ABSTRACT

LIANG, FEIFEI. Three Essays on Retail-Shelf Nutrition Labels. (Under the direction of Xiaoyong Zheng.)

This dissertation consists of three essays examining the effectivemess of NuVal, a retail-shelf nutrition label, on the quantity and quality of consumer food purchase.

The objective of Chapter 1 is to estimate the value of information provided by the NuVal shelf nutrition label, a prominent example of a new interpretive approach to front-of-package nutrition labeling that provides a multiple-level nutrition symbol. Using the rollout of NuVal at a supermarket in a Midwest town, I estimate a mixed logit demand model for yogurt using household and barcode-level scanner data. I found the NuVal label promoted purchases of healthier yogurts. The average value of NuVal information in the yogurt category is estimated to be about 3% of the total expenditure on yogurt. There is evidence suggesting that households who made less use of conventional nutrition labels prior to the NuVal rollout may stand to benefit more from NuVal labels. Overall, my results indicate that there is a significant willingness to pay, on the part of consumers, for a universal adoption of an interpretive multiple-level shelf or front-of-package nutrition label.

Previous studies have examined the within-store adoption effect of this kind of label without considering potential spillover effects. In Chapter 2, I examine both the within-store and spillover effects of NuVal shelf nutrition label on yogurt sales, and investigate different channels through which the spillover effect occurs. The NuVal label is found to have an economically and statistically significant spillover effect on consumers demand in stores without the label. On average, the spillover effect is equivalent to a price reduction of $0.10, which is approximately 6.8% of the average yogurt price during the sample period. There is also evidence suggesting that both the within-store and spillover effects are larger for households who were less health conscious prior to the NuVal rollout. In addition, I found evidence that the spillover effect occurs through both the self observation direct channel and the word-of-mouth indirect channel. Overall, my analysis indicates that spillover cannot be ignored when evaluating the effectiveness of retail-shelf nutrition labeling.

After studying how NuVal label affects consumer demand for yogurt products in Chapters 1 and 2, I study the effects of the NuVal label on the quantity and quality of a basket of food products consumers purchase, including yogurt, frozen dinner, salty snacks and cold cereals. I apply the synthetic control method to study whether the adoption of NuVal label has a significant effect on the amount of calories consumers purchase and the healthfulness of the products in their shopping baskets. The NuVal label is found to have a statistically significant effect on the quantity and quality of consumers' food purchase. On average, the treated

households reduced 220.26 kcal per month during the teratment period, which is equivalent to a 4.36% reduction of what they would have purchased if NuVal had not been introduced; they also purchased food products with an average NuVal score 0.67 points higher, which is equivalent to a 2.69% increase compared to what they would have purchased. The treatment effects faded over time and varied by different demographic groups.

Three Essays on Retail-Shelf Nutrition Labels

by
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A dissertation submitted to the Graduate Faculty of
North Carolina State University
in partial fulfillment of the
requirements for the Degree of
Doctor of Philosophy

Economics

Raleigh, North Carolina

2018

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DEDICATION

To my parents.

BIOGRAPHY

The author was born in Xinyi, a small city in Guangdong, China. She earned her bachalor's and master's degree in economics from Capital University of Economics and Business in Beijing, China. In 2014, She entered North Carolina State University to pursue a Ph.D. degree in economics. After graduation, she will join National School of Agricultural Institution and Development in South China Agricultural University in China.

ACKNOWLEDGEMENTS

I would like to express my thankfulness to all my committee members for their support of my research every step along the way. I am first indebted to Dr. Xiaoyong Zheng, the chair of my committee. Without his guidance and persistent help this dissertation would not have been possible. I would like to thank Dr. Walter Thurman, Dr. Tomislav Vukina, Dr. Zheng Li and Dr. Roderick Rejesus for their in-depth knowledge and feedback regarding my research.

In addition, a thank you to Sisley Song and Mr. Han, who introduced me to academic opportunities abroad and suffered from my "harassment."

Nobody has been more important to me in the pursuit of a Ph.D. degree than the members of my family. I would like to thank my parents, Quanfang Luo and Shisen Liang, my sister Dandan Liang, and my best friend Cathy Chen, for providing me with unwavering support and continuous encouragement throughout my years of study. My family has always been supportive with every decision I have made. This accomplishment would not have been possible without them.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter 1

Measuring the Value of Information in the NuVal Shelf Nutrition Label

1.1 Introduction

The diet for the majority of the U.S. population does not meet the Dietary Guidelines for Americans (DGA) (USDA and DHHS, 2010). Per capita caloric intake from solid fats and added sugars exceeds the recommended limit by 180%, the highest percentage of foods and food components consumed excessively by Americans, followed by refined grains (100%) and sodium (49%) (USDA and DHHS, 2010). Processed and packaged foods and beverages account for over 50% of total calories consumed by an average American (Eicher-Miller, Fulgoni III, and Keast, 2012). To increase taste, improve mouth feel, reduce production cost, and/or increase shelf life, many processed products are high in saturated fat, added sugar, and sodium.

Alarmed by the low nutritional quality of some processed foods, a number of policy interventions have been proposed to reduce consumption of some of the least nutritious food products. A prominent example is the set of proposals for large excise taxes on sugar-sweetened beverages (SSBs) that appear to be gaining momentum in recent years. As of February 2017, seven U.S. cities, led by Berkeley, CA, have passed excise taxes of at least one penny per ounce on SSBs (County Health Rankings and Roadmap, 2017). An evaluation of the Berkeley tax estimates that the policy reduced SSB consumption by 25% relative to comparison cities (Falbe et al., 2016). Although, by the law of demand, large taxes targeted at less nutritious foods reduce consumption of the taxed foods, this policy can be costly to consumers in lost consumer surplus at least in the short run.[1]

An alternative, and perhaps less controversial, policy is to provide nutrition information

[1]In the long run, it is possible for the benefit of improved health to outweigh the cost if such taxes result in healthier total diet, and if a change in information or preference occurs.

