit (mixed logit) model to estimate the demand for yogurt product lines. Most importantly, by assuming that the distribution of unobserved heterogeneity for each household's attribute preference is correlated with other households' preferences, I derive substitution patterns that reflect preferences for nutrients, and allow these preferences to be shaped by marketing strategies. Specifically, I estimate the price, promotion and feature elasticities among subcategories to examine the sensitivity of the competitive landscape among yogurt subcategories to changes in the marketing environment. Because the introduction of Greek yogurt represents the addition of another, completely new subcategory, it provides clean and exogenous variation to identify the parameters.

More formally, the utility obtained by household i from consuming subcategory j depends on sub-category preference α_{ij}, price and non-price marketing-mix elements x_j (i.e., price, promotion, display, and feature), and nutritional attributes z_{kj} where k represents the nutritional attributes (i.e., fat, protein, and carbohydrates), and an i.i.d. error term ε_{ij} that captures the unobservable household heterogeneity in preferences for the product line. The utility for household i from product line j is given by:

$$U_{ij} = \mu_{ij} + \alpha_{ij} + \sum_k \eta_{kj} x_j + \sum_m \gamma_{mj} z_{mj} + \varepsilon_{ij}, \qquad (3)$$

where the marketing-mix elements matrix x_j includes price and non-price marketing-mix variables, and the nutritional attributes matrix z_{mj} contains the attributes of calorie, fat, protein, carbohydrate of alternative j.

I include binary indicators to account for fixed subcategory effects. The subcategories in my model are Light, Regular, Rich, and Greek yogurt. In addition, I included brand indicators (i.e., Yoplait, Dannon, and other brands) to capture brand-specific preferences. These brand intercepts (μ_{ij}) and subcategories intercepts (α_{ij}) are allowed to vary over households, consequently, they capture unobserved preferences for subcategories and brands. Dummies for each product line are omitted from the model because nutritional attributes reflect the unique information for each product line, so are perfectly correlated. The error ε_{ij} in (2) is assumed to be extreme-value distributed and consumers choose the subcategory that provides the maximum utility.

The subcategory-preference intercept (α_{ij}), non-price marketing-mix variables (promotion, display, and feature) response parameters (η_{kj}), and nutritional-attribute (protein, fat, and carbohydrate) preferences (γ_{mj}) are assumed to be random to account for unobserved heterogeneity in consumers' category and nutritional attribute preferences and marketing-mix sensitivities.

In order to test how preferences for nutritional attributes interact with elements of the marketing-mix in influencing product-line demand, I allow for correlation among nutrient and marketing-mix parameters. I use a correlated random parameter approach similar to Train (1998), Singh, Hansen, and Gupta (2005)[10] and Richards (2017). In the analysis of fishing site choices, Train (1998) specified the coefficients of the values that anglers place on factors regarding the site, such as the fish stock, aesthetic, and trip cost to be correlated, and found positive correlation among them. These positive correlations suggest that these attributes tend to be valued as a group relative to other attributes (Train 1998). Richards (2017) uses a similar approach to study the potential umbrella effects associated with private-label strategies, and finds that consumers' preferences for private label brands are correlated with their price sensitivities across private label categories. Hess and Train (2017) explain that the correlation among utility coefficients reflect the insight that consumers' preference for one attribute is correlated with their preference for

[10] Singh, Hansen and Gupta (2005) use a different statistical approach, but their insight is similar to the other two examples.

another attribute, and these correlations can occur for many reasons. While these studies are conceptually similar, neither addresses the specific issue at hand here, namely the correlation among other marketing-mix elements and nutritional attributes. I follow these studies, and examine the correlation among different marketing-mix elements and nutritional attributes in order to understand the deeper question of how marketing strategies can alter consumers' nutrient-consumption profiles. In this context, introducing a new product provides the sharp changes in nutrient consumption necessary to identify any changes in nutrient consumption that may result. Therefore, by examining the correlations among marketing-mix elements and nutritional attributes, I am able to to identify how changes in marketing-mix elements induce substitutions between the new product and other existing alternatives. These substitutions between the new product and other products allows for variations in nutrients required to identify changes in consumption, which implies how marketing-mix elements affect nutirent consumption.

I allow the random parts of the subcategory-preference intercepts, marketing-mix, and nutrient attribute parameters to be correlated. These correlations represent the interaction effects of marketing sensitivity and attribute preference. For example, if I find that the sensitivity to price promotion and preference for fat are positively correlated, then this suggests that price-promotion is an effective means of increasing the demand for relatively fat-dense products.

More formally, allowing for correlation among model parameters yields a covariance matrix with off-diagonal estimates that identify patterns of inter-dependence among attributes (Hensher and Greene 2003). Follow Train (1998), the coefficient vectors

α_{ij}, η_{kj} and γ_{mj} are modeled as: $\alpha_{ij} = \alpha_{ij} + L_{\alpha}\nu_{ij}^{1}$, $\gamma_{mj} = \gamma_m + L_{\gamma}\nu_{mj}^{2}$, $\eta_{kj} = \eta_k + L_{\eta}\nu_{kj}^{3}$, where γ_m and η_k are the means of the coefficients, ν_{ij}^{1} , ν_{mj}^{2}, $and\ \nu_{kj}^{3}$ are the deviations from the mean, and L is a lower-triangular Choleski factor of the covariance matrix of the coefficients Ω, therefore $\Omega = LL'$. ν_{ij}^{1} , ν_{mj}^{2}, $and\ \nu_{kj}^{3}$ are distributed joint normal such that (ν_{ij}^{1} , ν_{mj}^{2}, ν_{kj}^{3}) ~ MVN (0, Ω). The correlated random-parameters approach enables me to test the underlying hypotheses about how marketing strategies are likely to affect nutrient preferences and, ultimately, the demand for each type of nutrient.

Evidence provided in the data section showed that price is indeed endogenous, therefore, I need to address price endogeneity to avoid biased estimates. I explain my identification strategy in the following subsection.

Identification Strategy

There are (at least) two approaches commonly used to address the problem of price endogeneity: a simulated generalized method of moments (SGMM) approach (Berry, Levinsohn, and Pakes 1995) or a control function approach (Park and Gupta 2009; Petrin and Train 2010; Richards and Hamilton 2015). The SGMM approach is very sensitive to sampling errors and therefore more suitable for samples with multiple markets and multiple stores (Berry, Linton, and Pakes 2004). Therefore, I employ the control function approach in the estimation process.

The control function approach consists of two steps. First, I regressed prices on a set of instrumental variables, which include input prices such as milk price, sugar price, HFCS price, wages, utility, fuel oil, electricity, as well as a set of store- and product-line-specific intercepts. In the second step, I include the residuals obtained from the first stage in the demand model as an explanatory variable, denoted by CF (π_j), where pi are the residuals from the first-stage regression. These residuals account for the unobserved factors that may be correlated with the error term in the demand equation, and therefore control for potential bias that may result (Petrin and Train 2010; Park and Gupta 2009). With the control function term CF (π_j) added, I re-write (3) as:

$$U_{ij} = \alpha_{ij} + \sum_k \eta_{kj} x_j + + \sum_m \gamma_{mj} z_{mj} + \mathrm{CF}\ (\pi_j) + \varepsilon_{ij}. \qquad (4)$$

According to Nevo (2000), the mean utility from the outside option is not identified without making additional assumptions, thus the standard practice is to set η_{kj}, γ_{kj}, and CF (π_j) in (4) to zero for the outside option. The intercept α_{ij} will eventually vanish because it is common to all products lines (Nevo 2000) and it is equivalent to normalizing the utility from the outside product lines to zero. Therefore, the utility for outside option is then given by

$$U_{i0} = \alpha_{ij} + \sum_k \eta_{k0} x_0 + \sum_k \gamma_{k0} z_0 + \mathrm{CF}\ (\pi_0) + \varepsilon_{i0.} \qquad (5)$$

With these assumptions, the probability of choosing subcategory j is the integral of equation (4) over all possible values of parameters α_{ij}, η_{kj} and γ_{mj} weighted by the density of these paramters. That is, the probability of choosing product-line j is given by,

$$\mathrm{P}_j = \iiint \frac{exp(\alpha_{ij}+\sum_k \eta_{kj} x_j+\sum_m \gamma_{mj} z_{mj}+\mathrm{CF}\ (\pi_j))}{(\sum_{l\epsilon J} exp(\alpha_{ij}+\sum_k \eta_{kj} x_j+\sum_m \gamma_{mj} z_{mj}+\mathrm{CF}\ (\pi_j)))}\, f(v_{ij}^1) g(v_{mj}^2) h(v_{kj}^3) dv_{ij}^1 dv_{mj}^2 dv_{kj}^3. \quad (6)$$

where $f(\cdot), g(\cdot), and\ h(\cdot)$ are standard normal density functions. I solve this equation using simulated maximum likelihood (SML, Train 2003, Train, 2009; Petrin and Train, 2010; Park and Gupta, 2009). SML yields a faster and more efficient estimation by using random draws from the consumer heterogeneity distribution. I use 50 Halton draws because the simulation variance in the estimation of mixed logit parameters is lower with 50 draws than 100 or 500 random draws, and to improve the efficiency of the estimation routine (Train 1999; Bhat 2003).

I also estimate two versions of the model on different sub-samples: one with the sample before the introduction of Greek yogurt and one with the sample after introduction. I then compare the estimates from the two models, and examine if marketing-mix sensitivities and nutrient valuations change due to the introduction of Greek yogurt.

Intra-Category Substitutions

After estimating the structural model of yogurt demand, I demonstrate how variation in marketing strategy affects product line demand, and nutrient profiles at the aggregate level using elasticitiy matrices.

I calculate the own-and-cross elasticities of each product line with respect to changes in each marketing-mix element in order to show how marketing strategies affect the own demand for each product line, and intra-category substitution patterns. The probability-of-choice expression in equation (6) suggests that the elasticities depend on variables that affect the demand for all product lines, which is the essence of how mixed logit models are able to capture substitution patterns in a very flexible way (Train 2009). Using the estimates form the structural model, I calculate elasticity matrices by computing the incremental change in the predicted probability household purchase a subcategory from 1 percentage change in marketing-mix element of own or other subcategory. With these matrices, I reveal how the pattern of substitution varies among yogurt alternatives with respect to each marketing-mix element.

Structural Model Results and Discussion

In this section, I present and interpret the results obtained from estimating the structural empirical model. Before presenting the results from the preferred specification, I first compare the fit obtained from the preferred model to other, more parsimonious specifications. Then, I discuss and interpret the results of the structural estimates, correlations among the parameters, and the own- and cross elasticities with respect to each marketing element. Last, I report the result of the counterfactual simulations.

I first examine whether the most comprehensive expression for utility in (4) represents the best fit to the data. To do so, I begin with the simplest, most parsimonious specification for the problem, and then move to more complete descriptions of the model. Because the simpler expressions are nested within the maintained model in (4), I use likelihood ratio (LR) tests to compare the goodness-of-fit between specifications. For this purpose, the simpler version of the maintained model allows for no correlation among the model parameters, but still retains the underlying mixed-logit structure.

Table 3.10 shows the estimates from three mixed logit models with subcategory preference parameters, nutritient-attribute preferences, and marketing-mix variable parameters allowed to vary randomly. Model 1 is the simplest specification without the control function; Model 2 includes control function; and Model 3 is the maintained model that includes both the control function and allows the subcategory preference parameters, nutritional attributes preferences, and marketing-mix variable parameters to be correlated.

LR tests show that Model 3 is the preferred model among the three alternatives. The Chi-square statistic value between Model 1 and Model 2 is 4027.746, which is greater than the critical value of 3.841 (at the 5% level of significance is with 11 degrees of freedom). Therefore, I can conclude that Model 2 fits better than Model 1. However, Model 2 does not allow correlations among the parameters. Therefore, I compare the fit of Model 2 with a more complete version that allows for correlated random parameters, and controls for price-endogeneity. The Chi-square test statistic value between Model 2 and Model 3 is 2670.696, which is also greater than the critical Chi-square value 19.675 (at the 5% level of significance is with 11 degrees of freedom). In sum, these results clearly suggest that Model 3 fits better than Model 2.

Comparing model 2 with model 3 in terms of individual parameter estimates, however, suggests that the differences are very small. The marginal effect of price does not differ much among the models. The only dramatic difference is the marginal value of carbohydrates between the two models. Namely, the magnitude of the marginal value of carbohydrates is about 3 times as large in Model 3, and it becomes closer in magnitude to the magnitude of the marginal value of other nutrients. This difference suggests that there is still a small amount of bias involved when the less-comprehensive version of model does not allow for correlations among the parameters.

I also estimate Model 4 with the sample before the introduction of Greek yogurt and Model 5 with the sample after introduction (See Table 3.11). Comparing estimates from the two models reveals how marketing-mix sensitivities and nutrient valuations change due to the introduction of Greek yogurt. The estimates in this table show that the parameters are remarkably stable before and after introduction. Most significantly, the only real change is that the marginal value of protein is nearly 4 times as large in Model 4. This finding suggests that the introduction of Greek yogurt increased the marginal value of protein. Given the relative protein-density of Greek yogurt, this finding suggests that the introduction of a new product, one that highlights protein as an important nutrient, has increased consumers' attention to protein as a nutritional attribute.

Table 3.10 Model Estimates (Model 1-3)

	Model 1 Mixed Logit without Control Function and Correlations		Model 2 Mixed Logit without Correlations		Model 3 Mixed Logit with Correlations	
Variables	Estimate	Z	Estimate	Z	Estimate	Z
Light yogurt	-3.6426***	-43.6700	-4.0433***	-43.4100	-4.5715***	-40.0000
Regular yogurt	-3.0229***	-60.6700	-3.2473***	-50.4000	-3.2002***	-49.0800
Rich yogurt	-4.0553***	-56.3600	-4.2012***	-47.0000	-4.4782***	-38.7700
Greek yogurt	-5.3920***	-15.3900	-7.6654***	-17.7200	-10.3125***	-20.0400
Yoplait	1.0108***	36.0100	1.3070***	40.9400	1.6671***	48.4700
Dannon	0.5434***	18.4000	0.7277***	21.6900	0.8843***	24.4700
Price	-1.1720***	-40.5700	-1.2009***	-20.1000	-1.0482***	-17.5200
Display	1.1290***	28.7700	1.0989***	20.6800	1.0100***	16.3700
Promotion	0.2920***	6.5000	0.2643***	6.0900	0.2901***	4.9000
Feature	0.2480***	4.7800	0.2025***	3.9900	0.1808***	2.9200
Fat	-0.5400***	-20.9900	-0.4133***	-13.2000	-0.3009***	-9.6500
Protein	0.2790***	10.4500	0.3074***	17.9500	0.5479***	27.9800
Carbs	-0.1130***	-21.6000	-0.0768***	-16.5400	-0.2355***	-41.0100
CF			-0.1130**	0.0280	-0.1484***	-2.8200
Std. dev. of random parameters						
Light yogurt	1.1957***	30.5700	-2.5558***	-42.6600	4.7291***	38.5400
Regular yogurt	1.5332***	40.3600	1.6433***	42.8600	2.4720***	45.4800
Rich yogurt	1.4023***	24.9800	1.6613***	31.9000	1.9955***	23.7700
Greek yogurt	0.4660	1.2800	1.7467***	3.7900	5.6261***	11.2700
Price	0.4384***	22.2400	0.7662***	26.6000	1.1368***	33.0700
Display	0.0129	0.2100	0.6888***	11.8500	0.7585***	12.2500
Promotion	0.2109***	6.6100	-0.1260***	-3.5300	0.4717***	8.8000
Feature	0.2809***	8.2500	0.4638***	11.5300	0.5037***	9.9800
Fat	0.9434***	44.8300	0.9299***	38.9800	1.3178***	48.8700
Protein	0.3355***	26.5700	0.6114***	28.5900	0.7711***	46.2300
Carbs	0.1096***	39.3300	0.1489***	49.7100	0.2195***	53.6800
LLF	-31140.954		-29127.081		-27791.733	
Chi-Square	13206.34		17227.15		19897.85	

Note: ***, **, * => Significance at 1%, 5%, 10% level

Table 3.11 Model Estimates (Model 4-5)

	Model 4 Before Greek Introduction			Model 5 After Greek Introduction		
Variables	Estimate		Z	Estimate		Z
Light yogurt	-4.2436	***	-42.6300	-4.5715	***	-40.0000
Regular yogurt	-3.2253	***	-55.7900	-3.2002	***	-49.0800
Rich yogurt	-3.8361	***	-53.2700	-4.4782	***	-38.7700
Greek yogurt				-10.3125	***	-20.0400
Yoplait	1.3223	***	40.5100	1.6671	***	48.4700
Dannon	0.7087	***	20.5100	0.8843	***	24.4700
Price	-0.9681	***	-18.0700	-1.0482	***	-17.5200
Display	1.2543	***	25.6900	1.0100	***	16.3700
Promotion	0.3439	***	6.7100	0.2901	**	4.9000
Feature	0.2015	***	3.7600	0.1808	***	2.9200
Fat	-0.4889	***	-18.2300	-0.3009	***	-9.6500
Protein	0.1508	***	8.9700	0.5479	***	27.9800
Carbs	-0.0853	***	-18.4200	-0.2355	***	-41.0100
CF	-0.1267	**	-2.5700	-0.1484	**	-2.8200
Std. dev. of random parameters						
Light yogurt	3.5192	***	36.3500	4.7291	***	38.5400
Regular yogurt	2.3492	***	44.7900	2.4720	***	45.4800
Rich yogurt	1.2118	***	20.0700	1.9955	***	23.7700
Greek yogurt				5.6261	***	11.2700
Price	0.8581	***	31.3000	1.1368	***	33.0700
Display	0.4594	***	8.4600	0.7585	***	12.2500
Promotion	0.3520	***	5.7600	0.4717	***	8.8000
Feature	0.3177	***	4.7600	0.5037	***	9.9800
Fat	0.9705	***	51.4800	1.3178	***	48.8700
Protein	0.7789	***	48.3800	0.7711	***	46.2300
Carbs	0.2199	***	56.6300	0.2195	***	53.6800
LLF	-27651.163			-29452.545		
Chi-Square	15389.10			16564.05		

Note: ***, **, * => Significance at 1%, 5%, 10% level

Table 3.12 Attributes and Marketing Mix Preference Correlations

	Light	Regular	Rich	Greek	Price	Promo	Display	Feature	Fat	Protein	Carbs
Light	1.0000										
Regular	0.3220	1.0000									
Rich	0.1403	0.6128	1.0000								
Greek	0.0441	0.1276	0.3193	1.0000							
Price	0.0899	0.3772	0.2691	0.0542	1.0000						
Promotion	0.0332	0.0462	0.0101	-0.0302	0.0653	1.0000					
Display	0.0135	0.0573	0.0412	-0.0340	0.0523	-0.0674	1.0000				
Feature	0.0155	0.0634	0.0238	0.0632	0.0519	-0.0358	-0.7996	1.0000			
Fat	0.3030	0.7082	0.1650	-0.1787	0.1701	0.0615	0.0549	0.0146	1.0000		
Protein	-0.3217	-0.4403	0.0530	-0.1252	-0.0548	-0.0257	-0.0421	0.0207	-0.5244	1.0000	
Carbs	0.2882	0.7279	0.3261	0.1374	0.3428	0.0390	0.0678	0.0410	0.4088	-0.5939	1.0000

Structural Estimates

In all models, the marginal values for all three nutritional attributes are statistically significant, as expected. Fat and carbohydrates have negative marginal valuations, whereas protein has a positive marginal value. While both of these macro-nutrients may have favorable qualities in yogurt, smoothness and energy, respectively, these estimates suggest that consumers would prefer to have lower values of each. In other words, the signs of the three nutritional attributes suggest that low-fat, low-sugar, and high-protein are the preferred characteristic for yogurt products.

The estimates of the nutritional attributes also imply that consumers are more sensitive to changes in protein content than to changes in fat and carbohydrate content. That is, comparing the magnitude of the nutrient-preference parameters, the estimates suggest that items with higher protein content are likely to imply greater utility levels relative to yogurts with lower fat or carbohydrate content. This finding indicates that consumers place a higher marginal value on protein and are willing to pay more for another gram of protein than they are another gram less of fat or carbohydrates.

The parameters of the marketing-mix variables are all statistically significant and have expected signs – price has a negative marginal effect and the other three marketing-mix elements each have positive marginal effects on demand.

Among the fixed-subcategory effects, consumers appear to prefer Greek yogurt the most, which means that the willingness to pay is highest for Greek yogurt. This finding is consistent with previous studies that show consumers have hiher willingness to pay for products with a functional attribute (West et al. 2002; Markosyan, McCluskey, and Wahl 2009)

These structural estimates provide insights into consumers' preferences and their responsiveness to each marketing-mix element, but I am more interested in their interactions. That is, how does marketing strategy influence preferences for different nutrients? I interpret the correlation estimates between nutrient-preferences and marketing-mix elements in the next sub-section.