so that consumers can make their own informed decisions. The benefit of this information provision approach is that any reduction in consumption of less nutritious foods would be due to preference changes toward healthier diets. Consequently, there is no loss in consumer surplus. Traditionally, information disclosure has been central to U.S. nutrition policymaking. The Nutrition Labeling and Education Act (NLEA) of 1990 mandating standardized Nutrition Facts labels on most packaged foods by 1994 and the required disclosure of trans fat content on Nutrition Facts labels by 2006 are representative of this policy. These regulations had some success in improving population diet quality. For example, although still above DGA recommended levels, intake of saturated fats has declined across demographic subgroups largely due to mandatory fat content disclosure under the NLEA (Mathios, 2000) together with voluntary health claims (Ippolito and Mathios, 1995) and diffusion of fat-heart-disease information (Chern, Loehman, and Yen, 1995). The nutrition facts label would be most effective if consumers correctly process the disclosed information, which is often in lengthy format on the back of side of the package, and act on it by choosing healthier products. However, this may not be an easy and natural process for some, especially those who are time-constrained and less health-conscious. The literature documents that food label use varies significantly across sociodemographic subgroups (Ollberding, Wolf, and Contento, 2011) and that diet and health knowledge is one of the strongest predictors of label use (Drichoutis, Lazaridis, and Nayga Jr, 2006). Over the decade following NLEAs full implementation, consumer use of most nutrition labels had declined (Todd and Variyam, 2008). These and the continuing post-NLEA increases in prevalence of obesity (Flegal et al., 2002) and obesity-related medical costs (Finkelstein et al., 2009) further warrant the quest for new labeling strategies that potentially supplement the Nutrition Facts label.

One strategy is to present simplified nutrient information on the front of package (FOP). Research concludes that consumers prefer short FOP labels to lengthy Nutrition Facts labels hidden on the back or side of the package (Drichoutis et al., 2006). The food industry has developed a number of FOP nutrition labeling systems (Hersey et al., 2013). In a recent example, the trade associations Grocery Manufacturers Association (GMA) and Food Marketing Institute (FMI), in 2011, unveiled a nutrient-based FOP nutrition labeling system, called Facts Up Front, with both absolute amounts and percentage daily values (%DV) of calories, saturated fat, sodium, and sugars per serving of the product. Participant companies have the option to include amounts and %DVs of two of eight nutrients (potassium, fiber, protein, vitamin A, vitamin C, vitamin D, calcium, and iron) to encourage (GMA and FMI). It is worth nothing that nutrient-specific FOP labels such as Facts Up Front do not provide additional information not already on the required Nutrition Facts labels. Instead, these labels make select nutrition facts more prominent and, thus, have the potential to reduce consumer search cost. There is mixed evidence on whether nutrient-specific FOP labels actually lead to healthier purchases.

One observational study found Facts Up Front to reduce calories and nutrients that DGA recommends to limit in purchases of 22 breakfast cereal brands (Zhu, Lopez, and Liu, 2015). However, a randomized controlled trial found no effect of nutrient-specific labels on food purchases (Ducrot et al., 2016).

There is concern, as was the case in the United Kingdom (Hersey et al., 2013), that a proliferation of different FOP label systems could confuse consumers and mitigate their potential effectiveness. In response, in 2009, the U.S. Food and Drug Administration (FDA) launched the Front-of-Package Labeling Initiative, the goal of which is to determine whether a single standardized FOP nutrition symbol should be used across all packaged foods (FDA, 2009). In the same year, at the request of Congress, the Centers for Disease Control and Prevention (CDC) and FDA, the Institute of Medicines (IOMs) Committee on Examination of Front-of-Package Nutrition Rating Systems and Symbols was commissioned to review current approaches and propose guidance on a standardized FOP label. In its report released in 2011, the committee recommended the development of a summary multiple-level nutrition symbol that goes on the fronts of packages and provides a clear ranking of the healthfulness of the labeled product (Nathan et al., 2012). The IOM report encourages the FDA to shift from the current approach of providing more nutrition facts to an interpretive one that provides simple, direct, and science-based guidance to consumers on the nutritional quality of the product.

Interpretive shelf nutrition labels are a tool that provides summary multiple-level rating of the overall nutrition quality of a food product. It is interpretive because the rating reflects the interpretation of nutrition facts by nutrition and health experts based on scientific evidence on diet-health links. These labels distinguish from conventional FOP labels/symbols in two respects. First, compared to nutrient-specific labels such as Facts Up Front that simply feature select nutrition facts label information more prominently, interpretive shelf labels have the potential to provide new nutrition cues to consumers at the point of purchase. Second, although FOP symbols such as Walmarts Great For You and American Heart Associations Heart-Check are also interpretive in that products bearing these symbols meet some pre-specified criteria, they are not multiple-level, the type recommended by IOM (RTI International, 2012). Also, these symbols are absent from products that either do not meet the selection criteria or do not participate in the specific labeling program, which could cause confusion among consumers. In addition, there is evidence that consumers may not deduce the lower nutrition quality of unlabeled products by observing healthier labeled products (Mathios, 2000).

There are two major shelf nutrition label systems in U.S. grocery stores: Guiding Stars (introduced in 2006) and NuVal (introduced in 2008). Guiding Stars ranks food products between no star (least healthy) and 3 (healthiest) stars, although, in practice, products that earn no star are often not labeled at the point of sale. By contrast, NuVal (introduced in 2008) scores and labels products on a 1-100 scale with 1 indicates being least healthy and 100 the healthiest. At the participating retailer, the NuVal score is integrated into the shelf price tag (see Figure 1 as an example). As of February 2017, 16 retail chains had NuVal shelf labels compared with 5 chains using Guiding Stars. Recent research has shown Guiding Stars and NuVal to encourage healthy purchases (Rahkovsky et al., 2013; Zhen and Zheng, 2018).

NuVal scores foods based on an algorithm known as ONQI that profiles the content of 21 nutrients and the quality of four nutrition factors (Katz et al., 2010). The ONQI algorithm was developed by an expert panel independent of food industry interest. It penalizes nutrients (e.g., saturated fat, sodium, and sugar) and nutrition factors generally considered to have unfavorable health effects and rewards those (e.g., fiber, potassium) that are beneficial to health. Therefore, the higher the NuVal score, the healthier the food. In a test of the utility of ONQI, Chiuve, Sampson, and Willett (2011) used the algorithm to evaluate the diet quality of over 100,000 health professionals who were followed for over two decades in two longitudinal surveys. They found that baseline diets scored lower by ONQI are associated with higher risks of total chronic disease, cardiovascular disease, diabetes, and all-cause mortality (Chiuve et al., 2011).