Correlations among Parameters

The parameter correlations derived from the preferred mixed logit specification (Model 3) are shown in Table 3.12. The matrix includes correlations between parameters of the subcategory dummies, nutritional attributes, and marketing-mix variables. Because estimating correlation patterns in models like this leads to a proliferation of results, I will interpret only the most salient among them. I use these correlations[11] to test the hypotheses regarding the relationships between marketing-mix elements and nutrient content developed above.

[11] It is important to note that the correlation parameters refer to relationships among the estimated coefficients, not the variables, so must be interpreted in terms of the sign of each estimated parameter. When both parameters are of the same sign, therefore, the interpretation is relatively straightforward. However, when the parameters differ in sign, the interpretation becomes considerably more complicated. A positive correlation between a positive and a negative parameter means that the two parameters may shift in the same direction, and negative correlation means that the parameters move in opposing directions, but the signs of the parameters may not change. For example, the parameter for price is negative and the parameter for display is positive, but the positive correlation between price and display does not change the sign of the price parameter. If consumers are more sensitive to display, for example, they still prefer a lower price. The positive correlation in this case simply means that a higher display sensitivity is associated with lower price sensitivity, and vice versa. Both parameters become more positive, which is consistent with lower price sensitivity. I interpret each of the other relationships in an analogous way.

I begin by focusing on the relationships among the nutrient-preference parameters, and then among the marketing-mix elements before considering the interactions among the two groups. The correlation estimates in table 3.12 show that preferences for fat and carbohydrates are positively correlated with each other, but they are both negatively correlated with protein. In other words, consumers who prefer high-protein yogurt also prefer low-fat and low-sugar yogurt. This is intuitive as the structural estimates suggest that consumers who prefer more indulgent yogurts, or those higher in fat and carbohydrates, are less likely to prefer high-protein yogurts, and *vice versa*.

Among the marketing-mix sensitivities, the estimates in table 3.12 provide some critical insights into the relative effectiveness of each in shaping market demand. Most importantly, I find an inverse relationship among each of the non-price marketing tools and price-response. Positive correlations, as discussed above, suggest that if one is more sensitive to promotion, display, or feature, he or she is less sensitive to price changes. This is an important finding as it suggests that non-price marketing tools, regardless of the form, will decrease price sensitivity, and raise markups. While this finding is well understood in empirical marketing research (Shankar and Krishnamurthi 1996; Erdem, Keane, and Sun 2008), my estimates provide confirmation in a deeply parameterized model that includes many different types of marketing-mix elements, and controls for variation in product attributes.

The relationships between each of the nutrient values and price-sensitivity support my hypothesis regarding how price affects the preference for nutritional quality. Recall that my overall hypothesis is that the preferences for "unhealthy" nutrients such as fat and carbohydrates have stronger correlation with sensitivity to price, promotion, and display than "healthy" nutrient such as protein (H1, H2), whereas consumers who prefer "healthy" nutrient such as protein are more sensitive to featuring (H3). Among the correlations between price and the nutrient parameters, the strongest correlation is between carbohydrates and price (0.3428), followed by the correlation between fat and price (0.1701), and the smallest is between protein and price (-0.0548). These results support H1 that price has a positive correlation with "unhealthy" nutrients, while having a negative correlation with protein. A negative correlation between the preference for protein and price sensitivity implies that if a consumer prefers higher protein content, he or she may be more price-sensitive. But, the magnitude of the correlation is much smaller than the correlation between price and carbohydrates, and between price and fat. Namely, consumers who prefer higher protein content are comparably less price-elastic than consumers who prefer lower fat or lower carbohydrate content.

Consumers who are more responsive to promotion and display are also more likely to have higher preference for fat and carbohydrates than protein, which again supports H1 and H2. A positive correlation between preferences for fat and carbohydrates and to display and promotion imply that consumers who have stronger preferences for low-fat or low-carb characteristics (i.e., the absolute value of the negative fat and carbohydrates parameters become larger), are less sensitive to display and promotion (parameters of these marketing-mix elements become smaller). On the other hand, the negative correlations between protein and display and promotion suggest that households that have strong preferences for high-protein content are likely to be less sensitive to display and promotion. However, the correlation between the preference for protein and the non-price marketing-mix elements are weaker than the correlations between the preferences for other nutrients and these marketing-mix elements. These results again support my hypothesis that marketing tools such as display and promotion are more closely related to the preferences for the “unhealthy” nutrients such as fat and carbohydrates than to “healthy” nutrients.

Featuring, however, is positively correlated with the preference for protein, which supports H3, and this correlation is stronger than that between feature and fat. In fact, the preference for carbohydrates is even more strongly correlated with featuring. However, as discussed above, because carbohydrates have a negative marginal effect on demand, the positive correlation between featuring and carbohydrate-preference implies that consumers are less sensitive to featuring when they have a stronger preference for lower-carbohydrates. Comparing all the correlations between the non-price marketing-mix elements and the preference for protein, I again find feature to be most effective in changing demand. As discussed in the background section, the benefits of protein are less likely to be expressed through display activity, using product-displays is not very effective in increasing the market share for yogurts that are high in protein. Therefore, these results support H3 in that featuring is more effective than other non-price marketing-mix in promoting yogurts with high protein content. Taken together, these correlation patterns suggest that featuring is positively and closely correlated with the preference for protein content, rather than the preferences for fat or carbohydrates. This finding suggests that marketers may want to consider allocating more marketing expenditures on featuring products that are high in protein content.

Overall, these results support my hypotheses that featuring products with healthy product attributes is more effective in increasing demand, whereas promotion and display are more likely to increase the consumption of fat and carbohydrates, which are more unhealthy. Correlation patterns, however, are directional only and do not provide quantitative information on exactly how sensitive product-demand is to each marketing tool.

Elasticities

Ultimately, the effectiveness of marketing strategies in selling yogurts that vary in their nutritional composition is reflected in the own-and-cross elasticities with respect to each marketing tool. Table 3.13 shows the own-and-cross elasticities matrices for each marketing-mix element.

The own-price elasticities are all elastic while the own- elasticities for other marketing-mix are inelastic. The own-price elasticities range between -3.45 to -6.00, which are similar to ranges of own-price elasticities estimated by other yogurt studies. For example, Bonanno (2013)'s yogurt elasticities varies from -1.22 to -6.86, while Draganska and Jain (2006) estimate a range between -2.45 and -6.25, and Richards, Allender, and Hamilton (2013) present the own-price elasticities in a range between -1.26 and -4.73.

Among all the subcategories, Rich yogurts are most price-elastic. This finding is consistent with H1 that preference for “unhealthy” products is highly correlated with price sensitivity.

The off-diagonal elements in this matrix provide some insight into the competitive landscape of the yogurt market, with higher cross-price elasticities suggesting products that are closer substitutes for each other, and lower elasticities suggesting that products are less substitutable, or more effectively differentiated. For example, comparing cross-price elasticities, I find that the cross-price elasticity between Light and Greek yogurt (0.58) is much higher than other cross-price elasticities, suggesting that Light yogurt seems to be a strong competitor for Greek yogurts. This finding is intuitive given that Greek yogurt and Light yogurt are both positioned as having more healthy nutritional attributes than other yogurts, even though they differ from one another largely on protein and calorie content. However, from the perspective of Light yogurt, Greek yogurt is not its strongest competitor. The same pattern also applies to elasticities in the panels of promotion, display, and feature in Table 3.13.

Table 3.13 Yogurt Subcategories Own- and Cross- Marketing-mix Elasticities

	Price					Promotion			
	Light	Regular	Rich	Greek		Light	Regular	Rich	Greek
Light	-3.45442	0.14445	0.06261	0.00267	Light	0.39545	-0.01602	-0.00246	-0.01608
	(-114.5072)	(141.6212)	(78.1573)	(13.7353)		(34.3672)	(-76.7279)	(-40.9837)	(-7.2471)
Regular	0.16701	-4.34612	0.10400	0.00073	Regular	-0.02244	0.47322	-0.00619	-0.00047
	(-102.5959)	(-64.2201)	(81.1573)	(6.5767)		(-67.2214)	(23.5492)	(-42.8855)	(-4.1998)
Rich	0.19347	0.36013	-6.00317	0.00131	Rich	-0.01208	-0.02894	0.41192	-0.00066
	(62.4936)	(69.4860)	(-58.8103)	(2.1545)		(-21.9709)	(-24.8053)	(15.6344)	(-1.6223)
Greek	0.57774	0.03197	0.04354	-4.33999	Greek	-0.00907	-0.00221	-0.00269	0.27663
	(7.6097)	(1.8189)	(1.8689)	(-5.2491)		(-3.0381)	(-1.9792)	(-1.7468)	(2.3636)

	Display					Feature			
	Light	Regular	Rich	Greek		Light	Regular	Rich	Greek
Light	0.48612	-0.02041	-0.00188	-0.00507	Light	0.28638	-0.06578	-0.00195	-0.00899
	(16.7455)	(-38.4723)	(-18.5552)	(-7.7837)		(23.6365)	(-51.9645)	(-38.7127)	(-4.7910)
Regular	-0.01979	0.52090	-0.00279	-0.00424	Regular	-0.00727	0.19738	-0.00299	-0.00514
	(-29.1112)	(15.7218)	(-15.7380)	(-8.5494)		(-35.1764)	(26.5351)	(-31.9812)	(-3.9672)
Rich	-0.01456	-0.02210	0.19527	-0.00405	Rich	-0.01985	-0.02559	0.45169	-0.01194
	(-12.9325)	(-13.2987)	(6.7011)	(-2.6593)		(-25.0734)	(-22.6426)	(12.5522)	(1.9787)
Greek	-0.00443	-0.00252	-0.00012	0.14132	Greek	-0.01504	-0.00268	-0.00176	0.19033
	(-1.6906)	(-1.2499)	(-4.0556)	(3.6052)		(-0.5015)	(-1.1613)	(-0.6101)	(2.7131)

Conclusion and Future Research

In this study, I investigate consumers' purchase of products within the same category but with different nutritional profiles. I examine the effect of nutrient preferences and marketing actions on consumers' demands for various alternatives in the category using IRI household purchase data. If firms are interested in helping consumers make more healthful choices, then they should understand how their own marketing decisions are likely to change the mix of products purchased by consumers and, thereby, the nutrients they consume.

My findings suggest that after the introduction of Greek yogurt, consumers who regularly bought Greek yogurt had a higher intake of protein and calories, and a lower intake of fat and carbohydrate than those who did not buy Greek yogurt. My findings also support my hypothesis that feature is more effective for "healthy" products such as Greek yogurt or Light yogurt that either contains high-protein and low levels of "unhealthy" nutrient.

On the other hand, promotion and display are more effective in promoting products that provide more hedonic taste values by containing higher sugar or fat content. In particular, consumers who prefer a product that contains high levels of carbohydrates are more sensitive to displaying, whereas consumers who prefer a product that contains high levels of fat are more sensitive to promotion. The preferences for yogurt that are both high in sugar and fat, the rich yogurt subcategory, have a strongest positive correlation with the sensitivity to display-frequency than with other non-price marketing mix elements. In general, featuring is most effective in increasing the demand for products that contain nutrition attributes that provide more health benefits, whereas promotion and display are more effective in promoting products that are less healthy and provide more taste benefits.

I find that pricing decisions are still the most important in affecting the demand for all types of yogurt, and especially for yogurts that are high in carbohydrates. Although non-price marketing-mix tools decrease price sensitive, it’s still important to consider the effects of price in making marketing-mix plans.

My findings also have potential implications for food retailers, and manufacturers. Overall, my empirical model results suggest that households with specific nutrient preferences respond differently to different marketing strategies. . From a manufacturer’s perspective, price reductions, promotions, or product displays may be more effective in promoting low-fat or low-carbohydrate products than high-protein products. Food manufacturers may want to focus on incentivizing retailers to feature high-protein yogurts. My findings suggest that manufacturers need to understand how their promotion decisions are likely to interact with product-design decisions if they are truly interested in changing the nutritional outcomes of their buyers..

Future research may examine potential negative spillover effects of some specific nutritional attributes. One of the primary purposes of product line extension is to satisfy the various needs of different consumer segments (Aaker et al., 1994). Consumers’ horizontal needs for choosing among different varieties of the same category has been widely documented, and they may buy multiple alternatives from the same category in a single shopping trip (Bucklin, Gupta, and Siddarth, 1998; Guo, 2010; Harlam and Lodish, 1995; Kim, Allenby, and Rossi, 2002). The primary shopper may need to buy a variety of products for family members in the household to meet their composite needs of differing tastes, textures, or nutritional contents. For a category such as a yogurt that can be purchased and consumed in individual units, it is very likely that a household's shopping list would contain a particular combination of products from different product lines. When the price of a particular product on the list increases, the shopper may be less likely to buy other products in the same category on the list to avoid any conflict among family members. If the primary shopper realizes that she cannot meet everyone's need, she would rather buy nothing. Therefore, a complementary pattern emerges in such situation.

CHAPTER 4

NOT ALL DIETERS ARE THE SAME: DEVELOPMENT OF THE MODERATION TENDENCY SCALE

In recent years, the U.S. government has made several efforts to curb the obesity crisis, such as the USDA's "Choose My Plate" campaign and Michelle Obama's "Let's Move" campaign. Nevertheless, obesity rates have remained steady over the last decade (Ogden et al., 2014), and some experts believe that half of the U.S. population will be obese by 2030 (Wang et al. 2011), in spite of the wide variety of policies examined and implemented (Seiders and Petty 2004). One example of a policy effort that was particularly unsuccessful was the USDA's Food Pyramid. The Food Pyramid was in effect for 19 years, during which time American obesity rates increased by 61% (Carroll, 2002). It is clear that many Americans suffer from self-control lapses. However, it is also likely that a "one size fits all" approach to ending obesity is ineffective due to important individual differences among dieters. In this research, I propose that there are different types of dieters, namely abstainers and moderators, and that different strategies may work best for these different dieters when trying to reach their weight loss goals.

Most government attempts to curb obesity have taken the approach of "everything in moderation," in which no foods are off-limits, and that people who wish to lose weight should simply "eat less and move more." While this approach has strong intuitive appeal, it has clearly failed for many dieters. Recent research suggests that while calorie counting results in short-term weight loss, most dieters eventually regain the weight loss (Benton and Young 2017), and that calorie counting does not account for other factors such as hormone imbalance (Camacho and Ruppel 2017) or psychological reactions to perceived scarcity. In response to these new insights, many Americans have started to shun the word "diet" in favor of terms like "clean eating" or "healthy eating" (Brodesser-Akner, 2017; Guardian 2017). Observers of this trend eschew certain ingredients (such as gluten, sugar, or heavily processed foods), rather than counting calories.

In the current research, I introduce the construct of eating-related moderation tendency, and I demonstrate how it is distinct from other constructs. I base this construct on Rubin (2001), which defined a "moderator" as an individual who is better off avoiding absolute rules and instead moderating consumption of vices and virtues. In contrast, an "abstainer" is an individual who is better off strictly restraining from any indulgent behaviors. The domain of drinking restriction offers similar examples: Alcoholics Anonymous (AA) maintains that alcoholics should never drink (abstaining), whereas Moderation Management (MM) supports alcoholics reducing rather than eliminating alcohol consumption (moderating).

In my first two studies, I develop and validate a scale of eating-related moderation tendency, which identifies moderators and abstainers in the diet domain. Across several studies, I show that people's moderation tendency predicts (1) whether they choose to indulge and (2) how easily they get back on track after an indulgence. In doing so, I add to the body of research on goal pursuit, and particularly the question of why people sometimes engage in balancing behavior (such as compensation, or getting back on the wagon after an indulgence), and why they sometimes engage in reinforcement behavior (such as the what-the-hell effect, or falling off the wagon) (Cochran and Tesser 1996; Huber, Goldsmith and Mogilner 2008).

Identifying these two types of dieters and their different behaviors may have important implications for public policy makers, and may contribute to existing theory on dieting psychology and food well-being. Block et al. (2011) defines food well-being as "a positive psychological, physical, emotional, and social relationship with food at both the individual and societal levels (p.6)," Thus far, the majority of research on dieters has addressed differences in the psychology and behavior of dieters versus non-dieters (e.g., Scott at al. 2008). However, emerging research has just begun to explore the potentially important issue of individual differences among dieters. For example, researchers have identified several differences between successful versus unsuccessful dieters, such as cognitions (Papies, Stroebe, and Aarts 2008) and lay beliefs about whether diet is more effective than exercise (McFerran and Mukhopadhyay 2013). Another stream of research has begun to identify physiological differences among individuals, such as genetics (Dalle Molle et al., 2017), brain activity (Dube 2010), and the gut microbiome (e.g., Alcock, Maley, & Aktipis, 2014) that may determine obesity and weight loss. Yet another stream draws on economic theory to identify the different self-control patterns of time-consistent, naïve, and sophisticated consumers (Mandel et al., 2017). However, to my knowledge, the differences identified by these prior streams did not include moderation versus abstinence tendencies. Establishing this new differentiating factor has the potential to help dieters feel more relaxed and at peace with their food choices, in their ultimate pursuit of food well-being. It may also offer the potential to foster the development of policies to encourage healthy eating for both types of dieters

Theoretical Development

Goal-inconsistent Behavior

According to the theory of goal systems (Kruglanski et al., 2002), many environmental, social, and personal factors can activate goal-inconsistent motivations, leading people to engage in goal-inconsistent behavior, such as eating an indulgent food while on a diet. For example, if people perceive their main course to be healthy, they are more likely to order a drink, a side dish or a dessert (Chandon & Wansink, 2007). Consuming products with low-fat labels eases guilt feelings and thus leads to more snacking (Wansink & Chandon, 2006). Perceived goal progress may directly affect goal-inconsistent behavior: if people perceive their goal progress as too fast (Fishbach & Dhar, 2005) or too slow (Cutright & Samper, 2014), they are more likely to engage in goal-inconsistent behavior. For example, Fishbach, Ratner and Zhang (2011) showed that when consumers perceive increasing progress towards the goal of weight loss, they activate hedonic taste goals and ultimately consume more snacks like chocolate bars. In addition, consumers are prone to impulsive and indulgent choices when they experience depletion after exerting self-regulation (Muraven, Tice, and Baumeister, 1998; Vohs and Faber, 2007).

One way to understand when and why people deviate from their goals is the idea of reinforcement versus balancing (Huber, Goldsmith, and Mogilner 2008). When making progress toward a goal, consumers may develop good habits and gradually build momentum, thus increasing their goal-consistent behavior over time (known as “reinforcement”). Indeed, some research has shown that consumers exhibit certain reinforcement behaviors (Dhar, Huber, and Khan 2007). For example, Wing and Phelam (2005) found that after people have maintained their weight loss for two to five years, the chance of longer-term success was greatly increased. The negative side of reinforcement is the “what-the-hell effect,” in which consumers increase their goal-*inconsistent* behavior over time (Cochran and Tesser, 1996; Soman and Cheema 2004). In other words, a dieter who has already engaged in indulgence may reinforce that behavior by continuing to indulge. For example, a dieter who has already exceeded his calorie quota for the day and then eats some apple pie may subsequently say “what the hell” and thereby go on an eating binge (Cochran and Tesser 1994; Soman and Cheema, 2004).

In contrast, consumers may sometimes engage in balancing behavior, in which they alternate between goal-consistent and goal-inconsistent behaviors (also known as licensing). Khan and Dhar (2006) argue that engaging in virtuous, goal-consistent behavior can boost the self-concept, thereby leading consumers to subsequently engage in vices. For example, people who act ethically on one occasion may later reward themselves by purchasing a luxury product (Khan and Dhar 2006), or by acting less ethically on a second occasion (Merritt, Effron, and Monin 2010). In some of the diet-related examples discussed in the preceding paragraphs, dieters may have believed that they had made sufficient progress toward their dieting goal, thereby rewarding themselves with an indulgence. For example, dieters who chose a “low fat” product may have rewarded themselves by unwittingly overconsuming that product (Wansink and Chandon 2006). The positive side of balancing is compensation, in which people offset an indulgence in one setting with a virtuous behavior in a subsequent setting. For example, some people demonstrate compensation after eating a high calorie snack such as chocolate by lowering their caloric intake at their next meal (e.g., Appleton, McKeown and Woodside, 2015).

In this research, I examine whether and when an indulgence (defined as a goal-inconsistent behavior, such as eating unhealthy food while on a diet) leads to subsequent reinforcement (i.e., the what-the-hell effect) or balancing (i.e., compensation). In other words, if a dieter has already consumed an indulgence, what determines whether he or she gets back on track or falls off the wagon? In their conceptual review, Huber et al. (2008) proposed several factors that may determine reinforcement versus balancing, such as construal level, self-perception, and lifestyle strategies (including religious adherence and choice of diet program). I experimentally investigate their last proposed factor by introducing a new construct, moderation tendency, that offers the potential to explain (1) why some people choose to balance whereas others choose to reinforce; and (2) whether a given indulgence leads to subsequent balancing or reinforcement.

Lay beliefs about abstinence versus moderation

Instead of holding universal theories about the self and others, people hold different implicit theories, and these theories play critical roles in influencing motivation (Dweck, 1999), self-efficacy and task performance (Park and Roedder John, 2014), and self-regulation (Job, Dweck, and Walton, 2010; Molden & Dweck, 2006). For example, entity theorists believe that people's personalities are largely fixed, whereas incremental theorists believe that people's personalities can change and improve (Chiu, Hong and Dweck 1997). As another example, people have lay beliefs about the capacity of self-control, which ultimately affect their behavior (Job et al. 2010). More specifically, if people believe self-control can be depleted, they are more likely to engage in unhealthy eating and procrastination behaviors (Job et al. 2010). Furthermore, people who believe that obesity is due to lack of exercise tend to weigh more than those who believe it is due to poor diet choices (McFerran and Mukhopadhyay 2013). In this research, I extend these previous findings on lay theories by examining a new type of lay theory: dieters' lay theories about whether abstaining or moderating is a superior strategy for achieving one's dieting goals, which I hereby call "moderation tendency."

Based on Rubin (2001), I define moderators as people who believe that it is better to avoid absolute rules and instead find a balance between vices and virtues. In contrast, I define abstainers as people who believe that it is better to strictly restrain from all indulgent behaviors. Moderators and abstainers deal with temptation in different ways. According to Rubin's (2012) blog, moderators usually need an occasional indulgence to satisfy their hedonic needs and strengthen their resolve, and they are afraid of even thinking of the word "never." However, for abstainers, "never" is a simple and efficient strategy because it saves time and energy battling with indulgence, whereas moderating seems to require more self-control. More specifically, abstainers may fear that if they indulge, they will fall victim to the what-the-hell effect and have trouble restoring goal-consistent behavior. In contrast, moderators may believe that occasional indulgence not only leads to compensation, but may help them restore their depleted self-regulatory resources.

To my knowledge, the only scholarly article that has examined the abstainer/moderator distinction was conceptual in nature. More specifically, Huber et al. (2008) propose (but do not test) individual differences in philosophies regarding reinforcement versus balancing. For example, the Calvinist philosophy encourages reinforcement and abstention by leading a consistently virtuous life, whereas the Catholic philosophy encourages moderation and balancing, in which sinners may achieve forgiveness by performing penance (Huber et al., 2008). In observing market offerings in industries such as health, medicine, and weight loss, it seems evident that culture also plays a role in these different approaches. For example, Alcoholics Anonymous (AA) maintains that alcoholics should never drink, and that even one small misstep is the equivalent of 100 binges (Glaser 2015). This approach to alcoholism is deeply ingrained among Americans. In contrast, countries such as Finland encourage a moderation approach, in which doctors prescribe alcoholics with a drug called naltrexone or nalmefene that allows them to reduce alcohol consumption to moderate levels (Glaser 2015). In addition, many eastern religions such as Taoism, Confucianism, and Buddhism advocate moderation and avoiding extremes. The two approaches, moderation and abstinence are also reflected in the diet industry, with some options encouraging moderation (e.g., Weight Watchers and My Fitness Pal), and others encouraging abstinence (e.g., Atkins, Paleo, and vegan diets). In this research, I are interested in how such beliefs affect people's behavior. Developing a measure of these lay beliefs will allow us to compare the two approaches in terms of resulting behavior after indulgences.

My moderation tendency construct is distinct from entity and incremental theories (Dweck, 1999) because it specifically looks at consumers' beliefs about moderation. It does so in a way that also differs from the willpower depletion beliefs scale (Job, Dweck, and Walton, 2010), which asks whether people believe that willpower must be refueled after depletion, for example by "having a break, watching TV, doing nothing, or eating snacks." Items such as these could correspond with my conceptualizations of either moderators or abstainers. On the one hand, the belief that willpower is limited seems similar to the philosophy of abstainers, who are afraid that temptations might cause them to fall off the wagon. But on the other hand, the belief that occasional breaks or snacks can help refuel willpower seems similar to the philosophy of moderators, who believe that occasional indulgences are necessary to stay on the right track.

In addition, my new measure digs deeper into the notion of renewability, which Job et al. (2010) briefly touched on. More specifically, I expect moderators to agree that an occasional indulgence helps to refuel their willpower, and for abstainers to agree on the opposite: that *abstinence* helps to refuel their willpower. I will provide evidence in my scale validation (Study 2) to show that the moderation tendency scale is distinct from other health-related or self-control related scales.

How do dieters recover from an indulgence? Self-fulfilling prophecies and compensatory responses

Once I have developed my moderation tendency scale, I seek to test how abstainers and moderators recover differently from indulgences. First, I expect that in general, dieters will exhibit a self-fulfilling prophecy after an indulgence, in which they enact their lay beliefs. The literature on self-fulfilling prophecy (Merton, 1948) and behavior confirmation (Snyder 1984; 1992) illustrates that people's beliefs and expectations of what they will do leads them to behave exactly as they expect themselves to act. Plaks, Grant, and Dweck (2005) also show that people's implicit theories play a critical role in establishing their subjective sense of prediction and control. Therefore, I predict that dieters will generally act in line with their expectations. In other words, after an indulgence, moderators should be more likely than abstainers to balance out their indulgence by lowering their subsequent caloric consumption. This prediction also allows us to test the nomological validity, or how well my measure empirically demonstrates findings consistent with conceptual expectations (Cronbach and Meehl 1955; Lastovicka et al. 1999). If the scale accurately identifies moderators and abstainers, then the measure should accurately predict their behavior after an indulgence.

However, I also propose that there will be differential effects of a recalled indulgence, in which dieters recall a time when they indulged on a diet, versus an induced indulgence, in which dieters are instructed to eat an indulgent food. After a recalled indulgence, I expect the self-fulfilling prophecy to operate, because people give substantial weight to easily recalled experiences in forming their predictions (Gilovich, Griffin, and Kahneman, 2002). Thus, their resulting behavior should conform to their expectations (Snyder 1984; 1992). However, after an induced indulgence, a different mechanism may determine how dieters' beliefs affect their behavior. In particular, I expect that dieters may activate compensatory responses when they feel that their beliefs have been threatened (Howell 2016). For example, Plaks, Grant, and Dweck (2005) showed that people tend to be motivated to “regain” their implicit theories when they feel there is a threat coming from contradicting information. When they are induced to indulge, abstainers may perceive a discrepancy between their beliefs (that indulging is bad) and their behaviors (having recently indulged), leading them to display compensatory behaviors to address the discrepancy. Specifically, after an induced indulgence, I expect abstainers to pursue a direct resolution strategy by subsequently lowering their food consumption (Mandel, Rucker, Levav, and Galinsky, 2017). The literature on cognitive dissonance (Festinger and Carlsmith 1959) also supports this argument: when people perform an action that contradicts what they believe, they adjust their beliefs to conform to their behavior. Therefore, when abstainers indulge in prohibited foods, they may adjust their beliefs to act more like moderators, and thus compensate by eating less than if they only recalled an indulgence experience. But for moderators, an indulgence is something that they believe is beneficial to their diet; thus having an induced indulgence should not create self-discrepancy between their beliefs and behavior. Thus, they should always compensate by lowering subsequent consumption after an indulgence.

Taken together, I propose that moderation tendency will interact with the form of indulgence (recalled vs. induced indulgence) in influencing subsequent eating. When recalling an indulgence, dieters will follow a self-fulfilling prophecy: consistent with their expectations, moderators should more likely to balance out the indulgence than abstainers. Therefore, after a recalled indulgence, moderators should eat less than abstainers. However, in contrast, after an induced indulgence, abstainers should compensate by eating less due to the perceived discrepancy, while moderators will not perceive any discrepancy, because they believe that having an occasional indulgence is fine and even beneficial to their diet. Thus, abstainers should eat even less than moderators after an induced indulgence.

The Current Research

I conducted a series of studies to (1) develop and validate a new scale to assess moderation tendency, and (2) used this new measure to investigate how dieters' lay beliefs affect their behaviors after recalled and induced indulgences.

Study 1 developed and validated a sixteen-item scale (see Appendix A) to assess moderation tendency, and asked about past diet experiences. Study 2 tested the convergent, discriminant, and nomological validity of the scale. Study 3 investigated the two types of dieters' subsequent consumption of a snack after recalling either indulging in or resisting a temptation. Study 4 examined how much of a snack the two types of dieters consumed after a recalled indulgence versus an induced indulgence.

Study 1

In study 1, I developed and validated a 16-item moderation tendency scale (Cronbach α = .89).

Method

I borrowed and rephrased some items from the screening questions proposed in Rubin's (2012) blog and created some items that were inspired by Job et al.'s (2010) scale (about implicit theories about willpower). In addition, I developed some new items based on the definitions of moderators and abstainers from Rubin (2001).

During the scale purification phase, I tested the initial version of the scale (26 items) using a student panel, and conducted factor analysis and reliability analysis (Cronbach's alpha) but the result did not yield a satisfying reliability– the Cronbach α was less than 0.7. I collected comments from participants at the end of the pre-test, and used this feedback to revise the items and make them more specific to the eating behavior domain. I also eliminated 10 items that had loading values less than 0.3 on any of the factors, or that negatively affected the reliability.

I tested the revised 16-item scale in study 1. I recruited participants from dieters' discussion boards on Facebook, SparkPeople, MyFitnessPal, and Reddit. Thus, the study was limited only to dieters. Items included, for example, "I find that an occasional food indulgence heightens my pleasure – and strengthens my resolve," "Refusing ANY food temptations is an easier strategy for me to keep my diet on track (R)." Participants rated their agreement on a 7-point rating scale (1=strongly agree to 7=strongly disagree).

Higher values of the total score indicate a moderation tendency, and lower values indicate an abstaining tendency.

In the study, participants first responded to the 16-item moderation tendency scale, and then they answered questions about their past dieting experiences. First, participants responded to the questions, “In your past diet experience, have you ever incorporated an indulgence in your diet for any reason?” (0 = No or 1 = Yes). For those who answered yes, I asked them follow-up questions about what happened after the indulgence experiences and how helpful they found the experiences to be for their diet (1 = not at all helpful to 7 = extremely helpful). Specifically, I asked them to indicate “If you indulge one day (not a deliberate indulgence, but a unplanned indulgence), do you eat healthfully the next day or keep eating junk food?” (1 = eat very unhealthy the next day or 7 = eat very healthy the next day); “How difficult is it for you to get your diet back on track once you feel that you are about to fall off the diet wagon?” (1 = very difficult to 7 = very easy); and “How likely do you find yourself falling off the wagon after having an indulgence?” (1 = extremely unlikely to 7 = extremely likely). I also asked participants to indicate “In your past diet experience, have you ever tried to completely abstain from certain foods or food groups?” (0 = No or 1 = Yes) and “ Did the absolute abstinence experience help your diet plan?” (1 = not at all helpful to 7 = extremely helpful). The purpose of this set of questions was to explore whether abstainers and moderators have different perceptions and evaluations toward their past indulgence and abstinence experiences.

At the end of the study, I asked participants to indicate “How often do you allow yourself to satisfy your cravings?” (1= never to 7 = always). I also asked them “What is the largest amount of weight you have ever lost (in pounds)?” and questions about their demographics, including height and weight, which I used to calculate BMI.

Results

Participants were 135 current dieters (M_{age} = 39.47 years, SD_{age} = 11.35 years, 86.67% female, M_{BMI} = 30.215, SD_{BMI} = 8.216). The large proportion of female participants is consistent with the fact that females are more likely to diet than males. In other studies, I have more balanced gender ratios.

An analysis of the sixteen scale items yielded good reliability (Cronbach $\alpha = 0.89$). I conducted an exploratory factor analysis (EFA) with the principal axis factoring method to assess how well the items represent the underlying concepts. Kaiser’s measure of sample adequacy (MSA; Kaiser 1974) for the 16-item moderation tendency scale was .891, which is very high and Kaiser described as “meritorious;” thus the data were appropriate for EFA. I used an Eigen-value of 1.0 criteria and a scree test to select the number of factors, and the result indicated that the 16 items, based on a 3-factor model, were able to explain 65.54% of the total variance. The factor loadings of the items on each factor are shown in Table 4.1. All of the items have at least a factor loading of .3 and most of the items (14 out of the total 16 items) loaded greater than .5. Evaluation of item content and their loading factors suggested that the three factors fall into three labels: Abstinence, Moderation, and Renewability. Thus, the items appear to represent the underlying aspects of the proposed moderation tendency measure.

Table 4.1 Factor structure of the Moderation Tendency Scale

Item number and content	Factor Loading Estimates		
	Abstinence	Moderation	Renewability
9. I am afraid of falling off the wagon once I surrender to food temptation. (R)	.904		
12. The best way for me to stick to a diet successfully is never breaking any rules during the diet. (R)	.735		
10. Sticking to a strict diet without any deviation from my diet plan strengthens my willpower. (R)	.707		
14. Controlling myself and abstaining from food treats can refuel my willpower and help me to stick to my diet. (R)	.704		
5. I find that occasional food indulgences weaken my resolve and willpower. (R)	.641		
3. Refusing ANY food temptations is an easier strategy for me to keep my diet on track. (R)	.590		
7. The word "never" makes things easier for me when I decide to avoid foods that I've decided are off-limits. (R)	.543		
11. When I have been sticking to a diet strictly for a while, I feel less able to keep doing it because my willpower is depleted.		.839	
13. After strictly resisting temptations during a diet, my willpower exhausts and cannot be refueled by resisting more temptations.		.716	
15. Once I feel exhausted of all my willpower from sticking to my diet, it's a bad idea to continue trying to diet.		.653	
16. After dieting for a while, I don't need to reward myself with a food treat to boost my ability to face future dieting challenges. (R)		-.520	
2. I get panicky at the thought of "never" eating something.		.439	
4. I treat myself with an occasional food indulgence when I feel tired of suppressing my desires and cravings.		.338	
1. I find that an occasional food indulgence heightens my pleasure – and strengthens my resolve.			.838
8. I feel more relaxed knowing that I have the chance to satisfy my cravings with an occasional food indulgence.			.678
6. Mild food indulgences activate my willpower and I become better able to resist temptations.			.640

Extraction Method: Principal Axis Factoring.

Rotation Method: Promax with Kaiser Normalization.

Loading value smaller than 0.3 is suppressed

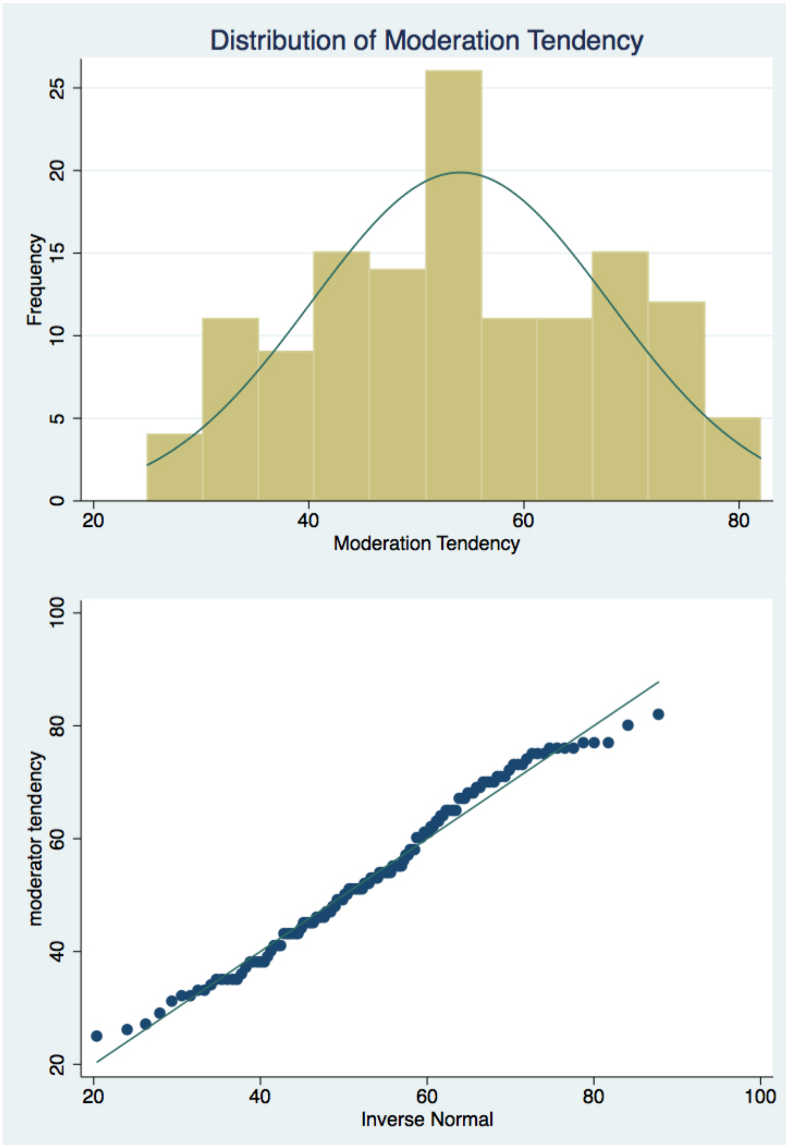


Figure 4.1
Moderation Tendency Distribution

Examining the distribution of the moderation tendency scale reveals that moderators and abstainers are nearly symmetrically distributed. Distribution plots in Figure 4.1 show that the moderation tendency in this study is normal distributing. The sample fits a normal distribution with fat tails, which suggest that more extreme moderators and abstainers exist in the distribution. The scale identifies substantial amount of moderators as well as abstainers. The normal distribution also suggests that there are a lot of people scored around the mean. These people are neither moderator nor abstainer, but holds beliefs that do not lean towards any one of the two approaches.

I next performed regressions with the responses to the past diet experience questions as dependent variables and moderation tendency as the independent variable. The results (summarized in Table 4.2) first suggest that abstainers seem to have many advantages over moderators. Participants with lower (vs. higher) scores on the moderation scale (i.e., abstainers) are less likely to allow themselves to satisfy their cravings than moderators (b = -.10, t(134) = -4.87, $p < .01$), their largest historical weight loss amount is greater than moderators (b = .53, t(134) = 2.09, $p < .05$), and their BMI is lower (b = -.20, t(134) = -3.44, $p < .01$).

Results for past dieting experience suggest that moderators are marginally more likely to have tried a diet plan that involved indulgences (b = .03, t(134) = 1.87, $p = .06$). Among participants who had had an indulgence experience (108 out of 135), relative to abstainers, moderators found dieting methods with allowed indulgences more helpful (b = -.10, t(107) = -4.53, $p < .01$), were better at recovering from indulgences and less likely to fall off the wagon (b = -.06, t(107) =-2.93, $p < .01$), and ate more healthfully the day after an indulgence (b = .04, t(107) = -2.29, $p < .05$).

Relative to moderators, abstainers were more likely to have tried an abstinent diet plan (b = -.04, t(134) = -2.4, $p < .05$). Among dieters who had such experience (109 out of 135), abstainers found abstinent dieting methods more helpful ($b = .07$, $t(108) = -3.29$, $p < .01$) than moderators.

In sum, abstainers reported being more successful with diets which require abstinence, while moderators reported being more successful with diets that permit occasional indulgences.

Table 4.2 Moderators And Abstainers' Evaluations Of Past Experiences

Questions				
"In your past diet experience, have you ever incorporated a preplanned cheat meal or cheat days in your diet for any reason?" (0 = No or 1 = Yes).	**M**	>	A	*
"Did these cheat meal or cheat day help your diet plan?" (1 = not at all helpful to 7 = extremely helpful)	**M**	>	A	***
"If you indulge one day (not a deliberate cheat day, but a unplanned indulgence), do you eat healthfully the next day or keep eating junk food?" (1 = eat very unhealthy the next day or 7 = eat very healthy the next day);	**M**	>	A	**
"How difficult is it for you to get your diet back on track once you feel that you are about to fall off the diet wagon?" (1 = very difficult to 7 = very easy);	M		A	
" How likely do you find yourself falling off the wagon after having a cheat day/meal?" (1 = extremely unlikely to 7 = extremely likely).	M	<	**A**	***
"In your past diet experience, have you ever tried to completely abstain from certain foods or food groups?" (0 = No or 1 = Yes)	M	<	**A**	**
" Did the absolute abstinence experience help your diet plan?" (1 = not at all helpful to 7 = extremely helpful)	M	<	**A**	***
"How often do you allow yourself to satisfy your cravings?" (1= never to 7 = always)	**M**	>	A	***
" What is the largest amount of weight you have ever lost? (in pounds)"	M	<	**A**	**
BMI	M	>	**A**	***

M=Moderators; A=Abstainers
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Discussion

Study 1 provided preliminary evidence of the reliability and underlying factor structure of the moderator tendency scale. In addition, this study revealed insights about participants' past dieting experiences, successes, and failures. I found that abstainers generally perform better in weight loss and their BMI was slightly lower than moderators. Furthermore, they reported generally being better able to resist cravings. These results suggest that abstaining may indeed be a superior approach to dieting. However, abstainers also acknowledged that they are more likely (compared to moderators) to exhibit the what-the-hell effect after indulging in a treat. These results provide initial support for the nomological validity of the scale, as well as for my prediction that dieters' behaviors exhibit a self-fulfilling prophecy by acting in line with their beliefs after recalling an eating indulgence. However, the results were based only on dieters' self-reported memories and evaluations of their past behaviors. To provide more direct evidence of the effect of an indulgence on subsequent eating behavior, I conducted laboratory experiments in which I manipulated indulgences – recalled (studies 3 and 4) and induced (study 4) -- and assessed subsequent eating behaviors. However, before moving to laboratory experiments, I first turn to the issues of convergent and discriminant validity. Study 1 demonstrated the reliability of my new scale, but did not show whether my scale is distinct from other existing scales. In Study 2, I conducted convergent and discriminant validity analyses to show how my scale is distinct from scales that potentially confound my scale.