In this paper, I quantify the value of information embedded in the NuVal label. Using a grocery retailers adoption of NuVal shelf label in a Midwestern city allowed me to estimate the effect of shelf nutrition label on consumer preferences for yogurts as represented by a mixed logit demand. Based on the demand estimates, I calculate that the information value of NuVal label is about 3-4% of total yogurt expenditures at the store that adopted NuVal. This research fills three gaps in the literature. First, no previous study has estimated the value of information from multiple-level interpretive labelsthe type of nutrition labels IOM recommended to the FDA. As policymakers contemplate regulatory options on FOP labeling, the value of information provided by various types of labels can be a useful metric for comparing the benefits and costs of candidate policies.

Second, this is the first study to estimate value of food label information at the barcode level using household-level data from actual purchase transactions in a real shopping environment. Previous research on this topic has only estimated demand at food group level based on retail scanner data aggregated from the barcode level (Teisl, Bockstael, and Levy, 2001; Teisl, Roe, and Hicks, 2002). Because NuVal rating is multiple-level and specific to the product barcode, estimating demand at this level is more appropriate and likely to improve precision of the coefficient estimates compared to aggregating products to a higher level. By using micro-level purchase data, I are able to examine how value of information differ across demographic groups. I found that households headed by persons aged less than 65, without young children, or without college degree benefit more from NuVal labels.

Finally, I invented a procedure for recovering the value of information estimate from parameters of a mixed logit demand model. This new procedure is specific to discrete-choice demand models and, together with the procedure developed by Teisl et al. (2001) for continuous demand systems, completes the tool set for estimating value of label information based on consumer demand models.

The remainder of this article is organized as follows. I first review the emerging literature on demand effects of multiple-level interpretive nutrition labels, which is followed by a discussion of our mixed logit demand specification and estimation. I then introduce the conceptual framework of Foster and Just (1989) for measuring the welfare effect of information disclosure and our procedure for calculating value of information based on discrete-choice models. Next, the scanner data and variable constructions are described, followed by discussion of empirical results. The final section provides concluding remarks.

1.2 Interpretive Labels and Consumer Demand

A few papers have evaluated the impacts of multiple-level interpretive labels on actual food purchases. Of those examined the Guiding Stars program, all used scanner data from Hannaford Supermarkets. Sutherland, Kaley, and Fischer (2010) compared sales trend of zero-star vs. that of starred ready-to-eat (RTE) cereal products. They found that, two years into the Guiding Stars program, sales of products with 1-3 stars grew at a higher rate than those of zero-star products, while the opposite was true before implementation. Cawley et al. (2015) analyzed aggregate pre- and post-Guiding Stars sales of 102 categories of food. The authors found that sales of foods rated as zero star declined by 8% on average, while sales of foods rated one to three stars did not change significantly. Rahkovsky et al. (2013) estimated a store-level conditional Rotterdam demand with four categories of RTE cereals classified by the star rating. They concluded that Guiding Stars increased sales of starred cereals at the expense of unstarred cereals with the largest gains accrued to one- and two-star products. The authors also found the Guiding Stars label made cereal demand less price elastic. Unlike Sutherland, Kaley, and Fischer (2010) and Cawley et al. (2015) where the authors had only pre-post data from Hannaford stores, Rahkovsky et al. (2013) acquired sales data from a group of control stores where Guiding Stars was never implemented. This treatment-control design provides stronger credibility to the estimated treatment effects.

Two demand studies focused on NuVal. Nikolova and Inman (2015) analyzed purchase data collected through a retail chains loyalty card program and from a control group of households from non-NuVal retailers. They found share of healthier product purchases increased following rollout of NuVal at this chain. Lastly, Zhen and Zheng (2018) estimated a difference-in-differences model of yogurt demand using store-level data from one NuVal store and five non-NuVal stores in a city in the Midwest. They found that a one-point increase in NuVal score increases yogurt demand by 0.3%.

1.3 Empirical Strategy

1.3.1 Demand Model

To quantify the informational value of the NuVal label, I estimate a structural discrete choice demand model for yogurt, using the method proposed by McFadden (1973) and Train (2009). In a discrete choice framework, consumers face a choice set of J differentiated products. On each shopping trip, the consumer is assumed to purchase one unit of the product that yields her the highest utility. I allow the possibility that the consumer purchase a yogurt product that is not one of my selected choice set of UPCs whose demand I explicitly estimate in the mixed logit model; that is the choice set includes a *numéraire* or outside good. The *numéraire* is a composite good representing other excluded yogurt products. This setup is required to obtain correct measure of welfare changes (LaFrance and Hanemann, 1989).

Formally, the utility consumer i obtains from purchasing the jth yogurt product on shopping trip t is specified as

$$U_{ijt} = \gamma_{it}(y_i - p_{ijt}) + X_{jt}\beta_{it} + \sum_{s=1}^{5} \alpha_s d_s + \alpha_w w_t + \alpha_{w^2} w_t^2 + \epsilon_{ijt} \tag{1.1}$$

where $j = 1, ..., J_t$ and J_t is the number of yogurt products in my sample available to household i on shopping trip t; y_i is the income of household i; p_{ijt} represents the price per pint (16 liquid ounces) of product j on household i's trip t;X_{jt} is a $1 \times K$ vector of observable attributes of product j that include the NuVal treatment variables; d_s are store dummies; w_t is linear weekly trend; ϵ_{ijt} represents an independent and identically distributed error term; and $\gamma_{it}, \beta_{it}, \alpha_s, \alpha_w, \alpha_{w^2}$ are parameters to be estimated.

The observed product attributes include package size, and dummies for manufacturer, whether the product is a regular yogurt or yogurt drink, whether the product is NuVal-labeled, whether the product is on display or featured, and whether the price reduction is larger than five percent of the regular price. Our variable of interest is the dummy variable for whether the product is NuVal-labeled, one of the variables in X_jt. This variable, $Adopt_{jt}$ is equal to 1 if product j is labeled with a NuVal score at the store of trip t, and 0 otherwise. It captures the treatment effect of NuVal label on consumer demand for yogurt. I also include amounts of calories, total fat, saturated fat, cholesterol, sodium, carbohydrates, fiber, sugars, protein and calcium as additional attributes. Including a rich set of product characteristics, especially Nutrition Facts label information that is available to consumers at all times, is essential for controlling for omitted variables and avoiding spuriously attributing baseline taste differences as NuVal label effect.[2]

[2]An alternative way to lessen the omitted variable bias problem is to include a full set of product fixed effects.

Finally, to complete the model and for identification purpose, the utility consumer i obtains from purchasing the *numéraire* good is specified as

$$U_{i0t} = \gamma_{it} y_i + \epsilon_{i0t} \tag{1.2}$$

where subscript 0 denotes the outside good.

The $K \times 1$ parameter vector β_{it} describes household is taste for observable product attributes and NuVal labels, and γ_{it} represents household i's marginal utility of income on trip t. I assume these parameters are random. As marginal utility of income has to be positive, I assume γ_{it} follows a log normal distribution with log mean $\bar{\gamma}$ and log variance $(\sigma^{\gamma})^2$. For vector β_{it}, I assume its kth element β_{it}^k follows a normal distribution with mean $\beta^k + Z_i\theta^k$ and variance $(\sigma^k)^2$. As a result, (1.1) can be rewritten as

$$U_{ijt} = exp(\bar{\gamma} + \sigma^{\gamma}\mu_{it}^{\gamma})(y_i - p_{ijt}) + \sum_{k=1}^{K} x_{jt}^k(\beta^k + Z_i\theta^k) + \sum_{s=1}^{5} \alpha_s d_s + \alpha_w w_t + \alpha_{w^2} w_t^2 + \epsilon_{ijt} \tag{1.3}$$

where $\mu_{it}^{\gamma}, \mu_{it}^k, k = 1, ...K$ are i.i.d. standard normal random variables, and x_{jt}^k, $k = 1, ...K$, is the kth product attribute. This specification allows household tastes for product attributes to depend on both observed as well as unobserved household attributes, which is more general and realistic than other discrete choice models that do not allow random coefficients. In fact, as shown in McFadden and Train (2000), this mixed logit model is general in the sense that it can approximate arbitrarily close any discrete choice model.

Since I have 18 observed product attributes variables and 6 observed household demographic variables, potentially there could be 108 interaction variables $x_{jt}^k Z_i$ in (1.3). Again, this could lead to overfitting, poor identification and numerical issues in estimation. Therefore, I only include a selected few of them, guided by economic intuition. First, I interact our key variable of interest, $Adopt_{jt}$, with $Score_j$ and its square, and household demographic variables. $Score_j$ is product j's NuVal score. The interaction terms $Adopt_{jt} * Score_j$ and $Adopt_{jt} * Score_j^2$ give the model a triple-difference specification that accounts for the differential impact of the NuVal label on yogurts with varying nutrition profile. The square term $Score_j^2$ allows for the possibility of a nonlinear effect. The interactions between $Adopt_{jt}$ and household demographics are intended to capture heterogeneity in the labeling effect across household types. Second, I interact the package size variable with the household size variable as households with more family members are likely to purchase products packaged in larger containers. Finally, I in-

However, that approach is infeasible in our context because I have 199 yogurt products in our sample and including a full set of product dummies would lead to overfitting, poor identification of the parameters, and numerical issues for the nonlinear discrete-choice model. In a specification in which I did not include calorie and nutrient variables in the intercept, I obtained an implausibly large value of information estimate for NuVal equivalent to over 30% of total yogurt expenditures.

teract the dummy variable for whether the price reduction is larger than 5% of the regular price with the household income variable as households with higher income are less likely to respond to price reductions.

1.3.2 Demand Estimation

Assuming the error term ϵ_{ijt} is distributed i.i.d. with a Type I extreme value distribution, the probability for household to purchase product on trip can be written as (McFadden, 1973)

$$s_{ijt} = \int \frac{exp(V_{ijt})}{1 + \sum_{m=1}^{J_t} exp(V_{imt})} f(\mu_{it}) d\mu_{it} \tag{1.4}$$

where $V_ijt = -exp(\bar{\gamma} + \sigma^\gamma \mu_{it}^\gamma) p_{ijt} + \sum_{k=1}^{K} (\beta^k x_{jt}^k + \theta^k x_{jt}^k Z_i) + \sum_{s=1}^{5} \alpha_s d_s + \alpha_w w + \alpha_{w^2} w^2$ and $f(\cdot)$ represents the joint density for μ_{it}^γ and $\mu_{it}^k, k = 1, ...K$. As a result, I can write the log likelihood function for the estimation problem as

$$LL = \sum_{i=1}^{N} \sum_{t=1}^{T_i} \sum_{j=1}^{J_t} d_{ijt} ln s_{ijt} \tag{1.5}$$

where $d_{ijt} = 1$ if household i purchases yogurt product j on trip t and 0 otherwise, T_i is the number of trips taken by household i, and N is the number of households in my sample. The log likelihood function (1.5) is not directly estimable because μ_{it}^γ and μ_{it}^k are unobserved. I get around this problem by estimating the simulated version of (1.5), that is

$$SLL = \sum_{i=1}^{N} \sum_{t=1}^{T_i} \sum_{j=1}^{J_t} d_{ijt} ln \tilde{s}_{ijt} \tag{1.6}$$

where $\tilde{s}_{ijt} = \frac{1}{R} \sum_{r=1}^{R} s_{ijt}(\mu_{it}^r)$ and R is the number of simulations, which I set to 100. The variable μ_{it}^r, $r = 1, ..., 100$ are random numbers drawn from standard normal distributions.[3] This method is called the simulated maximum likelihood estimation (SMLE) method. The parameter estimates are obtained by searching for the maximum of (1.6) using the Broyden-Fletcher-Goldfarb-Shanno (BFGS) Quasi-Newton method. The software used was Matlab.