Study 2

In study 2, I aimed to investigate whether my moderation tendency scale is correlated with scales that are conceptually similar and distinct from scales that are conceptually different. As discussed above, my scale was to some extent conceptually similar to the implicit self-theories scale (Dweck, 1999) and willpower depletion beliefs measures (Job, Dweck, & Walton, 2010), as they all measure people' implicit self-beliefs. However, I also argued that my new scale is conceptually distinct from other lay theory scales because of the distinction between moderators and abstainers.

In addition, I also wanted to distinguish my measure from two additional potential confounders: psychological reactance (Hong & Felda, 1996) and self-efficacy (Schwarzer & Jerusalem, 1995). For example, moderators may dislike the word "never" because they dislike being told what to do (reactance). It is also possible that abstainers fear being able to regain control after an indulgence because they suffer from low levels of self-efficacy. I aimed to show that differences in moderation tendency are not due to differences in psychological reactance or self-efficacy.

Finally, the abstinence construct may relate to general healthy eating or, when taken to an extreme, disordered eating. Thus I also included the Eating Habits Questionaire (EHQ; Gleaves, Graham, & Ambwani, 2013) that measures healthy eating, which at extreme scores may represent obsessive dieting behaviors that involve spending overwhelming attention and time on dieting, keeping very strict diets, and feeling superior to others (known as orthorexia nervosa; Bratman & Knight, 2000). See the EHQ items in Appendix C.

Method

I recruited participants on mTurk and provided $1.20 compensation for them to complete the study online. In my recruiting ad, I emphasized that I only needed participants who had dieting experience. To ensure that all participants had at least some dieting experience and could relate to dieting behaviors, the first question of the survey asked participants “Have you ever been on a diet or tried to restrict your eating to healthier foods?” (0= No or 1 = Yes), and participants who had never dieted were screened out. As a result, my sample had a total of 145 respondents (M_{age} = 35.4 years, SD_{age} = 10.6 years, 47.56% female, M_{BMI} = 26.77, SD_{BMI} = 5.28).

Participants completed the scales of moderation tendency, implicit theories (Dweck, 1999), willpower depletion (Job, Dweck, & Walton, 2010), eating habits (EHQ; Gleaves, Graham, & Ambwani, 2013), Hong’s psychological reactance (HPRS; Hong & Felda, 1996), and general self-efficacy (GSE; Schwarzer & Jerusalem, 1995). In addition, I asked two questions about eating disorders: “Have you ever had an eating disorder? (0= No or 1 = Yes) and “Have you ever considered that you might have an eating disorder? (0= No or 1 = Yes).

I conducted an exploratory factor analysis to examine the scales’ factor loadings and see how they loaded on latent factors. I also used structural equation modeling to conduct a confirmatory factor analysis on the six scales to assess the correlations among the scales that provide evidence for convergent and discriminant validity.

Results

I first conducted an exploratory factor analysis on the six scales to assess discriminant validity and fitted a six-factor solution. The items of each scale loaded respectively on their own factors and with minor overlaps between scales. For example, the EHQ scales had a few items that loaded on the self-efficacy factor, suggesting that ”healthy eating” not only describes an eating habit but also involves self-efficacy evaluations. The moderation tendency measure mainly loaded on its own factor, with only few overlaps with the EHQ factor and the reactance factor. And as expected, a few willpower depletion items loaded on the moderation tendency factor, indicating that the willpower depletion scale contains some conceptual overlap with the moderation tendency scale. However, the low loading values of these few items (range from .32 to .41) indicate that they only explain a very small amount of variance on the moderation tendency factor. I further explored the relationships among the scales with confirmatory factor analysis.

Table 4.3 shows the simple correlations among the factors obtained from the confirmatory factor analysis. As expected, there was slight but not significant correlation between moderation tendency and conceptually similar scales such as the implicit theory scale ($r = -.16$, $p > 0.1$; suggesting that moderators are directionally more likely to be incremental vs. entity theorists), willpower depletion scale ($r = -.21$, $p = .11$, suggesting that moderators are directionally less likely to believe that willpower is a limited vs. unlimited resource). The correlations was marginally significant between moderation tendency and the psychological reactance scale ($r = -.15$, $p = .08$, suggesting that moderators are marginally less reactant than abstainers), and nonsignificant between moderation tendency and the self-efficacy scale (r = - .003, *p* = .95).

The moderation tendency scale was significantly correlated with the EHQ scale (r = - .23, *p* < 0.05), suggesting that high levels of healthy eating, and possibly orthorexia nervosa, are more likely to occur among abstainers, especially extreme abstainers. Nevertheless, my direct questions about disordered eating did not correlate with moderation tendency. I treated the two questions as a 2-item scale (each question takes the value of 1 or 2, and the total score is 0 or 1 or 2). The confirmatory factor analysis result showed that the correlation between moderation tendency and disordered eating (r = -.03, *p* = .14) was not significant.

Except for the EHQ scale, the correlations between moderation tendency and other scales were not significant,. Moreover, all of the correlations were far below the discriminant validity threshold of 0.85 (Kline 2011). A correlation value that is less than 0.85 suggests that discriminant validity exists between the scales. Therefore, the moderation scale is distinct from all of the other scales.

Table 4.3 Correlation Matrix Among Scales

Scales	Moderation Tendency	Implicit Theory	Willpower Depletion	GSE	Hong's	EHQ
Moderation Tendency	1					
Implicit Theory (Dweck)	-0.16	1				
Willpower Depletion (Job et al)	-0.21	0.05	1			
General Self-Efficacy Scale (GSE)	-0.003	-0.11	0.06	1		
Psychological Reactance Scale (Hong's)	-0.15	0.46**	0.002	-0.19	1	
Eating Habits Questionaire (EHQ)	-0.23**	0.12	0.09	0.02	0.11*	1

* p < 0.05; ** p < 0.01

Discussion

Study 2 established the discriminant validity of the moderation tendency scale. It also provided insights on the relationship between the moderation tendency construct and disordered eating. On the one hand, moderation tendency was uncorrelated with participants' self-reports of disordered eating. On the other hand, it was negatively correlated with the EHQ, a measure of "orthorexia nervosa," which suggests that abstaining can be unhealthy when taken to an extreme.

Study 3

After providing support for the reliability and validity of the moderator tendency scale, I conducted a lab experiment to test how dieters' moderation tendencies may determine their eating behavior after recalling an indulgence. In this laboratory study, I asked half of the participants to recall a past indulgence experience, and half of the participants to recall a past abstinence experience, and then I measured the amount of M&Ms they ate on a purportedly unrelated task. Thus, study 3 utilized a 2 (recalled experience: indulgence vs. abstinence) × continuous (moderation tendency scale) between-subjects design.

Method

Procedure

I divided the study into three individual small parts with filler tasks between parts to make them seem unrelated. The first part measured participants' moderation tendency.

After a filler task, I randomly assigned participants to either the recalled indulgence condition or the recalled abstinence condition. The recalled indulgence condition manipulation asked participants to describe a recent experience in which they had eaten a tempting food while they had a long-term health or weight goal. The instruction stated:

> "In this study, I are interested in knowing about your eating and dieting experiences. Please describe a recent experience in which you had a tempting food, but at the same time had a longer-term goal, such as a health or weight goal. For example, perhaps you had an indulgence in one meal during Thanksgiving, or you had an extra slice of birthday cake on your birthday. Please add as many details as you can remember. In addition, please indicate how you felt about that experience."

The abstinence condition asked participants to write about an experience when they avoided eating a tempting food:

> "In this study, I are interested in knowing about your eating and dieting experiences. Please describe a recent experience in which you avoided eating a tempting food, to achieve a longer-term goal, such as a health or weight goal. For example, perhaps you avoided having an indulgence during Thanksgiving, or you said "no" to a slice of birthday cake on your birthday. Please add as many details as you can remember. In addition, please indicate how you felt about that experience."

Participants wrote their essays in an empty text box with no word or time limits.

The last part of the study was a snacking task in which participants ate M&Ms while watching a neutral, unrelated video. The instructions stated that the purpose of the task was testing which types of snacks go the best with certain types of videos. I gave each participant a 16-oz bag of milk chocolate M&Ms and let them open the bag and eat at least some of the snack while watching the video. Participants provided ratings of the snack on the subsequent page. Participants who are unable to participate (e.g., if they had food allergies) or unwilling to perform the task were allowed to skip it and complete an alternative task (and thus were not included in the analysis). Before they ate, I asked about their levels of felt hunger, satisfaction, and fullness. After they watched the video, I asked them to evaluate the M&Ms regarding sweetness and how much they liked them. After participants finished the eating task, the leftover bags were collected. The experimenter weighted each bag of M&Ms before the study and again after the study. The difference between the before- and after- study weight for each participant served as the key dependent variable: the consumed amount. Finally, I asked about their height and weight (used to calculate their BMI) and other demographic information.

Sample

Participants were undergraduate business students at a large U.S. state university. To ensure that all participants had at least some dieting experience and could relate to dieting behaviors, I asked participants “Have you ever been on a diet or tried to restrict your eating to healthier foods?” (0= No or 1 = Yes), and removed participants who had never dieted from the sample. I had a resulting sample size of 201, with 97 in the indulgence condition and 104 in the abstinence condition (M_{age} = 21.6 years, SD_{age} = 2.39 years, 44.78% female, M_{BMI} = 22.89, SD_{BMI} = 3.88).

It is worth noting that these participants were within normal weight range, which is very different from the participants in study 1 who were mostly in the range of overweight and even obese. Consistent with study 1, moderators had a marginally higher BMI (b = .37, t(197) = 2.6, p = .09) than abstainers in this sample. The two types of dieters also differed in age and gender. I found that younger people (b = 4.27, t(197) = 2.6, $p < .05$) and females (b = -.82, t(197) = -2.58, $p < .05$) were more likely to be moderators. Moderators and abstainers did not differ in their felt hunger, satisfaction, fullness, assessments of the sweetness of the M&Ms, or how much they liked them.

Results

Subsequent snack consumption. To examine the hypothesized interaction, I ran a linear regression on M&M consumption level with a mixed factorial interaction. It contained three main independent variables: (i) a binary variable to represent the recalled experience, with 1 representing the recalled indulgence condition and 0 representing the recalled abstinence condition, (ii) moderation tendency score, (iii) the interaction of the moderation tendency scale and the recalled experience condition. Demographic variables have been shown to influence appetite (Gregersen et al. 2011) and food intake (Remick, Polivy, & Pliner, 2009);To control for the effects of BMI, age, gender, felt hunger, satisfaction, fullness, assessments of the sweetness of the M&Ms, and how much they liked the M&Ms, these variables were added as covariates. Adding these covariates did not change the significance levels of the three main variables.

The result revealed a significant moderation tendency X recalled experience interaction on subsequent M&Ms eaten (b = -.47, t(197) = -2.56, $p < .05$). Among the covariates, only gender (female=1, b = -4.54, t(197) = -2.28, $p < .05$), hunger (b = 1.91, t(197) = 2.47, $p < .05$), and how much they liked the snack (b = 2.79, t(197) = 4.06, $p < .001$) were significant in predicting the snacked amount. This result indicates that females did a better job controlling their snack amount for M&Ms in general, and dieters who were more hungry and liked M&Ms more ate more of it.

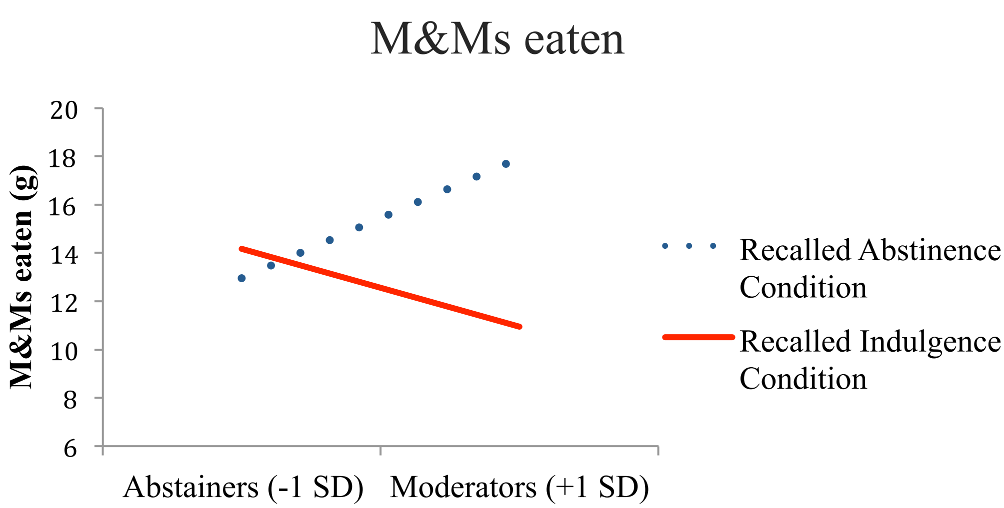


Figure 4.2
The Interactive Effect of Moderation Tendency and Recalled Experience Condition on M&Ms Eaten.

The slope of the solid line in Figure 4.1 indicated that moderators ate significantly less M&Ms than abstainers in the recalled indulgence condition (b = -.34, t(197) = -2.35, $p < .05$). This finding is consistent with my prediction that a positive self-fulfilling prophecy operates and assists moderators to get back on track after an indulgence experience. Because moderators believe that they can cope well with indulgences, they ate less than abstainers in the recalled indulgence condition. On the other hand, abstainers did not exhibit a strong self-fulfilling prophecy (with the exception of extreme abstainers, as discussed later). In other words, they did not succumb to the what-the-hell effect to the extent that they indicated in their scale item responses.

In contrast, the dotted line shows that moderators ate more M&Ms than abstainers in the recalled abstinence condition ($b = .26$, $t(197) = 2.06$, $p < .05$). This finding supports my prediction that dieters follow a self-fulfilling prophecy – moderators believe that they need occasional indulgences to heighten their willpower, and thus being abstinent could result in a rebound effect. In other words, their behavior reflected their beliefs: in the recalled abstinence condition, they performed worse than abstainers.

Comparing the two lines in Figure 4.1, it appears that moderators consumed more snacks after recalling an abstinence experience versus an indulgence experience, whereas abstainers consumed slightly more after recalling an indulgence experience versus an abstinence experience. I conducted a spotlight analysis at +/- 1 SD from the mean of moderation tendency to test these effects. At +1SD above the mean (moderators), there was a significant effect ($b = -.31$, $t(197) = -2.82$, $p < .01$) of recalled experience, suggesting that moderators compensate for a recalled indulgence (vs. abstinence) by eating less on a subsequent occasion, consistent with their beliefs. Spotlight analysis at -1 SD from the mean of moderation tendency (abstainers) showed no significant difference ($b = -.05$, $t(201) = .49$, $p = .62$) between the recalled indulgence and abstinence condition. This result suggests that contrary to their expectations, abstainers perform equally well after recalling an abstinence versus indulgence experience. In other words, in their responses to the moderation tendency scale, abstainers indicated a fear of losing control after indulging, but I found no evidence that they actually do so, at least in a recalled indulgence situation. In such cases, indulging does not hurt them as much as they expect.

I conducted floodlight analysis to find the scores on the moderation tendency scale where the differences between the lines became significant. I used the Johnson-Neyman technique available in the PROCESS macro (Hayes, 2013). The floodlight analysis showed that at the moderation tendency score of 66.7, which is slightly higher than the mean o 65.45, all the area to the right showed a significant difference between the two conditions. This result suggests that the majority of moderators (i.e., those scoring greater than the mean) ate less after recalling an indulgence than after recalling abstinence. For abstainers, I explored further to the left of - 1SD with a floodlight analysis. At – 5.5 SD from the mean (moderation tendency score = 12.65), the difference became significant. However, this point was not within the range in my sample, which only had a minimum moderation tendency score of 41. This result suggests that a recalled indulgence (vs. recalled abstinence) may be only harmful for the most extreme abstainers, who tend to be quite rare.

Discussion

These results suggest that moderators exhibit a self-fulfilling prophecy in their consumption patterns after recalling an indulgence experience, lending support to the nomological validity of my scale. Asking moderators to think about a time when they ate a tempting food has a more positive effect than asking them to recall a deprivation.

Although the findings of study 1 and study 3 suggest that moderators may not be doing so well with their moderating strategies in terms of weight loss and BMI, the findings of this study suggest that asking a moderator to abstain from "bad foods" is unlikely to work and may even backfire. On the contrary, dieters may be better off following the strategy (moderation) that they believe works better for them, and that allows them to get back on track fairly easily from occasional indulgences. The findings support the notion that instead of pursuing the "right" or "better" strategies, people should follow their beliefs and follow the strategy that they believe work the best, and those strategies work the best for them.

I note that this study compared eating after recalled indulgence versus abstinence experiences. Although memory is important, I are also interested in the effects of induced indulgent consumption experiences. Also, this study did not measure emotions to rule out their possible mediating effect. Do Vale et al. (2016) found that planned occasional indulgences enhance positive affect. Previous research has also demonstrated negative emotions' influence food consumption (Kemp, Bui, and Grier 2012). For example, guilt feelings may arise after a hedonic consumption, and may further impact on subsequent consumption (Goldsmith, Cho, and Dhar 2012). I address these limitations in study 4.

Study 4

I conducted study 4 to investigate the difference in the effects between a recalled indulgence and an induced indulgence (note that I did not include an abstinence condition in this study). I conducted a lab experiment with 210 undergraduate business student participants who earned course extra credit. Thus, I used a 2 (experience: induced indulgence vs. recalled indulgence; manipulated) × continuous (moderation tendency; measured) design. In addition, this study attempted to rule out the potential mediating effect of emotions.

Method

Procedure

To prevent demand artifacts, I divided the study into three parts and used filler studies to make them seem unrelated. The first "study" started by asking the participants whether they have ever dieted and thus allowed non-dieters to skip to the end. Then the remaining experienced dieters completed the moderation tendency scale.

The second "study" had two conditions: induced indulgence and recalled indulgence. In the induced indulgence condition, I informed the participants that I were interested in learning how evaluations change as people eat more of a product and asked them to consume a food item (a chocolate cupcake) and evaluate it several times: prior to consumption and at several times as they consumed it. The purpose of this cover story was to encourage participants to eat a large quantity of the cupcake, which was high in calories. If they did not want to eat it, they could choose to do another task. I also asked participants to finish as much as they could. The evaluation (cover story) questions asked participants to rate the cupcake on taste, texture, and how much they liked it. In the recalled indulgence condition, participants performed the recalled indulgence essay-writing task used in study 2 – writing about their recent experience of an indulgence. Then participants indicated their self-conscious emotions (guilt, shame, embarrassment, and pride, Tangney 2005) at the moment, in order to test the potential explanatory effects of these emotions. After completing a second filler task, participants performed the same snacking task as in study 2, but with a small bag of potato chips instead of M&Ms. They ate the chips while watching a video, and the experimenters weighed the chips before and after the eating task. After completing the task, participants answered questions about their demographic background and BMI.

At the end of the study, participants answered three manipulation check questions, which asked whether they considered the cupcake an indulgence for their diet in the induced indulgence condition. The three items were: 1."Recall the cupcake you have just had in the previous study, would you consider eating the cupcake an indulgence for your diet?", 0 = yes, it would be an indulgence for my diet or 1 = no, it wouldn't be an indulgence for my diet); 2. "How much does eating the cupcake mean an indulgence on your diet?" (1= not an indulgence at all to 7 = a extremely big indulgence); 3. "How much do you feel like you indulged?" (1 = far too little to 7 = far too much). Finally, there was one more question asking about what they thought the study was about, and no participants correctly guessed the true purpose.