One potential concern with our specification and estimation procedure is whether the price variable as well as other advertising related variables such as whether the products are on display or featured or have a price reduction larger than 5% of the regular price are endogenous in the demand model. This is the classical example for endogeneity if aggregate level demand

[3]To take a sequence of draws that provide a better approximation to the relevant integral and reduce the variance caused by simulation than a purely random sequence, I draw numbers from the Halton Sequences and then convert those numbers into random numbers from the standard normal distributions (Spanier and Maize, 1994).

function is estimated as stores and firms may base their pricing and advertising decisions on market demand conditions. This is less of a concern when the demand function is estimated at the household level as firms and stores are not likely to change their decisions in respond to demand by a particular household. Therefore, when micro or household level data are used for demand estimation, the price and advertising related variables are often treated as exogenous. Dubé, Hitsch, and Rossi (2010), Hendel and Nevo (2013) and Choi, Wohlgenant, and Zheng (2013) are recent examples.

1.3.3 Value of Information Calculation

In a seminal paper, Foster and Just (1989) resolved a paradox in measuring the value of information disclosure surrounding a food safety incident.[4] [5] In standard welfare analysis, demand and consumer surplus will decline due to food scare if the incident is reported. But does this justify withholding information from the public for the sake of avoiding consumer welfare loss? Intuition suggests depriving the public of knowledge of the incident cannot be justified. However, for economists, the question is how to properly estimate the value of information, or equivalently the cost of ignoring/withholding information, in this type of situation. Foster and Justs solution is to introduce the concept of compensating surplus (CS), which measures the welfare loss of the uninformed consumer. It is written as

$$CS = e(p_0, U_0, \theta_0) - \bar{e}(p_0, U_0, \theta_1 | q_0), \tag{1.7}$$

where p_0, q_0, U_0 and θ_0 are baseline price, purchase quantity, utility, and perceived product quality level, respectively; $e(\cdot)$ represents the expenditure function; θ_1 is the new level of perceived quality following the information release; and $\bar{e}(p_0, U_0, \theta_1 | q_0)$ is the level of expenditure necessary to maintain utility at U_0 given quality θ_1 and constraining purchase quantity at q_0. When perceived quality decreases from θ_0 to θ_1, CS is negative.

The welfare loss represented by CS comes from two sources. First, even if the consumer is fully informed of the incident, there is a welfare loss due to the decrease of quality from θ_0

[4] The term, "Value of Information", has been discussed in broad term in the field of economics of informatio, which is greatly influced by Machlup (1962, 1980, 1983). Individuals are assumed subject to either "technological" or "market" uncertainty according to Hershleifer (1973). "Technological" uncertainty refers to uncertain resource endowments and/or productive opportunities. "Market" uncertainty deals with imperfect information about supply and demand offers. And information could reduce uncertainty. So the value of information is defined as the exchange value of information as a public good (Taylor, 1986; Machlup, 1980) or as a product (Hilton, 1981; Taylor, 1982, 1984; Repo, 1986). It also defined as the value-in-use of information, meaning the willingness to pay and time savings (Wolfe and Aitchison, 1974; Hawgood, Morley, and Line, 1969; Griffiths, 1982).

[5] The term, "Value of Information", has been also broadly studied in the field of supply chain management. It refers to the amount a decision maker would be willing to pay for information prior to making a decision, and it is distinguised in to value of perfect information (value of clairvoyance), and value of imperfect information (Kirkwood, 2002; Howard, 1984).

to θ_1. This part of the welfare loss is represented by the compensating variation (CV), which is defined as $CV = e(p_0, U_0, \theta_0) - e(p_0, U_0, \theta_1)$ and is also negative for quality deterioration. Second, consumer welfare decreases because the consumer is unaware of the quality change and hence cannot make optimal choices. Foster and Just (1989) call this part of the welfare loss the cost of ignorance (COI). It is the difference between CS and CV:

$$COI = CS - CV = e(p_0, U_0, \theta_1) - \bar{e}(p_0.U_0, \theta_1|q_0) \tag{1.8}$$

By the LeChatelier Principle, COI is always negative no matter whether there is a decline or improvement in quality.

Teisl, Bockstael, and Levy (2001) is the first to recognize that Foster and Just's insight, although originally developed to aid welfare analysis of contamination incidents, can be used to evaluate the welfare impact of food labeling policies. To the extent that food labels change consumers perception of product quality, the value of information provided by the food labels is equal to the cost of ignorance (in absolute value) that would result if the labeling information was withheld from consumers. Using store-level sales data on six food categories collected from a field experiment in the late 1980s, the authors calculated the value of low-fat/sodium/cholesterol/calorie shelf labels, which are interpretive but not multiple-level and only appear on healthier products, to a representative consumer in an almost ideal demand model. They estimated the present value of these labels to range between \$1.4 billion (mayonnaise) and \$6.3 billion (milk) for U.S. consumers.

In our context, the introduction of the NuVal label didn't affect the underlying product quality, which could only change through reformulation.[6] However, the label could affect perceived quality by providing a useful rating on the products nutrition profile. This change in quality perception from θ_0 to θ_1 could lead to a shift in consumer demand, which can be identified by our structural demand model.

Specifically, I can compute value of information for every trip to the store that adopted the NuVal label (the treatment store) during the sample period in which the NuVal label was adopted (the treatment period) using the following procedure:

1. Set $Adopt_{jt} = 0$ for all j, compare level of utility across j and find the optimal choice d^0_{it}, that is, $d^0_{it} = argmax_j[U_{ijt} = \gamma_{it}(y_i - p_{ijt}) + X_{jt}\beta_{it} + \sum_{s=1}^{5} d_s\alpha_s + w_t\alpha_w + w_t^2\alpha_{w^2} + \epsilon_{ijt}]$. Recall that $Adopt_{jt}$ is the binary treatment variable included in the product attribute vector X_{jt}. Setting $Adopt_{jt}$ to zero means removal of NuVal labels. Product d^0_{it} therefore would be household is optimal choice for trip t if NuVal labels were not adopted. U^0_{it} is baseline utility associated with choice of d^0_{it}.

[6]This is a reasonable assumption for the short run. In the long run, manufacturers could potentially reformulate their lower-scoring products if sales of these less healthy foods are sufficiently depressed by NuVal or other nutrition profiling systems (RTI International, 2012).

2. Set $Adopt_{jt}$ equal to its observed value for all j during trip t. Then, the expenditure for household i to achieve baseline utility U_{it}^0 with the restriction that he must choose d_{it}^0 even with NuVal information posted is defined implicitly as

$$U_{it}^0 = \gamma_{it}(e(U_{it}^0, \theta_1 | d_{it}^0) - p_{id_{it}^0 t}) + X_{d_{it}^0 t}\beta_{it} + \sum_{s=1}^{5} d_s\alpha_s + w_t\alpha_w + w_t^2\alpha_{w^2} + \epsilon_{id_{it}^0 t}, \tag{1.9}$$

where $e(U_{it}^0, \theta_1 | d_{it}^0)$ is the restricted expenditure corresponding to $\bar{e}(p_0, U_0, \theta_1 | q_0)$ in (1.8) of the conceptual model with a single good.
3. Set $Adopt_j t$ equal to its observed $Adopt_j t$ for all j and find the optimal choice, that is, $d_{it}^1 = argmax_j[U_{ijt} = \gamma_{it}(y_i - P_{ijt}) + X_{jt}\beta_{it} + \sum_{s=1}^{5} d_s\alpha_s + w_t\alpha_w + w_t^2\alpha_{w^2} + \epsilon_{ijt}]$. Product d_{it}^1 therefore represents consumer is optimal choice when the NuVal label is posted. Then, the expenditure for the consumer to achieve the baseline utility U_{it}^0 without the restriction that he must choose d_{it}^0 is defined implicitly as

$$U_{it}^0 = \gamma_{it}(e(U_{it}^0, \theta_1) - p_{id_{it}^1 t}) + X_{d_{it}^1 t}\beta_{it} + \sum_{s=1}^{5} d_s\alpha_s + w_t\alpha_w + w_t^2\alpha_{w^2} + \epsilon_{id_{it}^1 t} \tag{1.10}$$

where $e(U_{it}^0, \theta_1)$ corresponds to $e(p_0, U_0, \theta_1)$ in (1.8).
4. After equating (1.9) and (1.10) and rearranging terms, the value of NuVal information is

$$e(U_{it}^0, \theta_1 | d_{it}^0) - e(U_{it}^0, \theta_1) = \frac{[-\gamma_{it} p_{id_{it}^1 t} + X_{d_{it}^1 t}\beta_{it} + \epsilon_{id_{it}^1 t}] - [-\gamma_{it} p_{id_{it}^0} t + X_{d_{it}^0 t}\beta_{it} + \epsilon_{id_{it}^0 t}]}{\gamma_{it}} \tag{1.11}$$

By definition of d_{it}^1, $[-\gamma_{it} p_{id_{it}^1 t} + X_{d_{it}^1 t}\beta_{it} + \epsilon_{id_{it}^1 t}] > [-\gamma_{it} p_{id_{it}^0} t + X_{d_{it}^0 t}\beta_{it} + \epsilon_{id_{it}^0 t}]$. So the value of information is positive by construction regardless whether NuVal 1) increases or decreases the perceived nutritional quality of each labeled product, and 2) induces the consumer to choose healthier or less healthy.

To calculate the value of information using (1.11), I need product price and observed product attributes, which I have. I also need to know the value of the parameters, which are obtained by estimating the mixed logit model using sample data. Finally, I also need to know the errors in the random coefficients, that is, μ_{it}^γ and $\mu_{it}^k, k = 1, ..., K$, and the error term $\epsilon_{ijt}, j = 1, ..., J_t$, which are neither observed nor estimated. To overcome this problem, I again use simulations. For each observed shopping trip, I simulate $R = 100$ sets of error terms. For each set, I compute the value of information for that trip using the procedure above. I then average the R values of information computed as the value of information for that trip.

1.4 Data

I analyze yogurt purchases by IRI BehaviorScan (Bronnenberg et al., 2008) panel households from a small town in the Midwest. I chose yogurt as the case study for three reasons. First, most consumers are familiar with yogurt and at least some consumers perhaps have an understanding of the nutrition of different yogurt products even before NuVal is available. This allows us to examine how the advent of NuVal labels changes the taste and nutrition perceptions. Second, there is a large variation in the nutrition ranking of individual products as reflected by the NuVal score. This variation is important for identifying the effect of NuVal score on demand. Third, yogurt is relatively homogenous in the types of ingredients used. This likely makes yogurt products to be more or less substitutable with each other, which is important for model specification purposes because discrete-choice models restrict products to be substitutes.

The IRI BehaviorScan not only tracked household purchases but also weekly retail sales from the universe of grocery stores in this small town. By observing store sales, I know what products were available at what prices when a household visited the store even if the household did not purchase those products.[7] The benefit of possessing this extra piece of information is to reduce measurement error in the estimation of cross-price effects. I focus on trips to six grocery stores in the IRI data.[8] Of the six, one is owned by a regional grocery chain, which adopted the NuVal label in August 2010. Among the remaining five, two are each owned by a local independent grocer, two by a local food co-op, and one by another regional grocery chain. None of these five stores adopted the NuVal or other shelf nutrition labels during our sample period. Below, I call the store that adopted the NuVal label the NuVal store and other stores non-NuVal stores.

Because our treatment store (i.e., the NuVal store) adopted NuVal labels in August 2010 and estimation with many products and/or observations is computationally intensive, I focus the analysis on the two months before the adoption event (i.e., June and July 2010) and the two months after the event (i.e., September and October 2010). A total of 1,666 households made 63,120 trips to the six stores during this sample period. On 27,218 of these trips, yogurt was purchased. As NuVal scores are specific to the Universal Product Code (UPC), I model yogurt demand at the barcode level.[9] From the household scanner data, I observe, on each shopping trip, the UPC of the yogurt purchased (if any) and price paid. I have household demographic data including household income, household size, presence of and age group of children, and

[7] Of course, if the entire store did not sell a single unit of a product, I would not know whether the product was available and its price. However, the bias created by this scenario is likely to be economically insignificant due to the zero market shares of such products.

[8] I dropped two other IRI stores in this town because they sold very few yogurt products.

[9] Throughout the empirical discussion, I use the terms product and UPC interchangeably.

the age and education level of the household head.