Sample

The screening question at the beginning of the study about whether the participants have ever been on a diet only allowed those who answered yes to continue, resulting in 136 observations (M_{age} = 21.14 years, SD_{age} = 2.59 years, 54.64% female, M_{BMI} = 24.53, SD_{BMI} = 5.36), with 71 in the induced indulgence condition and 65 in the recalled indulgence condition.

In this sample, moderators and abstainers did not differ in BMI (*p* = .142). Consistent with study 3, I found that females (b = -4.7, t(197) = -1.84, *p* = .07) were marginally more likely to be moderators in this sample. Moderators and abstainers did not differ in their felt hunger, satisfaction, fullness, evaluations of the chips, or how much they liked the chips.

Results

Manipulation check. In the induced indulgence condition, 71.23% of participants considered the chocolate cupcake an indulgence for their diet, suggesting that the induced indulgence manipulation was successful. In addition, there was no significant difference between moderators and abstainers' ratings regarding whether they considered eating the cupcake an indulgence, how much they considered eating the cupcake as an indulgence, and how much they felt they had indulged.

Subsequent snack consumption.

I ran a linear regression on potato chip consumption with a mixed factorial interaction. The regression contained three independent variables: (i) a binary variable indicating the experience condition, (ii) a continuous moderation tendency score, and (iii) the interaction of the moderation tendency scale and the binary variable. The binary variable took the value of 1 representing the induced indulgence condition and 0 representing the recalled indulgence condition. I also included BMI, age, gender, felt hunger, satisfaction, fullness, assessments of the chips, and how much they liked chips as covariates.

The main effects of the regressions indicated that the induced indulgence condition resulted in significantly lower chip consumption than the recalled indulgence condition (*b*= -42.08, *t*(132)= - 4.95, $p < 0.001$). More importantly, there was a significant moderation tendency X experience interaction (b = .52, t(132) = 4.15, $p < 0.001$; see Figure 4.2). Among the covariates, only hunger (b = 1.94, t(132) = -2.98, $p < .01$) was significant in predicting the snacked amount, indicating that more hungry participants ate more chips.

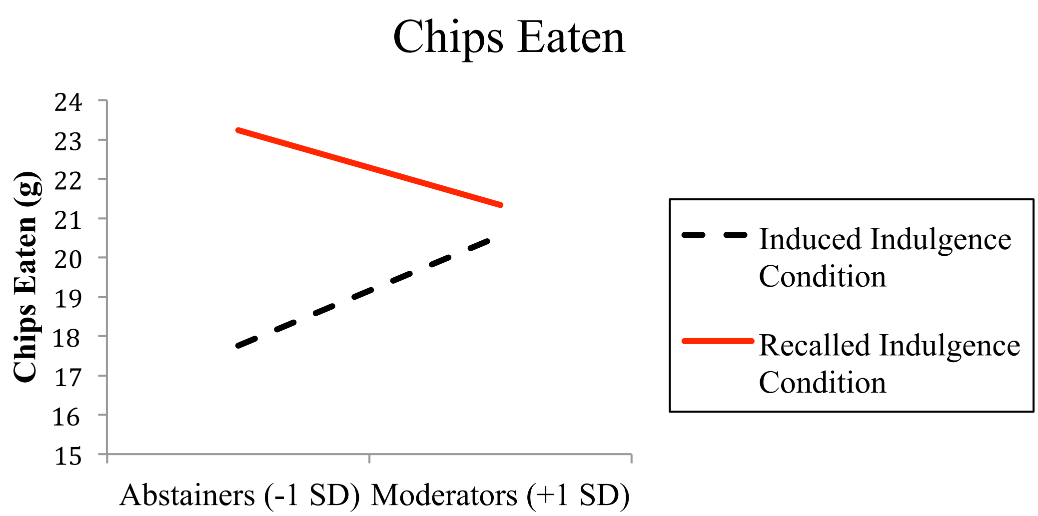


Figure 4.3
The Interactive Effect Of Moderation Tendency And Manipulated Experience On Potato Chips Eaten

First, consistent with my predictions and the results of study 3, the slope for the recalled indulgence condition was significant (solid line, b = - .24, t(132) = - 2.57, $p < .05$), indicating that after a recalled indulgence, moderators ate less than abstainers, thereby exhibiting a self-fulfilling prophecy. In contrast, the slope of the line of the induced indulgence condition was significant (dashed line, b = .27, t(132) = 2.65, $p < .05$)

in the opposite direction, suggesting that abstainers snacked significantly less than moderators in the induced indulgence condition. This finding supports my prediction that abstainers would compensate by eating less when they perceived a self-discrepancy between their beliefs and behaviors. In contrast, moderators showed a similar compensatory response in both indulgence conditions, because they are adapted to having indulgences and so an induced indulgence experience did not create any self-discrepancy.

Spotlight analysis showed that at +1 SD from the mean of the moderation tendency (i.e., moderators), there was no significant difference between the two conditions. In other words, moderators' snack amount would be almost the same no matter whether they had an indulgence and no matter what form (induced or recalled) the indulgence was. I conducted floodlight analysis to examine if on there is a point in the area to the right that the difference between the conditions became significant. But within the sample's moderation tendency scores scope, there was no significant difference. By comparison, at the -1 SD from the mean of moderation tendency (abstainers), participants ate significantly more chips in the recalled indulgence condition than in the induced indulgence condition (b = .29, t(132) = 2.46, $p < .05$).

I conducted floodlight analysis to find moderation tendency score where the differences between the lines became significant. I used the Johnson-Neyman technique available in the PROCESS macro (2013). At the moderation tendency score of 65.87, which is very close to the mean of 65.45, all the area to the left showed significant difference between the recalled and induced indulgence conditions. This result suggests that the majority of abstainers (i.e. those below the mean of moderation tendency) demonstrated compensation by eating less after an induced indulgence than after a recalled indulgence.

Self-conscious emotions. I used ANOVA to examine if there were any differences in self-conscious emotions after the manipulations. I found that guilt, embarrassment, and shame feelings were not significantly different between the induced indulgence condition and the recalled indulgence condition (p = .438). However, reported pride was lower (p < .01) in the induced indulgence condition (M= 1.66) than the recalled indulgence condition (M= 2.32). This difference suggests that participants felt less proud after indulging than after recalling an indulgence.

To examine whether the emotions affected chips consumption, I included the four self-conscious emotions in the linear regression discussed above as independent variables. The regression results indicated that pride (b = -1.94, t(132) = -2.89, p < .05) had a significant impact on the snacking amount. Participants who had higher pride feelings snacked less. To examine whether the feelings served as mediators to affect the chips consumption, I used Hayes' model in PROCESS macro (Hayes, 2013). However, mediation analysis showed that pride did not mediate the effect of the indulgence experience on consumption. The other three self-conscious emotions – guilt, embarrassment and shame – did not vary among conditions.

Discussion

Study 4 showed the differential effects of recalling a recent indulgence experience and having an induced indulgence on subsequent consumption. The results showed that abstainers respond quite differently to an induced indulgence than to a recalled indulgence. An abstainer ate significantly less following an induced indulgence versus a recalled indulgence, suggesting that they compensated for the indulgence. In contrast, the snacking amount of moderators did not significantly vary between the two indulgence conditions. These findings suggest that the impact of a recalled indulgence experience is not as powerful as just-happened indulgence for abstainers. Abstainers adjust their current eating behavior shortly after they have just had an indulgence. Moderators, as showed in the previous studies, are capable of dealing with indulgences. Moderators may have adapted to having indulgences once a while, and thus they tend not to binge after either recalling or experiencing an indulgence.

Conclusion and General Discussion

In this research I showed that dieters are not all the same. First, I developed a new measurement scale to identify moderators versus abstainers, and I provided evidence for the measure's reliability and convergent, discriminant, and nomological validity. The findings of studies 1-2 suggest that the scale effectively distinguishes moderators from abstainers

My findings suggest that dieters are better off following the approach that they believe will work best for them. Dieters seem to have identified what works best for them, and are most comfortable thinking about eating in ways consistent with their self-theories: moderators are better off with moderation diets, and abstainers are better off with abstaining diets. I also showed that the two groups of dieters deal with different forms of indulgences in different ways. When recalling an indulgence, both moderators and abstainers exhibit a self-fulfilling prophecy: abstainers eat more than moderators after recalling an indulgence, whereas moderators eat more than abstainers after recalling abstinence. Finally I showed that abstainers are better than they expect at recovering from lapses. When they experience an induced indulgence, abstainers better compensate than moderators by down-regulating their subsequent consumption. Abstainers ate significantly less after an induced indulgence than after a recalled indulgence experience. By comparison, the different forms of indulgence did not have differing effects on moderators' subsequent consumption, suggesting that they can easily handle any form of indulgence without affecting their dieting.

Taken together, my findings suggest that eating recommendations are not one-size-fits-all, but that individuals develop coping strategies consistent with their own self-theories, and that these strategies enable them to pursue their goals in the face of temptation. As such, my findings have the potential to help marketers identify appropriate segments. For example, dieting apps such as MyFitnessPal and Weight Watchers may differentiate abstainers and moderators so they can offer different plans for the two groups of dieters. Likewise, diet meal delivery services such as bistroMD, Fresh N' Lean, and Diet-to-Go could incorporate items from the moderation tendency scale in their sign-up questionnaires (e.g., similar to Stich Fix's detailed Style Quiz) to provide customized plans and services. Alternatively, they could evaluate prospective customers' dieting styles based on their Facebook, Instagram, or other social network profiles and posted content, and their tailor diet plans accordingly.

My results also provide insights for positioning and developing brands or product lines that explicitly target moderators or abstainers. For example, the Oikos Triple Zero yogurt is likely targeting abstainers, thus was designed to have zero fat, zero added sugar, and zero artificial sweeteners. In contrast, Target's store brand Simply Balanced provides a collection of food products with healthy ingredients and emphasizes the balance between healthy intentions and pursuit of tastiness. This product would be more likely to attract moderators. However, there have also been several failures of products that were designed for moderators, such as Coke Life, Coke C2, Pepsi Edge, Pepsi Next (which all contained "half and half" combinations of sugar and artificial sweeteners). Part of their failure may be due to their misunderstanding of moderators, who are not looking for products that simply cut calories in half, but desire products that provide occasional hedonic indulgences.

Implications for Food Well-Being

My findings suggest that abstainers and moderators will respond differently to government efforts such as public service announcements (PSAs) and tax codes aimed at solving obesity. For example, a PSA that urges consumers to "eat less and move more" may work for moderators, but is unlikely to work and may even backfire for abstainers, who need a more structured approach to eating. Moreover, "sin taxes" on unhealthy foods, such as the soda tax in Chicago (Marotti et al. 2017) and proposed bacon tax in Australia (McDonough 2017), may backfire among certain consumers (e.g. Pham et al. 2016; Stewart and Martin 1994) and particularly among moderators, who feel that they should be allowed to eat anything in moderation, and that they can successfully compensate for one indulgence by eating less of something else. Recent research on control deprivation also supports the notion that when people feel deprived of control, they may compensate by re-exerting control via consumption (Chen, Lee and Yap 2016), in this case via overeating. By recognizing that different consumers control their eating through different strategies, i.e., some by abstaining and some by moderating, I can develop customized healthy eating interventions and policy strategies to prevent and reduce obesity while enhancing food well-being.

CHAPTER 5

CONCLUSION AND DISCUSSION

Nutritional outcomes at the individual level are the result of a complex interplay of informational cues, marketing strategies, and behavioral patterns. This dissertation makes a substantial contribution to the literatures on nutrition labeling, nutrient demand, and healthy eating by studying these three mechanisms that underlie food choice. I use multiple methodologies, including an eye-tracking experiment, econometric modeling, and a series of behavior experiments to illustrate how consumers react to nutrition labels, new food products with fundamental differing nutritional attributes, and food indulgences. My dissertation illustrates the importance of individual differences that lead to various and even opposite responses to the nutrition contents of food products, marketing mix elements, and temptations in their daily dietary behaviors.

The FDA believes that a new, enhanced Nutrition Facts Panel can help consumers make better-informed food-purchasing decisions. In my first essay, I conduct an experiment using eye-tracking technology to determine whether the new NPD label helps consumers gather the correct information, and whether it works for all consumers in similar ways. The results from my first essay suggest that the modified Nutrition Facts label may help low-involvement or less-familiar consumers to pay more attention to the Nutrition Facts label, while helping high-involvement or more-familiar consumers save time looking for critical nutritional information. Although the descriptive statistics show no significant shifts in consumers' attention with the modified Nutrition Facts label, my findings suggest that the effect of the modified label can actually be broken down into two, directionally-opposing effects on high- and low- involvement consumers. Namely, I find that involvement moderate the effect of label format on consumers' attention. As consumers become more health conscious and more involved with their food-consumption choices, important individual factors such as involvement and familiarity need to be considered more carefully in studying consumers' attention during food purchases.

In my second essay, I consider the effect of marketing strategies on consumers' nutritional outcomes, and take advantage of a unique, transformational product introduction to help test my hypotheses. In this essay, I demonstrate that consumers' sensitivity to different marketing-mix elements – prices, price-promotion, product-displays, and features – vary according to their nutrient preferences. That is, consumers tend to be most sensitive to featuring when they prefer high-protein or other "healthy" nutritional characteristics such as low-fat or low-carbohydrate, whereas display and promotion are more effective in promoting products that are more "tasty," and are more likely to be rather more "unhealthy". My findings provide insights that can help food manufacturers change the nature of the products consumers' buy, without necessarily resorting to costly new product reformulations. By choosing the appropriate marketing-mix to promote products with "healthy" or "tasty but not so healthy" nutritional characteristics, food manufacturers may be able to nudge consumers into making more healthy food choices.

The third essay argues that dieters are not all the same. Some dieters tend to stay strictly on their diet while others prefer to moderate their diet with occasional indulgence. Building on implicit self-theories, I develop and validate a new scale that measures implicit self-theories about abstinence vs. moderation. My findings from a series of experiments indicate that how dieters' reactions to recalled vs. actual indulgences are different for those who believe it is best to abstain consistently or it is best to indulge in occasional goal-inconsistent behavior, but that compensatory coping strategies provide paths for people with both implicit self-theories to recover after an indulgence, in their own ways.

This dissertation is not without limitations. First, with regard to the first essay, consumers' attention to different labels may vary as the consumers may have different goals and tasks (van Herpen and Trijp 2011; Rik Pieters and Warlop 1999). Different goals may be manipulated in future research to test whether the modified label has a consistent effect across different goals. Future research could also investigate the impact of the modified label under more constraint conditions (e.g., time constraint). In addition, an extension of the present research could go beyond attention and focus on consumers' food choices.

Future research should also expand the idea of nutrient demand in other nutrient dimensions. As nutrients such as potassium, vitamin D, and added sugar receive growing public attention, the modified the Nutrition Facts panel added information of these nutrients to the panel. In addition, it may be of interest to explore how information regarding positive versus negative nutrients can have different impact on demand, especially when emphasized in an advertisement

This research focused specifically on the food domain, but it is possible that my findings may generalize to other domains. Future research may consider looking at other domains such as exercising and rest, study and procrastination, saving money and luxury product consumption, which are topics that relate to goal-inconsistent behaviors and people's different beliefs regarding these behaviors. In all of these domains, people who have goals that require exerting some extent of self-regulation, effort, or energy to achieve their goals, yet also have to occasionally satisfy their hedonic needs, might be considered moderators. In each domain, there are likely to always be some abstainers who advocate consistent effort. Furthermore, the same people may be moderators in some domains and abstainers in other domains. Future research should further explore whether and how consumers can better enjoy indulgences, and help different types of people improve their general well-being in multiple self-control domains.

In addition, there is the question of how being a moderator or abstainer affects food well-being. Study 1 suggests that, relative to moderators, abstainers have lost more weight and have lower BMI, but are less comfortable with indulgences. Further research is needed to investigate whether lowering BMI or enjoying indulgent foods is weighed more heavily in food well-being for individuals in each group.

However, a dark side of occasional indulgence is that it may result in a higher overall level of calorie intake. That is, eating the cupcake did not make participants pass up the chips, and thus they had a net gain of calories (the cupcake plus the chips). Looking solely at this criterion, the findings of study 4, suggest that no one should indulge, because eating the cupcake led to higher calorie consumption overall. The difference in chips consumed, i.e., recalled indulgence – induced indulgence, was 23g-17g=6g. Six grams of chips contain about 32 calories, while a small cupcake contains 131 calories, (according to Google), so for participants who ate more than a quarter (32/131) of the cupcake, eating it led to an increased total calories consumed. This is consistent with my reported descriptive statistics suggesting that abstainers seem to be generally more successful dieters than moderators. This finding does not, however, mean that they have greater food well-being. As long as moderators feel that they have satisfied their hedonic cravings, then indulgences may still be helpful. Indeed, consistent with the philosophy of moderators, Cornil and Chandon (2016) find that if people focus on the pleasure of eating a hedonic food, they will eat less of it.

Further research is also needed to acquire additional insight into individuals' expectations for their own behavior. My descriptive data provide self-reports that abstainers think they fall off the wagon whenever they consume indulgent foods, but in Study 4, after eating cupcake, they ate only half of a small bag of chips. While it is clear that this is not a binge, further research is needed to see how this compares to their expectations and how it affects food well-being.

Finally, my studies only focused on dieters. I specifically focused on people who had explicit dieting goals and thus likely had some extent of weight and body image issues. In particular, the dieters that I recruited from online discussion boards and mTurk in studies 1-2 had higher average BMI than the student dieter samples in study 3 and 4. Even though the results were consistent across my studies, I cannot conclude that they also apply to people who are not dieters or people who merely want to eat healthy in general. In fact, it seems likely that many of the doctors, nutritionists and public policy makers who widely advocate for moderation strategies (such as eating less and moving more) or abstinence strategies (such as avoiding all sweets) have never been overweight themselves. Future research may extend my work by comparing dieters' and non-dieters' approaches to moderation versus abstinence strategies.

REFERENCES

Abadie, Alberto. 2005. “Semiparametric Difference-in-Differences Estimators.” *Review of Economic Studies* 72 (1):1–19.

Adelaja, Adesoji O, Rodolfo M Nayga, and Tara C Lauderbach. 1997. “Income and Racial Differentials in Selected Nutrient Intakes.” *American Journal of Agricultural Economics* 79 (5):1452–60.

Ainslie, a., and P. E. Rossi. 1998. “Similarities in Choice Behavior Across Product Categories.” *Marketing Science* 17 (February 2015):91–106.

Akin, John S., David K. Guilkey, and Barry M Popkin. 1983. “The School Lunch Program and Nutrient Intake: A Switching Regression Analysis.” *American Journal of Agricultural Economics* 65 (3):477–85.

Alba, Joseph W., and J. Wesley Hutchinson. 1987. “Dimensions of Consumer Expertise.” *Journal of Consumer Research* 13 (4):411.

Alcock, Joe, Carlo C. Maley, and Aktipis, C. Athena 2014. “Is eating behavior manipulated by the gastrointestinal microbiota? Evolutionary pressures and potential mechanisms.” *Bioessays,* 36(10), 940-949.

Anderson, John R. 2005. *Cognitive Psychology and Its Implications*. Worth Publishers.

Angrist, Joshua D, and Alan B Krueger. 1999. “Empirical Strategies in Labor Economics.” *Handbook of Labor Economics* 3:1277–1357.

Austin, Peter C. 2011. “An Introduction to Propensity Score Methods for Reducing the Effects of Confounding in Observational Studies.” *Multivariate Behavioral Research* 46 (3):399–424.

Appleton, Katherine M., Pascal P. McKeown , and Jayne V. Woodside 2015. “Energy compensation in the real world: Good compensation for small portions of chocolate and biscuits over short time periods in complicit consumers using commercially available foods.” *Appetite*, 85, 104-110.

Balasubramanian, S. K., and C. A. 2002. Cole. 2002. “Consumers ’ Search and Use of Nutrition Information : The Challenge Promise of the Nutrition and Labeling and Education Act” 66 (3):112–27.

Barreiro-Hurlé, J., S. Colombo, and E. Cantos-Villar. 2008. “Is There a Market for

Functional Wines? Consumer Preferences and Willingness to Pay for Resveratrol-Enriched Red Wine." *Food Quality and Preference* 19 (4):360–71.

Basiotis, Peter, Mark Brown, S R Johnson, and Karen J Morgan. 1983. "Nutrient Availability, Food Costs, and Food Stamps." *American Journal of Agricultural Economics* 65 (4):685–93.

Becker, Gary S., and Kevin M. Murphy. 1988. "A Theory of Rational Addiction." *Journal of Political Economy* 96 (4):675–700.

Becker, Sascha O, and Marco Caliendo. 2007. "Sensitivity Analysis for Average Treatment Effects." *The Stata Journal* 7 (1):71–83.

Benton, David, and Hayley A. Young 2017. "Reducing Calorie Intake May Not Help You Lose Body Weight." *Perspectives on Psychological Science*, June. SAGE Publications, 1745691617690878, 1-12.

Berry, Steve, Oliver B. Linton, and Ariel Pakes. 2004. "Limit Theorems for Estimating the Parameters of Differentiated Product Demand Systems." *Review of Economic Studies* 71 (3):613–54.

Berry, Steven, James Levinsohn, and Ariel Pakes. 1995. "Automobile Prices in Market Equilibrium." *Econometrica* 63 (4):841.

Berry, Steven T. 1994. "Estimating Discrete Choice Models of Product Differentiation." *The RAND Journal of Economics*.

Bhasin, Kim. 2012. "How Chobani Became A $750 Million Business In Only Five Years." 2012.

Bhat, Chandra R. 2003. "Simulation Estimation of Mixed Discrete Choice Models Using Randomized and Scrambled Halton Sequences." *Transportation Research Part B: Methodological* 37 (9):837–55.

Bialkova, Svetlana, and Hans van Trijp. 2010. "What Determines Consumer Attention to Nutrition Labels?" *Food Quality and Preference* 21 (8). Elsevier Ltd:1042–51.

Bimbo, Francesco, Alessandro Bonanno, and Rosaria Viscecchia. 2016. "Do Health Claims Add Value? The Role of Functionality, Effectiveness and Brand." *European Review of Agricultural Economics* 43 (5):761–80.

Blattberg, Robert C., Richard Briesch, and Edward J. Fox. 1995. "How Promotions

Work." *Marketing Science*.

Block, Lauren, Sonya Grier, Terry Childers, Brennan Davis, Jane Ebert, Shiriki Kumanyika, Russ Laczniak, Jane Machin, Carol Motley, Laura Peracchio, Simone Pettigrew, Maura L. Scott, and Mirjam van Ginkel Bieshaar (2011), "From Nutrients to Nurturance: A Conceptual Introduction to Food Well-Being," *Journal of Public Policy & Marketing*, 30 (1), 5-13.

Bonander, Ross. 2007. "5 Things You Didn't Know: Starbucks." Bspcn.com. 2007.

Bonanno, Alessandro. 2013. "Functional Foods as Differentiated Products: The Italian Yogurt Market." *European Review of Agricultural Economics* 40 (1):45–71.

Bratman, S., & Knight, D. 2000. *Health food junkies: Overcoming the obsession with healthful eating.* New York: Broadway Books.

Brodesser-Akner, Taffy 2017, "Losing It in the Anti-Dieting Age," *New York Times,* August 2. [available at https://www.nytimes.com/2017/08/02/magazine/weight-watchers-oprah-losing-it-in-the-anti-dieting-age.html?mcubz=1]

Bronnenberg, B. J., M. W. Kruger, and C. F. Mela. 2008. "Database Paper--The IRI Marketing Data Set." *Marketing Science* 27 (4):745–48.

Bucklin, Re, Sunil Gupta, and S Siddarth. 1998. "Modelling the Effect of Purchase Quantity on Consumer Choice of Product Assortment." *Journal of Forecasting* 301:281–301.

Burton, Scot, Abhijit Biswas, and Richard Netemeyer. 1994. "Effects of Alternative Nutrition Label Formats and Nutrition Reference Information on Consumer Perceptions, Comprehension, and Product Evaluations." *Journal of Public Policy & Marketing* 13 (1):36–47.

Burden, Anne, Nicolas Roche, Cristiana Miglio, Elizabeth V Hillyer, Dirkje S Postma, Ron Mc Herings, Jetty A Overbeek, Javaria Mona Khalid, Daniela van Eickels, and David B Price. 2017. "An Evaluation of Exact Matching and Propensity Score Methods as Applied in a Comparative Effectiveness Study of Inhaled Corticosteroids in Asthma." *Pragmatic and Observational Research* 8. Dove Press:15–30.

Burton, Scot, Abhijit Biswas, and Richard Netemeyer. 1994. "Effects of Alternative Nutrition Label Formats and Nutrition Reference Information on Consumer Perceptions, Comprehension, and Product Evaluations." *Journal of Public Policy &*

Marketing 13 (1):36–47.

Busse, Meghan, Jorge Silva-Risso, and Florian Zettelmeyer. 2006. "$1,000 Cash Back: The Pass-through of Auto Manufacturer Promotions." *American Economic Review* 96 (4):1253–70.

Cacioppo, JT, and RE Petty. 1986. "Central and Peripheral Routes to Persuasion: An Individual Difference Perspective." *Journal of Personality …* 51 (5):1032–43.

Camacho, Salvador, and Andreas Ruppel 2017. "Is the calorie concept a real solution to the obesity epidemic?." *Global Health Action*, 10(1), 1-12.

Canada, Health, Independent Consultant, Consulting Services, and Nutrition Policy. 2009. "Defining ' Healthy ' and " Unhealthy Foods : An International Review."

Cawley, John Horan. 1999. *Rational Addiction, the Consumption of Calories, and Body Weight*. University of Chicago, Department of Economics.

Carroll 2002, "The Government's Food Pyramid Correlates to Obesity, Critics Say," *Wall Street Journal,* June 13. [available at https://www.wsj.com/articles/SB1023915818486451160]

CDC Report. 2013. "Progress on Childhood Obesity." *Prevention, Disease Promotion, Health Nutrition, Division Activity, Physical*, no. August:1–4.

Celsi, RL, and JC Olson. 1988. "The Role of Involvement in Attention and Comprehension Processes." *Journal of Consumer Research* 15 (2):210–24.

Chaiken, Shelly. 1980. "Heuristic versus Systematic Information Processing and the Use of Source versus Message Cues in Persuasion." *Journal of Personality and Social Psychology* 39 (5):752–66.

Chandon, Pierre, and Brian Wansink 2007. "The Biasing Health Halos of Fast-Food Restaurant Health Claims: Lower Calorie Estimates and Higher Side-Dish Consumption Intentions." *Journal of Consumer Research* 34 (October): 301–14.

Chandon, Pierre, and Brian Wansink. 2012. "Does Food Marketing Need to Make Us Fat? A Review and Solutions." *Nutrition Reviews* 70 (10):571–93.

Chen, Charlene Y., Leonard Lee, and Andy J. Yap 2016. "Control Deprivation Motivates Acquisition of Utilitarian Products." *Journal of Consumer Research* 43(6), 1031-1047.

Christianson, S A, E F Loftus, H Hoffman, and G R Loftus. 1991. "Eye Fixations and Memory for Emotional Events." *Journal of Experimental Psychology. Learning, Memory, and Cognition* 17:693–701.

Christie, J, and R Klein. 1995. "Familiarity and Attention: Does What We Know Affect What We Notice?" *Memory & Cognition* 23 (5):547–50.

Cochran, Winona, and Abraham Tesser 1996 "The 'what the hell'effect: Some effects of goal proximity and goal framing on performance." *Striving and feeling: Interactions among goals, affect, and self-regulation* : 99-120.

Cole, Catherine A, and Siva K Balasubramanian. 1993. "Age Differences in Consumers' Search for Information: Public Policy Implications." *Journal of Consumer Research* 20 (1). University of Chicago Press:157–69.

Cornil, Yann, and Pierre Chandon 2016 "Pleasure as a Substitute for Size: How Multisensory Imagery Can Make People Happier with Smaller Food Portions." *Journal of Marketing Research*, 53(5), 847-864.

Cowburn, Gill, and Lynn Stockley. 2005. "Consumer Understanding and Use of Nutrition Labelling: A Systematic Review." *Public Health Nutrition* 8 (1):21–28.

Cronbach, Lee J. and Paul Meehl (1955), "Construct Validity in Psychological Tests," *Psychological Bulletin,* 56 (March), 81–105.

Cutright, Keisha M, and Adriana Samper 2014. "Doing It the Hard Way: How Low Control Drives Preferences for High-Effort Products and Services." *Journal of Consumer Research* 41 (3): 730–45.

Czyzewska, Maria, and Reiko Graham. 2008. "Implicit and Explicit Attitudes to High- and Low-Calorie Food in Females with Different BMI Status." *Eating Behaviors* 9:303–12.

Dalle Molle, Roberta, Hajar Fatemi, Alain Dagher, Robert D. Levitan, Patricia P. Silveira, and Laurette Dubé 2017, "Gene and environment interaction: Is the differential susceptibility hypothesis relevant for obesity?" *Neuroscience & Biobehavioral Reviews,* 73, 326-339.

Darmon, Nicole, and Adam Drewnowski. 2015. "Contribution of Food Prices and Diet Cost to Socioeconomic Disparities in Diet Quality and Health : A Systematic Review and Analysis." *Nutrition Reviews* 73 (January):643–60.

Dekimpe, M. G., and D. M. Hanssens. 1995. “The Persistence of Marketing Effects on Sales.” *Marketing Science* 14 (1):1–21.

Deubel, H., and W. X. Schneider. 1993. “There Is No Expressway to a Comprehensive Theory of the Coordination of Vision, Eye Movements and Visual Attention.” *Behavioral and Brain Sciences* 16 (3). Cambridge University Press:575–76.

Devaney, Barbara, and Thomas Fraker. 1989. “The Dietary Impacts of the School Breakfast Program.” *American Journal of Agricultural Economics* 71:932.

Devaney, Barbara, and Robert Moffitt. 1991. “Dietary Effects of the Food Stamp Program.” *American Journal of Agricultural Economics* 73 (1):202–11.

Dickson, Peter R., and Alan G. Sawyer. 1990. “The Price Knowledge and Search of Supermarket Shoppers.” *Journal of Marketing* 54 (3):42.

DiPrete, Thomas, and Markus Gangl. 2004. “Assessing Bias in the Estimation of Causal Effects.” *Sociological Methodology* 34 (1):271–310.

Dhar, Ravi, Joel Huber, and Uzma Khan (*2007*) “The Shopping Momentum Effect.” *Journal of Marketing Research*, 44 (3), 370-378.

do Vale, Rita Coelho, Rik Pieters, and Marcel Zeelenberg 2016. “The benefits of behaving badly on occasion: Successful regulation by planned hedonic deviations.”*Journal of Consumer Psychology*, 26(1), 17-28.

Douglas, Steve M., Laura C. Ortinau, Heather A. Hoertel, and Heather J. Leidy. 2013. “Low, Moderate, or High Protein Yogurt Snacks on Appetite Control and Subsequent Eating in Healthy Women.” *Appetite* 60:117–22.

Draganska, Michaela, and Daniel Klapper. 2007. “Retail Environment and Manufacturer Competitive Intensity.” *Journal of Retailing* 83 (2):183–98.

Drichoutis, Andreas C., Panagiotis Lazaridis, and Rodolfo M. Nayga Jr. 2007. “An Assessment of Product Class Involvement in Food-Purchasing Behavior.” *European Journal of Marketing* 41 (7/8):888–914.

Drichoutis, Andreas C., Panagiotis Lazaridis, and Rodolfo M., Jr. Nayga. 2006. “Food Involvement and Food Purchasing Behaviour.” *98th Seminar, June 29-July 2, 2006, Chania, Crete, Greece*. European Association of Agricultural Economists.

Drichoutis, Andreas C., Panagiotis Lazaridis, Rodolfo M. Nayga, Maria Kapsokefalou, and George Chryssochoidis. 2008. "A Theoretical and Empirical Investigation of Nutritional Label Use." *European Journal of Health Economics* 9:293–304.

Dubé, Laurette (2010). *Obesity prevention: the role of brain and society on individual behavior.* Academic Press.

Dweck, Carol S. 1999. *Self-theories: Their role in motivation, personality, and development. Essays in Social Psychology*.

Durisin, Megan. 2013. "The Success Story of Chobani Yogurt - Business Insider." 2013.

Erdem, Tülin, Michael P. Keane, and Baohong Sun. 2008. "Relating Price Sensitivity to Retailer Promotional Variables and Pricing Policy: An Empirical Analysis." *Quantitative Marketing and Economics* 6 (2):139–76.

Falbe, Jennifer, Nadia Rojas, Anna H. Grummon, and Kristine A. Madsen. 2015. "Higher Retail Prices of Sugar-Sweetened Beverages 3 Months after Implementation of an Excise Tax in Berkeley, California." *American Journal of Public Health* 105 (11):2194–2201.

Falbe, Jennifer, Hannah R. Thompson, Christina M. Becker, Nadia Rojas, Charles E. McCulloch, and Kristine A. Madsen. 2016. "Impact of the Berkeley Excise Tax on Sugar-Sweetened Beverage Consumption." *American Journal of Public Health* 106 (10):1865–71.

FDA. 2014. "Federal Register" 79 (41).

Festinger, Leon and James M. Carlsmith 1959. "Cognitive consequences of forced compliance." *The Journal of Abnormal and Social Psychology*, *58*(2), 203.

Fishbach, Ayelet, and Ravi Dhar 2005. "Goals as Excuses or Guides: The Liberating Effect of Perceived Goal Progress on Choice." *Journal of Consumer Research*, *32*(3), 370–377.

Fishbach, Ayelet, Rebecca K.Ratner, and Ying Zhang 2011. "Inherently loyal or easily bored?: Nonconscious activation of consistency versus variety-seeking behavior." *Journal of Consumer Psychology*, *21*(1), 38–48.

Folkes, Valerie, and Shashi Matta. 2004. “The Effect of Package Shape on Consumers’ Judgments of Product Volume: Attention as a Mental Contaminant.” *Journal of Consumer Research* 31 (2). The University of Chicago Press:390–401.

Fousekis, Panos, and Panagiotis Lazaridis. 2005. “The Demand for Selected Nutrients by Greek Households: An Empirical Analysis with Quantile Regressions.” *Agricultural Economics* 32 (3):267–79.

Gendall, Kelly A., Peter R. Joyce, Patrick F. Sullivan, and Cynthia M. Bulik. 1998. “Food Cravers: Characteristics of Those Who Binge.” *International Journal of Eating Disorders* 23:353–60.

Gensler, Sonja, Peter Leeflang, and Bernd Skiera. 2012. “Impact of Online Channel Use on Customer Revenues and Costs to Serve: Considering Product Portfolios and Self-Selection.” *International Journal of Research in Marketing* 29 (2):192–201.

Girma, Sourafel, and Holger Gorg. 2007. “Multinationals’ Productivity Advantage: Scale or Technology?” *Economic Inquiry* 45 (2):350–62.

Glaser, Gabrielle 2015, “The Irrationality of Alcoholics Anonymous,” *Atlantic,* April. [available at https://www.theatlantic.com/magazine/archive/2015/04/the-irrationality-of-alcoholics-anonymous/386255/]

Goldberg, Joseph H., Claudia K. Probart, and Robert E. Zak. 1999. “Visual Search of Food Nutrition Labels.” *Human Factors: The Journal of the Human Factors and Ergonomics Society* 41 (3):425–37.

Goldsmith, Kelly, Eunice Kim Cho, and Ravi Dhar 2012, “When Guilt Begets Pleasure: The Positive Effect of a Negative Emotion.” *Journal of Marketing Research*: 49(6), 872-881.

Graham, Dan J, and Robert W Jeffery. 2011. “Location, Location, Location: Eye-Tracking Evidence That Consumers Preferentially View Prominently Positioned Nutrition Information.” *Journal of the American Dietetic Association* 111 (11). Elsevier Inc.:1704–11.

Graham, Dan J., Jacob L. Orquin, and Vivianne H.M. Visschers. 2012. “Eye Tracking and Nutrition Label Use: A Review of the Literature and Recommendations for Label Enhancement.” *Food Policy* 37 (4). Elsevier Ltd:378–82.

Greene, William H. 2003. *Econometric Analysis*. *Journal of the American Statistical Association*. Vol. 97.

Gregersen, NikolajT, BenteK Møller, Anne Raben, SørenT Kristensen, Lotte Holm, Anne Flint, and Arne Astrup. "Determinants of appetite ratings: the role of age, gender, BMI, physical activity, smoking habits, and diet/weight concern." *Food & nutrition research* 55, no. 1 (2011): 7028.

Gretchen, Rubin 2001, The Happiness Project: Or, Why I Spent a Year Trying to Sing in the Morning, Clean My Closets, Fight Right, Read Aristotle, and Generally Have More Fun. New York: HarperCollins

——— 2012, "Back by Popular Demand: Are You an Abstainer or a Moderator?" October 10. [available at https://gretchenrubin.com/2012/10/back-by-popular-demand-are-you-an-abstainer-or-a-moderator/]

Griffin, Abbie, and Albert L. Page. 1993. "An Interim Report on Measuring Product Development Success and Failure." *Journal of Product Innovation Management* 10 (4):291–308.

Griffith, Rachel, Martin O'Connell, and Kate Smith. 2017. "The Importance of Product Reformulation Versus Consumer Choice in Improving Diet Quality." *Economica* 84 (333):34–53.

Grunert, Klaus G. 2008. "Pan-European Consumer Research on in-Store Observation, Understanding and Use of Nutrition Information on Food Labels, Combined with Assessing Nutrition Knowledge." EUFIC Forum, 4. 2008.

Guardian, The 2017, "Why We Fell for Clean Eating," *Guardian,* August 11. [available at https://www.theguardian.com/lifeandstyle/2017/aug/11/why-we-fell-for-clean-eating]

Guo, L. 2010. "Capturing Consumption Flexibility in Assortment Choice from Scanner Panel Data." *Management Science* 56 (10):1815–32.

Guo, Shenyang, and Mark W Fraser. 2010. *Propensity Score Analysis: Statistical Methods and Applications*. *Advanced Quantitative Techniques in the Social Sciences Series*. Vol. 11.

Hales, Craig M, Margaret D Carroll, Cheryl D Fryar, and Cynthia L Ogden. 2017. "Prevalence of Obesity Among Adults and Youth: United States, 2015–2016 Key Findings Data from the National Health and Nutrition Examination Survey." *National Center for Health Statistics* 1 (288):1–8.

Hamilton, Rebecca W., Debora V. Thompson, Zachary G. Arens, Simon J. Blanchard, Gerald Häubl, P. K. Kannan, Uzma Khan, et al. 2014. "Consumer Substitution Decisions: An Integrative Framework." *Marketing Letters* 25 (3):305–17.

Harding, Matthew, and Michael Lovenheim. 2017. "The Effect of Prices on Nutrition: Comparing the Impact of Product- and Nutrient-Specific Taxes." *Journal of Health Economics* 53:53–71.

Harlam, Bari a., and Leonard M. Lodish. 1995. "Modeling Consumers' Choices of Multiple Items." *Journal of Marketing Research* 32:404.

Harmening, Jeff. n.d. "General Mills Report for Fisical Year 2016."

Hausman, JA A. 1978. "Specification Test in Econometrics." *Econometrica* 46 (6):1251–71.

Hayes, AF. 2012. "PROCESS: A Versatile Computational Tool for Observed Variable Mediation, Moderation, and Conditional Process Modeling." *Manuscript Submitted for Publication*, 1–39.

Hayes, Andrew F. 2013, "Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach," Guilford Press.

Henningsen, Arne. 2010. "Estimating Censored Regression Models in R Using the censReg Package." *R Package Vignettes*, no. Mcmc.

Heckman, James J., Robert J. Lalonde, and Jeffrey A. Smith. 1999. "The Economics and Econometrics of Active Labor Market Programs." *Handbook of Labor Economics*.

Henningsen, Arne. 2010. "Estimating Censored Regression Models in R Using the censReg Package." *R Package Vignettes*, no. Mcmc.

Hensher, David a., and William H. Greene. 2003. "The Mixed Logit Model: The State of Practice." *Transportation* 30 (June):133–76.

Herpen, Erica van, and Hans C M Van Trijp. 2011. "Front-of-Pack Nutrition Labels. Their Effect on Attention and Choices When Consumers Have Varying Goals and Time Constraints." *Appetite* 57 (1). Elsevier Ltd:148–60.

Hess, Stephane, and Kenneth Train. 2017. "Correlation and Scale in Mixed Logit Models." *Journal of Choice Modelling* 23. Elsevier Ltd:1–8.

Hester, Reid K., Harold D. Delaney, and William Campbell. 2011. "ModerateDrinking.com and Moderation Management: Outcomes of a Randomized Clinical Trial with Non-Dependent Problem Drinkers." *Journal of Consulting and Clinical Psychology* 79 (2):215–24.

Hester, Reid K., Harold D. Delaney, William Campbell, and Nancy Handmaker. 2009. "A Web Application for Moderation Training: Initial Results of a Randomized Clinical Trial." *Journal of Substance Abuse Treatment* 37 (3):266–76.

Higgins, E. Tory 1989, "Knowledge Accessibility and Activation: Subjectivity and Suffering from Unconscious Sources," *Unintended Thought*, 3, 75-123.

Hill, A J, C F Weaver, and J E Blundell. 1991. "Food Craving, Dietary Restraint and Mood." *Appetite* 17:187–97.

Hoffman, JE. 1998. "Visual Attention and Eye Movements." *Attention*.