The store retail scanner data in BehaviorScan gives us the household's choice set for each trip and the prices for products the household did not purchase on each trip. For each UPC in the retail scanner data, I have information on weekly dollar and unit sales, whether the price mark-down is larger than 5%, and advertising and promotion activities in the store. The IRI data also provide product-specific information on the following time-invariant product characteristics for each UPC: the manufacturer, the package size and whether the product is regular yogurt, yogurt drink or smoothie.

The IRI scanner data, however, do not indicate whether a UPC was labeled with NuVal score at the treatment store. To construct the treatment variable $Adopt_{jt}$, I leverage a variable in the NuVal score dataset provided by NuVals licensing company, NuVal LLC, that records the date on which a product was first scored by the company. In our conversion with staff at NuVal LLC, I learned that the company sends NuVal scores of newly rated UPCs to its retail partners on a monthly basis. In light of this, I assume a 30-day lag between when NuVal first scored the product and when the label appears on store shelves.[10] Therefore, some UPCs may not be labeled in our demand model until sometime after September 1st, 2010 when our treatment period starts.

My sample stores offered over 500 yogurt UPCs. Estimating barcode-level demand for all yogurt products is computationally burdensome, if not impossible even with a discrete-choice model. I use the following procedure to select a subset from the universe of UPCs into our demand model. For UPC j to be included in trip t of the demand model, it has to satisfy all of the following three criteria. First, UPC j had to be available for purchase at the store to which trip t was made as determined by the retail scanner data. Second, the UPC had been scored by NuVal LLC by December 1st, 2010. This is to ensure that I have its nutrition facts data to use as control variables and that the product is likely to have been treated during our sample period. Third, the UPC had a dollar share of at least 0.001 in yogurt category in this town in 2010. Applying this selection procedure yields 199 yogurt UPCs accounting for 68% of the 2010 yogurt market in dollar sales in this town. The outside choice (i.e., the *numéraire*) encompasses purchase of a yogurt product that is not one of the 199 UPCs whose demand I explicitly estimate in the mixed logit model.

Table 1.1 reports the summary statistics of the time-invariant product characteristics variables including nutrient information for the 199 UPCs. Product nutrient information is from the Nutrition Facts label and provided to us by NuVal LLC. Note all variables have been scaled such that mean of the scaled variable ranges between 0 and 1. This was done to avoid numer-

[10] I recognize that this is not an impeccable assumption. However, to the extent that it introduces measurement error in the treatment variable, our estimate of the treatment effect will be biased toward zero. Therefore, our value of information estimates may be interpreted as lower bounds of the true values.

ical issues in nonlinear estimation caused by variables measured on different scales. 31% of the products are produced by Danone, while 48% of the products by General Mills. 96% of the products are regular or soy-based yogurt, while the rest are yogurt drinks or smoothies. The average package size is 0.77 pint, or 12.32 ounces. Finally, I can see that the NuVal scores of the 199 UPCs range from 23 to 100, with an average score of 52. This wide variation in product healthfulness will help identification of the NuVal effect. Table 1.2 reports the results from a regression of the NuVal score on the nutrient variables. As expected, the R squared is 0.85, indicating that the variation in NuVal scores is largely determined by the differences in nutrients. Also, yogurt products with higher cholesterol, sodium and calcium but less sugar receive higher scores.

Table 1.3 reports the summary statistics of household characteristics variables for the 1,666 households in our estimation sample. 61% of the households have a head aged between 35 and 64 and 37% of the households have a head aged 65 or above, while the rest are headed by a person younger than 35. 17% of the household heads have a college or higher degree. The average income for the households is about $50,000 and the average household size is 2.3.

Table 1.4 reports the summary statistics for all variables used in estimation. These are calculated based on 10,960,538 product-trip observations (the unit of observation is one UPC on one trip) from 63,120 trips. On average, there are about 174 UPCs in a consumers choice set on each trip. The average price over all products in the consumers choice set per trip was $2.06 per pint (16 ounces). There were not much advertising and promotion activities in the stores. Only about 4% and 8% of the product-trip observations are associated with display or feature ad, respectively. By contrast, about 26% of the product-trip observations are those where the price reduction was 5% or greater of the regular price.

1.5 Empirical Results

Table 1.5 presents the parameter estimates from our mixed logit demand model. Several results are noteworthy. First, because the marginal utility of income parameter γ_{it} is assumed to follow a lognormal distribution with log mean $\bar{\gamma}$ and log standard deviation σ^{γ}, the mean and median of γ_{it} take the form $exp[\bar{\gamma} + \frac{(\sigma^{\gamma})^2}{2}]$ and $exp(\bar{\gamma})$, respectively. Applying the estimates of $\bar{\gamma}$ and σ^{γ} to these formulas, the sample average marginal utility of income is 2.06 and the median is 1.84.

Second, most of the estimated coefficients on product characteristics ($\bar{\beta}^k$s) and their interactions with household characteristics (θ^ks) have the expected signs. Consumers have higher demand for products produced by the two leading firms of the industry, Danone and General Mills, and when the products are displayed, featured or promoted with a price reduction larger than 5% of the regular price. In addition, consumers have lower demand for larger packs on average; however, larger households have higher demand for large packs.

Finally, the posting of NuVal score is found to have a statistically significant effect on consumer demand. This effect first increases with the NuVal score up to a point but then decreases. The exact NuVal score associated with the maximum demand effect varies across household demographics. For example, for a household with a head younger than 35, without college degree and without children, this effect reaches its maximum at the score of 77. This may suggest that consumers associate yogurts rated as ultra-healthy (e.g., plain and nonfat) with lower palatability. There is some evidence for this from other food categories. In a field experiment, Kiesel and Villas-Boas (2013) found that a low-fat label reduces sales of microwave popcorns. However, Kiesel and Villas-Boas case is more extreme than ours because I still find the NuVal effect to be positive for yogurts above the threshold NuVal score, just not as large as the effect at the threshold score. The NuVal effect is lower for households headed by older adults (aged 65 and older) and for households with children. The former result would be plausible if older adults are more likely to use nutrition facts and other food labels even before rollout of NuVal labels so that the additional information in NuVal score has less of an effect on this demographic group. The literature, however, offers mixed evidence on whether older adults are more or less likely to use food labels (Drichoutis et al., 2006). Our result on households with children is consistent with expectations. Because these households are already more knowledgeable about the diet-health link and use food labels more often (Drichoutis et al., 2006), NuVal is expected to have a smaller effect.