Howell, Andrew J. (2016). "Implicit theories of personal and social attributes : Fundamental mindsets for a science of wellbeing." *International Journal of Wellbeing*, *6*, 113–130.

Huang, K.S., B.H. Lin, and United States. Dept. Agriculture. Economic Research Service. 2000. "Estimation of Food Demand and Nutrient Elasticities from Household Survey Data." *Nutrition*.

Huang, Kuo S. 1996. "Nutrient Elasticities in a Complete Food Demand System." *American Journal of Agricultural Economics* 78 (1):21–29.

Huang, Qingyi, Vincent R Nijs, Karsten Hansen, and Eric T Anderson. 2012. “Wal-Mart’s Impact on Supplier Profits.” *Journal of Marketing Research* 49 (2):131–43.

Huber, Joel, Kelly Goldsmith, and Cassie Mogilner. "Reinforcement versus balance response in sequential choice." *Marketing letters* 19, no. 3-4 (2008): 229.

Iacobucci, Dawn, Steven S. Posavac, Frank R. Kardes, Matthew J. Schneider, and Deidre L. Popovich. 2015a. “The Median Split: Robust, Refined, and Revived.” *Journal of Consumer Psychology* 25 (4):690–704.

———. 2015b. “Toward a More Nuanced Understanding of the Statistical Properties of a Median Split.” *Journal of Consumer Psychology* 25 (4):652–65.

Jacoby, Jacob, and Robert W Chestnut. 1977. “Consumer Nutrition Use and of Comprehension Information.” *Journal of Consumer Research* 4 (2):119–28.

Jensen, Jørgen Dejgård, and Sinne Smed. 2013. “The Danish Tax on Saturated Fat - Short Run Effects on Consumption, Substitution Patterns and Consumer Prices of Fats.” *Food Policy* 42:18–31.

Job, Veronika, Carol S Dweck, and Gregory M Walton 2010. “Ego depletion--is it all in your head? implicit theories about willpower affect self-regulation.” *Psychological Science : A Journal of the American Psychological Society / APS*, *21*(September), 1686–1693.

Kahneman, Daniel. 1973. “Attention and Effort.” *The American Journal of Psychology* 88 (2):339.

Kaiser, Henry F. 1974. An index of factorial simplicity. *Psychometrika*, *39*(1), 31–36.

Kekre, S., and K. Srinivasan. 1990. “Broader Product Line: A Necessity to Achieve Success?” *Management Science* 36 (Bitran 1988):1216–32.

Kell, John. 2017a. “General Mills Loses the Culture Wars The Company ’ S Yoplait Yogurt Brand Has Foundered , Falling behind Chobani — That ’ S Only One

Problem for the Packaged Food Giant . Can a New CEO Calm the Waters ?,” 2017.

———. 2017b. “Greek Yogurt Maker Chobani Is Going Traditional For The First Time.” Furtune. 2017.

Kemp, Elyris, My Bui, and Sonya Grier 2012, “When food is more than nutrition: Understanding emotional eating and overconsumption.” *Journal of Consumer Behaviour,* 12(3), 204–13.

Kessels, Loes T E, and Robert a C Ruiter. 2012. “Eye Movement Responses to Health Messages on Cigarette Packages.” *BMC Public Health* 12 (January):352.

Khan, Uzma, and Ravi Dhar. (2006) "Licensing effect in consumer choice." *Journal of marketing research* 43, no. 2, 259-266.

Kim, Jaehwan, Greg M. Allenby, and Peter E. Rossi. 2002. “Modeling Consumer Demand for Variety.” *Marketing Science* 21 (3):229–50.

Kivetz, Ran, and Yuhuang Zheng. 2017. “The Effects of Promotions on Hedonic versus Utilitarian Purchases.” *Journal of Consumer Psychology* 27 (1). Society for Consumer Psychology:59–68.

Kline, Rex B. 2011. Principles and practice of structural equation modeling. New York: Guilford Press. Teo, T. S. H.,

Kruglanski, Arie W., James Y. Shah, Ayelet Fishbach, Ron Friedman, Woo Young Chun, and David Sleeth-Keppler 2002. “A theory of goal systems.” *Advances in Experimental Social Psychology*, *Volume 34*, 331–378. New York: Academic Press.

Krugman, Herbert E. 1965. “A Comparison of Physical and Verbal Responses to Television Commercials.” *The Public Opinion Quarterly* 29 (2):323–25.

Kumar, Ashish, Ram Bezawada, Rishika Rishika, Ramkumar Janakiraman, and P.K. Kannan. 2016. “From Social to Sale: The Effects of Firm-Generated Content in Social Media on Customer Behavior.” *Journal of Marketing* 80 (1):7–25.

Kumar, V, and Robert P. Leone. 1988. “Measuring the Effect of Retail Store Promotions on Brand and Store Substitution.” *Journal of Marketing Research* 25:178–85.

Lancaster, Kelvin J. 1966. “A New Approach to Consumer Theory.” *Journal of Political Economy* 74 (2):132–57.

Lando, Amy M, and Serena C Lo. 2013. “Single-Larger-Portion-Size and Dual-Column Nutrition Labeling May Help Consumers Make More Healthful Food Choices.” *Journal of the Academy of Nutrition and Dietetics* 113 (2):241–50.

Larned, Victoria. 2018. “Obesity among All US Adults Reaches All-Time High.” CNN. 2018.

Lando, Amy M, and Serena C Lo. 2013. “Single-Larger-Portion-Size and Dual-Column Nutrition Labeling May Help Consumers Make More Healthful Food Choices.” *Journal of the Academy of Nutrition and Dietetics* 113 (2):241–50.

Lastovicka, John L., Lance A. Bettencourt, Renee Shaw Hughner, and Ronald J. Kuntze (1999). "Lifestyle of the tight and frugal: Theory and measurement." *Journal of Consumer Research* 26(1), 85-98.

Leeflang, Peter S.H., and W.Fred van Raaij. 1995. “The Changing Consumer in the European Union: A ‘meta-Analysis.’” *International Journal of Research in Marketing* 12 (1995):373–87.

Leidy, Heather J, Nadine S Carnell, Richard D Mattes, and Wayne W Campbell. 2007. “Higher Protein Intake Preserves Lean Mass and Satiety with Weight Loss in Pre-Obese and Obese Women.” *Obesity (Silver Spring, Md.)* 15 (2):421–29.

Leung, Pingsun, and Walter Miklius. 1997. “Demand for Nutrition vs. Demand for Tastes.” *Applied Economics Letters* 4 (5):291–95.

Liu, Qiang;, T. J. Steenburgh, and Sachin Gupta. 2015. “The Cross Attributes Flexible Substitution Logit : Uncovering Category Expansion and Share Impacts of Marketing Instruments.” *Marketing Science* 34 (January):144–59.

Mandel, Naomi, Maura L. Scott, Sunghoon Kim, and Rajiv K. Sinha 2017. "Strategies for improving self-control among naïve, sophisticated, and time-consistent consumers." *Journal of Economic Psychology* 109-125.

———, Derek D. Rucker, Jonathan Levav, and Adam D. Galinsky (2017). “The Compensatory Consumer Behavior Model: How self-discrepancies drive consumer behavior.” *Journal of Consumer Psychology*, 27(1), 133–146.

Marotti, Ally, Grace Wong, and Greg Trotter 2017, “Soda tax rollout leaves Chicago-area shoppers grumbling, confused,” *Chicago Tribune,* August 3.

Markosyan, Armenak, Jill J. McCluskey, and Thomas I. Wahl. 2009. “Consumer Response to Information about a Functional Food Product: Apples Enriched with Antioxidants.” *Canadian Journal of Agricultural Economics* 57 (3):325–41.

Mason, Charlotte H. 1990. “New Product Entries and Product Class Demand.” *Marketing Science* 9 (1):58–73.

McDonough, Keely 2017, “Bacon Tax Proposal,” *Daily Telegraph,* September 6.

McFerran, Brent, and Anirban Mukhopadhyay 2013. "Lay theories of obesity predict actual body mass." *Psychological Science* 24(8), 1428-1436.

McManus, Freda, and Glenn Waller. 1995. “A Functional Analysis of Binge-Eating.” *Clinical Psychology Review*.

Merritt, Anna C., Daniel A. Effron, and Benoît Monin. "Moral self-licensing: When being good frees us to be bad." *Social and personality psychology compass* 4, no. 5 (2010): 344-357.

Merton, Robert K. 1948. “The Self-Fulfilling Prophecy.” *The Antioch Review*, *8*(2), 193–210.

Meule, Adrian, Esther K. Papies, and Andrea Kübler. 2012. “Differentiating between Successful and Unsuccessful Dieters. Validity and Reliability of the Perceived Self-Regulatory Success in Dieting Scale.” *Appetite* 58 (3):822–26.

Molden, Daniel C. and Carol S. Dweck 2006. "Finding "meaning" in psychology: a lay theories approach to self-regulation, social perception, and social development." *The American Psychologist*, *61*(3), 192–203.

Moore, Latetia V., Courtney A. Pinard, and Amy L. Yaroch. 2016. "Features in Grocery Stores That Motivate Shoppers to Buy Healthier Foods, ConsumerStyles 2014." *Journal of Community Health* 41 (4):812–17.

Moss, By Michael. 2010. "The Hard Sell on Salt." *The New York Times*, 2010.

Mourdoukoutas, Panos. 2011. "How Greek Yogurt Captured The American Market: The Other Half Of The CNBC Story." 2011.

Muraven, Mark, Dianne M. Tice, and Roy F. Baumeister 1998. "Self-control as limited resource: regulatory depletion patterns." *Journal of Personality and Social Psychology*, *74*(3), 774–789.

NASM Blog. "Do Cheat Meals Make Diet Sense? " April 7, 2015.

Nayga, Rodolfo M. 1994. "Effects of Socioeconomic and Demographic Factors on Consumption of Selected Food Nutrients." *Agricultural and Resource Economics Review* 23:171–82.

Nayga, Rodolfo M., Daria Lipinski, and Nitin Savur. 1998. "Consumers' Use of Nutritional Labels While Food Shopping and At Home." *Journal of Consumer Affairs* 32 (1):106–20.

Neslin, Scott A, Caroline Henderson, and John Quelch. 1985. "Consumer Promotions and the Acceleration of Product Purchases." *Marketing Science* 4 (2):147–65.

Neuhouser, M L, A R Kristal, and R E Patterson. 1999. "Use of Food Nutrition Labels Is Associated with Lower Fat Intake." *Journal of the American Dietetic Association* 99:45–53.

Nevo, Aviv. 2000. "Mergers with Differentiated Products: The Case of the Ready-to-Eat Cereal Industry." *The RAND Journal of Economics* 31 (3):395–421.

Neuhouser, M L, A R Kristal, and R E Patterson. 1999. “Use of Food Nutrition Labels Is Associated with Lower Fat Intake.” *Journal of the American Dietetic Association* 99:45–53.

Nijs, Vincent R., Marnik G. Dekimpe, Jan-Benedict E.M. Steenkamps, and Dominique M. Hanssens. 2001. “The Category-Demand Effects of Price Promotions.” *Marketing Science*.

Ogden Cynthia L, Margaret D. Carroll, Brian K. Kit, and Katherine M. Flega 2014. “Prevalence of Childhood and Adult Obesity in the United States, 2011-2012.” *Journal of the American Medical Association,* 311(8), 806-814.

Ogden, Cynthia L, Margaret D Carroll, Brian K Kit, and Katherine M Flegal. 2013. “Prevalence of Obesity among Adults: United States, 2011-2012.” *NCHS Data Brief*, no. 131(October):1–8.

Ogden, Cynthia L., Margaret D. Carroll, Brian K. Kit, and Katherine M. Flegal. 2014. “Prevalence of Childhood and Adult Obesity in the United States, 2011-2012.” *JAMA* 311 (8). American Medical Association:806.

Olson, Jerry C., and Jacob Jacoby. 1972. “Cue Utilization in the Quality Perception Process.” SV - Proceedings of the Third Annual Conference of the Association for Consumer Research, Eds. M. Venkatesan, Chicago, IL : Association for Consumer Research. 1972.

Orquin, J. L., Scholderer, J., & Jeppesen, H. B. 2012. “What You See Is What You Buy: How Saliency and Surface Size of Packaging Elements Affect Attention and Choice.” SABE 2012. 2012.

Papies, Esther K., Wolfgang Stroebe, and Henk Aarts 2008, “Healthy cognition: Processes of self-regulatory success in restrained eating,” *Personality and Social Psychology Bulletin* 34.9, 1290-1300.

Park, Jaehong, and George C Davis. 2001. “The Theory and Econometrics of Health Information in Cross-Sectional Nutrient Demand Analysis.” *American Journal of Agricultural Economics* 83 (4):840–51.

Park, Juyeon, Jung Sug Lee, Young Ai Jang, Hae Rang Chung, and Jeongseon Kim. 2011. “A Comparison of Food and Nutrient Intake between Instant Noodle Consumers and Non-Instant Noodle Consumers in Korean Adults.” *Nutrition*

Research and Practice 5 (5):443–49.

Park, J I Kyung and Deborah Roedder John 2014. "I Think I Can, I Think I Can: Brand Use, Self-Efficacy, and Performance." *Journal of Marketing Research (JMR)*, *51*(April), 233–247.

Park, Sungho, and Sachin Gupta. 2009. "Simulated Maximum Likelihood Estimator for the Random Coefficient Logit Model Using Aggregate Data" Journal of Marketing Research: August 2009, Vol. 46, No. 4, pp. 531-542.

Pashler, Harold E. 1998. *The Psychology of Attention*. MIT Press.

Peter Basiotis, P., S. R. Johnson, Karen J. Morgan, and Jain Shing A Chen. 1987. "Food Stamps, Food Costs, Nuctrient Availbility, and Nutrient Intake." *Journal of Policy Modeling* 9 (3):383–404.

Petrin, Amil, and Kenneth E. Train. 2010. "A Control Function Approach to Endogeneity in Consumer Choice Models." *Journal of Marketing Research* 47 (1):3–13.

Petty, RE, and JT Cacioppo. 1986. *The Elaboration Likelihood Model of Persuasion*. Advances in Experimental Social Psychology.

Petty, Richard E, and John T Cacioppo. 1986. "Communication and Persuasion : Central and Peripheral Routes to Attitude Change ." *New York: Springer-Verlag*, 262.

Petty, Richard E, John T Cacioppo, and David Schumann. 1983. "Central and Peripheral Routes to Advertising Moderating Effectiveness :The Moderating Role of Involvement." *Journal of Consumer Research* 10 (2):135–46.

Pham, Nguyen, Naomi Mandel, and Andrea C. Morales 2016, "Messages from the Food Police: How Food-Related Warnings Backfire among Dieters," *Journal of the Association for Consumer Research (J-ACR)*, 1(1), 175-190.

Pieters, R, E Rosbergen, and M Hartog. 1996. "Visual Attention to Advertising: The Impact of Motivation and Repetition." *Advances in Consumer Research* 23:242–48.

Pieters, Rik, and Luk Warlop. 1999. "Visual Attention during Brand Choice: The Impact of Time Pressure and Task Motivation." *International Journal of Research in Marketing* 16 (1):1–16.

Pieters, Rosbergen, and Wedel. 1999. “Visual Attention to Repeated Print Advertising: A Test of Scanpath Theory.” *Journal of Marketing Research* 36 (4):424–38.

Plaks, Jason E, Heidi Grant, and Carol S Dweck 2005. “Violations of implicit theories and the sense of prediction and control: implications for motivated person perception.” *Journal of Personality and Social Psychology*, *88*(2), 245–262.

———, and Kristin Stecher 2007. “Unexpected improvement, decline, and stasis: A prediction confidence perspective on achievement success and failure.” *Journal of Personality and Social Psychology*, *93*(4), 667–684.

Poehlman, E T, J P Després, M Marcotte, A Tremblay, G Thériault, and C Bouchard. 1986. “Genotype Dependency of Adaptation in Adipose Tissue Metabolism after Short-Term Overfeeding.” *The American Journal of Physiology* 250:E480–85.

Polivy, Janet, C. Peter Herman, and Rajbir Deo. 2010. “Getting a Bigger Slice of the Pie. Effects on Eating and Emotion in Restrained and Unrestrained Eaters.” *Appetite* 55 (3). Elsevier Ltd:426–30.

Popper, ET, and KB Murray. 1989. “Communication Effectiveness and Format Effects on in-Ad Disclosure of Health Warnings.” *Journal of Public Policy & Marketing* 8 (May):109–23.

Prasad, Ashutosh, Andrei Strijnev, and Qin Zhang. 2008. “What Can Grocery Basket Data Tell Us about Health Consciousness?” *International Journal of Research in Marketing* 25 (4). Elsevier B.V.:301–9.

Rahtz, DR, and DL Moore. 1989. “Product Class Involvement and Purchase Intent.” *Psychology & Marketing* 6 (2):113–27.

Rayner, Keith. 1998. “Eye Movements in Reading and Information Processing: 20 Years of Research.” *Psychological Bulletin* 124(3):372–422.

Remick, A. K., Polivy, J., & Pliner, P. (2009). “Internal and external moderators of the effect of variety on food intake.” *Psychological bulletin*, *135*(3), 434.

Richards, Timothy J. 2017. “Analysis of Umbrella Branding with Crowdsourced Data.” *Agribusiness* 33 (2):135–50.

Richards, Timothy J., and Stephen F. Hamilton. 2015. “Variety Pass-Through: An Examination of the Ready-to-Eat Breakfast Cereal Market.” *Review of Economics and Statistics* 97(1) (March):166–79.

Richards, Timothy J., Paul M. Patterson, and Abebayehu Tegene. 2007. “Obesity and Nutrient Consumption: A Rational Addiction?” *Contemporary Economic Policy* 25:309–24.

Rishika, R., Ashish Kumar, Ramkumar Janakiraman, and Ram Bezawada. 2013. “The Effect of Customers’ Social Media Participation on Customer Visit Frequency and Profitability: An Empirical Investigation.” *Information Systems Research* 24 (1):108–27.

Roe, B, a S Levy, Brian Roe, Alan S Levy, B M Derby, and Brenda M Derby. 1999. “The Impact of Health Claims on Consumer Search and Product Evaluation Outcome...” *Journal of Public Policy* 18:89–105.

Roefs, Anne, Anita Jansen, Sofie Moresi, Paul Willems, Sara van Grootel, and Anouk van der Borgh. 2008. “Looking Good. BMI, Attractiveness Bias and Visual Attention.” *Appetite* 51 (3):552–55.

Rosenbaum, Paul R. 2002a. “Covariance Adjustment in Randomized Experiments and Observational Studies.” *Statistical Science* 17 (3):286–327.

———. 2002b. *Observational Studies*. Springer.

Rosenbaum, Paul R., and Donald B. Rubin. 1983. “The Central Role of the Propensity Score in Observational Studies for Causal Effects.” *Biometrika* 70 (1):41–55.

Rosenbaum, Paul R, and Donald B Rubin. 1985. “Constructing a Control Group Using Multivariate Matched Sampling Methods That Incorporate the Propensity Score Published by : Taylor & Francis , Ltd . on Behalf of the American Statistical Association Stable URL : http://www.jstor.org/stable/2683903 Your.” *The American Statistician* 39 (1):33–38.

Rubin, Donald B. 2006. *Matched Sampling for Causal Effects*. *Matched Sampling for Causal Effects*.

Sandrou, D. K., and I. S. Arvanitoyannis. 2000. "Low-Fat/Calorie Foods: Current State and Perspectives." *Critical Reviews in Food Science and Nutrition* 40 (5). TAYLOR & FRANCIS:427–47.

Sarmugam, Rani, and Anthony Worsley. 2015. "Dietary Behaviours, Impulsivity and Food Involvement: Identification of Three Consumer Segments." *Nutrients* 7 (9):8036–57.

Shankar, Venkatesh, and Lakshman Krishnamurthi. 1996. "Relating Price Sensitivity to Retailer Promotional Variables and Pricing Policy: An Empirical Analysis." *Journal of Retailing* 72 (3):249–72.

Scott, Maura L., Stephen M. Nowlis, Naomi Mandel, and Andrea C. Morales 2008, "Do 100-Calorie Packs Lead to Increased Consumption? The Effect of Reduced Food Sizes and Packages on the Consumption Behavior of Restrained Eaters and Unrestrained Eaters," *Journal of Consumer Research* 35 (October), 391-405.

Seiders, Kathleen and Ross D. Petty 2004, "Obesity and the Role of Food Marketing: A Policy Analysis of Issues and Remedies." *Journal of Public Policy & Marketing*, 23(2), 153-169.

Shell, Ellen Ruppel. 2002. *The Hungry Gene: The Science of Fat and the Future of Thin*. Atlantic Monthly Press.

Silberberg, Eugene. 1985. "Nutrition and the Demand for Tastes." *Journal of Political Economy* 93 (5):881–900.

Singh, Vishal P., Karsten T. Hansen, and Sachin Gupta. 2005. "Modeling Preferences for Common Attributes in Multicategory Brand Choice." *Journal of Marketing Research* 42 (2):195–209.

Snyder, Mark (1984). "When Belief Creates Reality." *Advances in Experimental Social Psychology*, *18*(C), 247–305.

Snyder, Mark 1992. "Motivational Foundations of Behavioral Confirmation." *Advances in Experimental Social Psychology*, *25*(C), 67–114.

Soman, Dilip, and Amar Cheema. "Earmarking and partitioning: increasing saving by low-income households." *Journal of Marketing Research* 48, no. SPL (2011): S14-S22.

Spiteri, Marine, and Louis-Georges Soler. 2017. "Food Reformulation and Nutritional Quality of Food Consumption: An Analysis Based on Households Panel Data in France." *European Journal of Clinical Nutrition*, December. Nature Publishing Group, 1.

Spruijt-Metz, Donna. 2011. "Etiology, Treatment and Prevention of Obesity in Childhood and Adolescence: A Decade in Review." *Journal of Research on Adolescence : The Official Journal of the Society for Research on Adolescence* 21 (1):129–52.

Staiger, Douglas, and James Stock. 1997. "Instrumental Variables Regression with Weak Instruments." *Econometrica* 65 (3):557–86.

Stein, Leslie J., Hajime Nagai, Masashi Nakagawa, and Gary K. Beauchamp. 2003. "Effects of Repeated Exposure and Health-Related Information on Hedonic Evaluation and Acceptance of a Bitter Beverage." *Appetite* 40 (2):119–29.

Stewart, David W., and Ingrid M. Martin 1994, "Intended and unintended consequences of warning messages: A review and synthesis of empirical research." *Journal of Public Policy & Marketing,* 1-19.

Stuart, Elizabeth A. 2010. "Matching Methods for Causal Inference: A Review and a Look Forward." *Statistical Science* 25 (1):1–21.

Thornton, Lukar E., Adrian J. Cameron, Sarah A. McNaughton, Anthony Worsley, and David A. Crawford. 2012. "The Availability of Snack Food Displays That May Trigger Impulse Purchases in Melbourne Supermarkets." *BMC Public Health* 12 (1).

Tangney, June Price (2005). "The Self-Conscious Emotions: Shame, Guilt, Embarrassment and Pride." In *Handbook of Cognition and Emotion* (pp. 541–568).

Tobin, J. 1958. "Estimation of Relationships for Limited Dependent Variables." *Econometrica: Journal of the Econometric Society* 26 (1):24–36.

Train, Kenneth. 1999. “Halton Sequences for Mixed Logit.” *Working Papers*, 1–18.

———. 2003. “Discrete Choice Methods with Simulation.” *Cambridge, MA: Cambridge University Press. U.S.*

———. 2009. *Discrete Choise Methods with Simulation*. *Cambridge University Press.*

Train, Kenneth E. 1998. “Recreation Demand Models with Taste Differences over People.” *Land Economics* 74 (2):230.

———. 2009. “Bibliography.” *Discrete Choice Model with Simulation*, no. 1994:371–83.

Trijp, Hans C M van. 2009. “Consumer Understanding and Nutritional Communication: Key Issues in the Context of the New EU Legislation.” *European Journal of Nutrition* 48 Suppl 1 (December):S41-8.

Verster, Joris C., and Juergen Koenig. 2017. “Caffeine Intake and Its Sources: A Review of National Representative Studies.” *Critical Reviews in Food Science and Nutrition* 0 (0). Taylor & Francis:1–10.

Villas-Boas, Sofia Berto. 2007. “Vertical Relationships between Manufacturers and Retailers: Inference with Limited Data.” *Review of Economic Studies* 74 (2):625–32.

Visschers, Vivianne H M, Rebecca Hess, and Michael Siegrist. 2010. “Health Motivation and Product Design Determine Consumers’ Visual Attention to Nutrition Information on Food Products.” *Public Health Nutrition* 13 (7):1099–1106.

Vohs, Kathleen D., and Ronald J. Faber 2007. “Spent Resources: Self-Regulatory Resource Availability Affects Impulse Buying.” *Journal of Consumer Research*, *33*, 537–547.

Walters, Amber, and Marilee Long. 2012. “The Effect of Food Label Cues on Perceptions of Quality and Purchase Intentions among High-Involvement Consumers with Varying Levels of Nutrition Knowledge.” *Journal of Nutrition*

Education and Behavior 44 (4). Elsevier Inc.:350–54.

Walters, Rockney G. 1991. "Assessing the Price Impact Promotions on Retail Product Substitution , Complementary Purchase, and Interstore Sales Displacemente." *Journal of Marketing* 55 (2):17–28.

Wang, Y. Claire, Kim McPherson, Tim Marsh, Steven L. Gortmaker, and Martin Brown (2011). "Health and Economic Burden of the Projected Obesity Trends in the USA and the UK." *Lancet* 378, 815-25.

Wansink, Brian, and Pierre Chandon 2006. "Can "low-fat" nutrition labels lead to obesity?" *Journal of Marketing Research*, *XLIII*(November), 605–617.

Wansink, Brian, and Pierre Chandon. 2006. "Can 'low-Fat' Nutrition Labels Lead to Obesity?" *Journal of Marketing Research* XLIII (November):605–17.

Wedel, Michel, and Rik Pieters. 2000. "Eye Fixations on Advertisements and Memory for Brands: A Model and Findings." *Marketing Science* 19 (4):297–312.

Wedel, Michel, and Robert H Smith. 2013. "Attention Research in Marketing: A Review of Eye Tracking Studies," 1–28.

Wedel, Michel. 2014. "Visual Attention to Advertising : A Segment-Level Analysis." *Journal of Consumer Research* 24 (3):305–14.

———. 2006. "Eye Tracking for Visual Marketing." *Foundations and Trends® in Marketing*.

West, Gale E., Carole Gendron, Bruno Larue, and Rémy Lambert. 2002. "Consumers' Valuation of Functional Properties of Foods: Results from a Canada-Wide Survey." *Canadian Journal of Agricultural Economics*.

Westerterp-Plantenga, M S, A Nieuwenhuizen, D Tomé, S Soenen, and K R Westerterp. 2009. "Dietary Protein, Weight Loss, and Weight Maintenance." *Annu Rev Nutr* 29.

Wiederman, Michael W., and Shannon R. Hurst. 1997. "Physical Attractiveness, Body Image, and Women's Sexual Self-Schema." *Psychology of Women Quarterly*.

Williams, Peter. 2005. "Consumer Understanding and Use of Health Claims for Foods." *Nutrition Reviews* 63 (7):256–64.

Wills, JM, KG Grunert, LF Celemín, and SS Bonsmann. 2009. “European Consumers and Nutrition Labelling.” *Food Engineering & Ingredients*, no. April:11–13.

Wing, Rena R., and Suzanne Phelan. 2005. “Long-Term Weight Loss Maintenance.” *The American Journal of Clinical Nutrition*.

Wogalter, Michael S, and S. David Leonard. 1999. “Chapter 7 Attention Capture and Maintenance.” In *Warnings and Risk Communication*, 123–148.

Wogalter, Michael S, and William J Vigilante. 2003. “Effects of Label Format on Knowledge Acquisition and Perceived Readability by Younger and Older Adults.” *Ergonomics* 46 (4):327–44.

Wolowczuk, Isabelle, Claudie Verwaerde, Odile Viltart, Anne Delanoye, Myriam Delacre, Bruno Pot, and Corinne Grangette. 2008. “Feeding Our Immune System: Impact on Metabolism.” *Clinical and Developmental Immunology* 2008.

Wooldridge, Jeffrey M. 2002. *Econometric Analysis of Cross Section and Panel Data*. *Booksgooglecom*. Vol. 58.

———. 2003. *Introductory Econometrics: A Modern Approach*. *Economic Analysis*. Vol. 2nd.

Worsley, Anthony. 1996. “Which Nutrition Information Do Shoppers Want on Food Labels?” *Asia Pacific Journal of Clinical Nutrition* 5:70–78.

Wu, De-Min. 1974. “Alternative Tests of Independence between Stochastic Regressors and Disturbances: Finite Sample Results.” *Econometrica* 42 (3):529–46.

“Yoghurt Market - Global Industry Analysis, Size and Forecast, 2015 to 2025.” n.d. Accessed February 23, 2018.

Zaichkowsky, J. 1985. “Measuring the involvement construct. ” *Journal of Consumer Research*, *12* (December).

APPENDIX A

APPENDIX FOR CHAPTER 2

Appendix A.1 List of the FDA proposed changes of the Nutrition Facts panel

(SourceFDA Federal Register, 2014)

- Increasing the type size of the total calorie number with bold type to make the calorie more prominent on the label.
- Highlighting the number of serving per container.
- Adding a line declaring “added sugar” beneath “sugars”. Replacing “Total Carbohydrate” with “Total Carbs”.
- Replacing vitamins A and C with vitamins D and Potassium to the list of mandatory nutrients.
- Shifting the column of Percentage Daily Value (DV %) to the left side of the table.
- Changing the portion size from how much consumer “should” eat to the amount they “actually” eat – known as reference amounts customarily consumed (RACCs), aiming at reducing the consumers’ confusion when they consult the nutrition labels.
- Removing the current footnote.

Appendix A.2 Products Stimuli

Appendix A.3 Physical Activity Scale

During the past month, which statement best describes the kinds of physical activity you usually did? Do not include the time you spent working at a job. Please read all six statements before selecting one.

	I choose
I did not do much physical activity. I mostly did things like watching television, reading, playing cards, or playing computer games. Only occasionally, no more than once or twice a month, did I do anything more active such as going for a walk or playing tennis.	
Once or twice a week, I did light activities such as getting outdoors on the weekends for an easy walk or stroll. Or once or twice a week, I did chores around the house such as sweeping floors or vacuuming.	
About three times a week, I did moderate activities such as brisk walking, swimming, or riding a bike for about 15-20 minutes each time. Or about once a week, I did moderately difficult chores such as raking or mowing the lawn for about 45-60 minutes. Or about once a week, I played sports such as softball, basketball, or soccer for about 45-60 minutes.	
Almost daily, that is five or more times a week, I did moderate activities such as brisk walking, swimming, or riding a bike for 30 minutes or more each time. Or about once a week, I did moderately difficult chores or played sports for 2 hours or more.	
About three times a week, I did vigorous activities such as running or riding hard on a bike for 30 minutes or more each time.	
Almost daily, that is five or more times a week, I did vigorous activities such as running or riding hard on a bike for 30 minutes or more each time.	

APPENDIX B

DID ANALYSIS WITH DIFFERENT DEFINITION OF REGULAR BUYERS

Appendix B. DiD Estimation with Different Thresholds.

The two tables below (Appendix 1.1 and 1.2) show the DiD analysis results with various purchase ratio thresholds for both the nutrient intake per ounce (Appendix 1.1) and total nutrient intake (Appendix 1.2). Results in the two tables reveal consistent results of changes in protein and fat intake, both the density and total value, no matter how much the purchase ratio is. On the other hand, results for calorie and carbohydrates changes with the thresholds changes. It is worth noticing that the results for calorie and carbohydrates contain few occasions that the difference-in-differences were not significant. When the threshold of purchase ratio is 30%, the between group differences were significant, meaning that regular Greek yogurt consumers consumed more calories than non-regular consumers. However, the final difference-in-difference that involved measuring the before and after difference was not significant. Nevertheless, at the very least, the finding was still consistent in comparing between the two consumer groups. Carbohydrates had more complicated results because there were more occasions that the difference-in-difference were not significant. For carbohydrates intake per ounce, when the purchase ratio increased its bar at and beyond 40%, the DiD of carbohydrates intake were not significant. For carbohydrates total intake, the DiD were more likely to be significant when the ratio threshold were higher. Again, even though the DiD may be insignificant, the comparison between the two groups were significant, suggesting that regular Greek yogurt buyers had lower intake density as well as total value of carbohydrates than non-regular buyers.

Appendix 1.1. DiD estimate of Greek yogurt introduction impact on the PER OUNCE nutrients intake due to yogurt consumption

	Protein					Fat				
	Ever	**20%**	**30%**	**40%**	**50%**	**Ever**	**20%**	**30%**	**40%**	**50%**
Before										
Non-Regular Buyer (C)	0.944	0.94	0.938	0.937	0.937	0.177	0.187	0.188	0.187	0.187
Regular Buyer (T)	0.93	0.889	0.892	0.911	0.912	0.195	0.18	0.135	0.161	0.163
Diff (T-C)	-0.013***	-0.051***	-0.04***6	-0.026	-0.024	0.017***	-0.007	-0.053***	-0.026**	-0.023
After										
Non-Regular Buyer (C)	0.916	0.965	0.985	0.993	0.998	0.164	0.173	0.171	0.169	0.168
Regular Buyer (T)	1.082	1.433	1.633	1.717	1.763	0.167	0.099	0.049	0.041	0.042
Diff (T-C)	0.166***	0.468***	0.648***	0.724***	0.765***	0.003	-0.074***	-0.121***	-0.12***8	-0.126***
Diff-in-Diff	0.179***	0.519***	0.694***	0.75***	0.789***	-0.014***	-0.068***	-0.069***	-0.103***	-0.103***

	Carbohydrates					Calorie				
	Ever	**20%**	**30%**	**40%**	**50%**	**Ever**	**20%**	**30%**	**40%**	**50%**
Before										
Non-Regular Buyer (C)	3.481	3.522	3.512	3.512	3.507	20.027	20.247	20.222	20.203	20.183
Regular Buyer (T)	3.527	3.284	3.282	2.925	3.03	20.309	19.2	18.65	17.737	18.065
Diff (T-C)	0.047***	-0.237***	-0.23***	-0.587***	-0.477***	0.282***	-1.047***	-1.572***	-2.466***	-2.118***
After										
Non-Regular Buyer (C)	3.378	3.392	3.377	3.373	3.368	19.368	19.786	19.821	19.831	19.832
Regular Buyer (T)	3.349	3.073	2.956	2.866	2.888	20.22	20.438	20.547	20.582	20.942
Diff (T-C)	-0.029***	-0.318***	-0.422***	-0.507***	-0.4***	0.852***	0.652***	0.727***	0.751***	1.11***
Diff-in-Diff	-0.076***	-0.081**	-0.191***	0.08	-0.003	0.57***	1.699***	2.298***	3.217***	3.228***

T - treatment group, C - control group

***, **, * => Significance at 1%, 5%, 10% level

Appendix 1.1. DiD estimate of Greek yogurt introduction impact on the PER OUNCE nutrients intake due to yogurt consumption

	Protein					Fat				
	Ever	**20%**	**30%**	**40%**	**50%**	**Ever**	**20%**	**30%**	**40%**	**50%**
Before										
Non-Regular Buyer (C)	0.944	0.94	0.938	0.937	0.937	0.177	0.187	0.188	0.187	0.187
Regular Buyer (T)	0.93	0.889	0.892	0.911	0.912	0.195	0.18	0.135	0.161	0.163
Diff (T-C)	-0.013***	-0.051***	-0.04***6	-0.026	-0.024	0.017***	-0.007	-0.053***	-0.026**	-0.023
After										
Non-Regular Buyer (C)	0.916	0.965	0.985	0.993	0.998	0.164	0.173	0.171	0.169	0.168
Regular Buyer (T)	1.082	1.433	1.633	1.717	1.763	0.167	0.099	0.049	0.041	0.042
Diff (T-C)	0.166***	0.468***	0.648***	0.724***	0.765***	0.003	-0.074***	-0.121***	-0.12***8	-0.126***
Diff-in-Diff	0.179***	0.519***	0.694***	0.75***	0.789***	-0.014***	-0.068***	-0.069***	-0.103***	-0.103***

	Carbohydrates					Calorie				
	Ever	**20%**	**30%**	**40%**	**50%**	**Ever**	**20%**	**30%**	**40%**	**50%**
Before										
Non-Regular Buyer (C)	3.481	3.522	3.512	3.512	3.507	20.027	20.247	20.222	20.203	20.183
Regular Buyer (T)	3.527	3.284	3.282	2.925	3.03	20.309	19.2	18.65	17.737	18.065
Diff (T-C)	0.047***	-0.237***	-0.23***	-0.587***	-0.477***	0.282***	-1.047***	-1.572***	-2.466***	-2.118***
After										
Non-Regular Buyer (C)	3.378	3.392	3.377	3.373	3.368	19.368	19.786	19.821	19.831	19.832
Regular Buyer (T)	3.349	3.073	2.956	2.866	2.888	20.22	20.438	20.547	20.582	20.942
Diff (T-C)	-0.029***	-0.318***	-0.422***	-0.507***	-0.4***	0.852***	0.652***	0.727***	0.751***	1.11***
Diff-in-Diff	-0.076***	-0.081**	-0.191***	0.08	-0.003	0.57***	1.699***	2.298***	3.217***	3.228***

T - treatment group, C - control group

***, **, * => Significance at 1%, 5%, 10% level

APPENDIX C

APPENDIX FOR CHAPTER 4

Appendix C.1 Eating Habit Questionnaire (EHQ) items.

1. I am more informed than others about healthy eating.
2. I turn down social offers that involve eating unhealthy food.
3. The way my food is prepared is important in my diet.
4. I follow a diet with many rules.
5. My eating habits are superior to others.
6. I am distracted by thoughts of eating healthily.
7. I only eat what my diet allows.
8. My healthy eating is a significant source of stress in my relationships.
9. I have made efforts to eat more healthily over time.
10. My diet affects the type of employment I would take.
11. My diet is better than other people's diets.
12. I feel in control when I eat healthily.
13. In the past year, friends or family members have told me that I'm overly concerned with eating healthily.
14. I have difficulty finding restaurants that serve the foods I eat.
15. Eating the way I do gives me a sense of satisfaction.
16. Few foods are healthy for me to eat.
17. I go out less since I began eating healthily.
18. I spend more than three hours a day thinking about healthy food.
19. I feel great when I eat healthily.
20. I follow a health-food diet rigidly.
21. I prepare food in the most healthful way.

Note: Choices include F = False, not at all true; ST = Slightly true; MT = Mainly true; VT = Very true.

APPENDIX D

IRB Approval Letters

EXEMPTION GRANTED

Carola Grebitus
Agribusiness, Morrison School of
- Carola.Grebitus@asu.edu

Dear Carola Grebitus:

On 4/9/2014 the ASU IRB reviewed the following protocol:

Type of	Initial Study
Title:	Consumers' Preferences for Frozen Meals
Investiga	Carola Grebitus
IRB ID:	STUDY00000948
Fund	None
Grant	None
Grant	None
Documents Reviewed:	• Protocol, Category: IRB Protocol; • 2014_P_Questionnaire Nutrition facts_09.pdf, Category: Measures (Survey questions/Interview questions /interview guides/focus group questions); • Email Flyer Fionna.pdf, Category: Recruitment Materials; • Focus Group Letter Fionna.pdf, Category: Recruitment Materials; • Recruitment_material_Fionna.pdf, Category: Recruitment Materials; • Flyer Fionna.pdf, Category: Recruitment Materials; • Poster focus group Fionna.pdf, Category: Recruitment Materials;

The IRB determined that the protocol is considered exempt pursuant to Federal Regulations 45CFR46 (2) Tests, surveys, interviews, or observation on 4/9/2014.

In conducting this protocol you are required to follow the requirements listed in the INVESTIGATOR MANUAL(HRP103).

Sincerely,

IRB Administrator

cc:
Yi Xie
Dan Wang

EXEMPTION GRANTED

Naomi Mandel
WPC - Marketing
480/727-7274
Naomi.Mandel@asu.edu

Dear Naomi Mandel:

On 10/23/2015 the ASU IRB reviewed the following protocol:

Type of	Initial Study
Title:	Cheat Meal Study
Investiga	Naomi Mandel
IRB ID:	STUDY00003346
Fund	None
Grant	None
Grant	None
Documents Reviewed:	• Cheat Meal Recruitment Letter - Study1, Category: Recruitment Materials; • Cheat Meal Consent Form - Study2, Category: Consent Form; • Cheat Meal Protocal, Category: IRB Protocol; • Cheat Meal Study Measures - Study 1, Category: Measures (Survey questions/Interview questions /interview guides/focus group questions); • Cheat Meal Recruitment Letter - Study2, Category: Recruitment Materials; • Cheat Meal Study Measures - Study 2, Category: Measures (Survey questions/Interview questions /interview guides/focus group questions); • Cheat Meal Consent Form - Study1,

The IRB determined that the protocol is considered exempt pursuant to Federal Regulations 45CFR46 (2) Tests, surveys, interviews, or observation on 10/23/2015.

In conducting this protocol you are required to follow the requirements listed in the INVESTIGATOR MANUAL (HRP-103).

Sincerely,

IRB

Administrator

cc:

Yi Xie