1.5.1 Elasticity Estimates

Once the structural parameters are obtained, I can use them to compute the elasticities. From (1.4), I can derive the own-price elasticity for product j by household i on trip t as follows,

$$\begin{aligned} e_{it,jj} &= \frac{p_{ijt}\partial q_{ijt}}{q_{ijt}\partial p_{ijt}} \\ &= \frac{p_{ijt}}{q_{ijt}} \int \left\{ \frac{exp(\bar{\gamma} + \sigma^{\gamma}\mu_{it}^{\gamma})exp(V_{imt})exp(V_{ijt})}{[1 + \sum_{k=1}^{J} exp(V_{ikt})]^2} \right\} f(\mu_{it})d\mu_{it} \end{aligned} \tag{1.12}$$

For each of the 63,120 trips in our sample, I computed the own- and cross-price elasticities for all sample products sold in the store when the household made the trip using (1.12) and (1.13), respectively. From these, I obtained the product-specific median own- and cross-price elasticities for all 199 sample products. Table 1.6 summarizes the 199 median own-price elasticities. The median own-price elasticities range from -1.43 to -4.93 with an average of -3.01. This finding of very elastic product-level demand is consistent with expectations because of the large number of substitutes at the barcode level.

To save space, I report the median cross-price elasticities for seven UPCs in Table 1.7. These products are leading regular yogurts (i.e., not yogurt drinks or smoothies) in 6-ounce packages, whose NuVal scores range from 26 to 99. As apparent in Table 1.7, the cross-price elasticities are small in magnitude, ranging from less than 0.001 to 0.021. This is expected for a demand system of 199 UPCs because the cross-price effect of one products price change is dispersed across its 198 substitutes.

1.5.2 Value of Information in the NuVal Label

I now use the estimated structural parameters to quantify the informational value of NuVal labels. On 3,447 of the trips consumers made to the NuVal store after the NuVal label was adopted, one of the 199 sample products was purchased. I computed the informational value NuVal labels brought to the consumers who made these trips using the 4-step procedure detailed above. The standard errors of the estimated value of information are obtained by bootstrapping with 200 iterations. Table 1.8 reports the results. On average, the value of NuVal information is equivalent to 1.4 cents per trip and it is statistically significant. This is equivalent to about 3.1% of the expenditure on yogurt.

I also examined how value of NuVal labels varies across household types. In Table 1.9, I report the mean of the value of information by demographic group. My results show that households with a head aged less than 65 benefit more from NuVal than households headed by older adults. This is in line with our earlier results that the demand effect of NuVal is lower for older adults: those who consider NuVal information to be less useful are less likely to respond to these labels. I also find that households without children aged 12 or younger and headed by a person without college degree benefit more from the NuVal labels than those households with a young kid or headed by a person with a college degree. This is consistent with the idea that people with more education and with young kids may already know a lot about the nutritional value of the yogurt products they purchase and hence the NuVal labels bring them less additional information.

1.5.3 Spillover Effects

Our empirical model and analyses so far have assumed that the NuVal effect is limited to households shopping at the treatment store, that is, the effect does not spillover to other stores that do not have NuVal labels. In reality, this assumption may not hold given that our data comes from a small town. Consumers may have the habit of visiting multiple stores for their grocery needs and, therefore, the new information they acquired from NuVal labels at the NuVal store may affect their food choices at other non-NuVal stores. Another potential source of spillover effect is that consumers who shop at the NuVal store may pass the information to their neighbors and friends, who shop at other stores. In these cases, consumer behavior in other stores will also be affected by NuVal.

To take the spillover effect into account, I re-estimated our empirical model with spillover variables. Specifically, $Spillover_{jt}$ is added to the observed product attributes vector X_{jt}. It is a dummy variable that equals one if trip t was to one of the five control stores and if product j was sold and labeled with a NuVal score at the treatment store in the same week trip t occurred, and zero otherwise. Similar to the adoption variable $Adopt_{jt}$ for identifying treatment effect at the NuVal store, I specify the coefficient for the spillover variable to be random and depend on the NuVal score and other consumer demographic variables. The summary statistics for $Spillover_{jt}$ and its interactions with other variables are reported in Table 1.10.

Results for the estimation with the spillover effects are reported in Table 1.11. The estimated coefficients are very similar to those reported in Table 1.5, both in terms of magnitudes and statistical significance, indicating the robustness of our main estimation results above. As expected, the estimated spillover effect is smaller than the main effect at the NuVal store. For example, for a household with a head younger than 35, without college degree and without children, the average treatment effect for a product with NuVal score of 50 is an increase in consumer utility by 0.76 util while the spillover effect is only an increase of 0.39 util.

I then computed the value of information for all trips to the NuVal store and the control stores after the NuVal store adopted the label using the 4-step procedure described above. The average value of information for all trips and then by consumer demographic are reported in Tables 1.12 and 1.13, respectively. I found that on average, the informational value of NuVal to shoppers at the NuVal store is equivalent to about 4.2% of the expenditure on yogurt, while the value to consumers at other stores (i.e., value of the spillover effect) is equivalent to about 2.4% of yogurt expenditure. The average value of information by consumer demographic follows the same pattern with the size of the main effect being roughly twice that of the spillover effect. Also, the results show that households with a head aged less than 65 benefit more from NuVal than their older counterparts, and those without children aged 12 or younger and headed by a person without college degree benefit more from NuVal labels than those with young children or headed by a person with a college degree. These are again the same as the those reported in Table 9. In summary, our main results are robust to inclusion of a spillover effect.

1.6 Conclusions

In this paper, I used a supermarkets voluntary adoption of NuVal shelf labels to measure the value of NuVal information to shoppers. To this end, I first estimated changes to purchase behavior due to the presence of NuVal labels under a mixed logit demand framework. This follows the simple logic that information has value if it induces changes in consumer behavior. Using yogurt purchase as a case study, I found that NuVal has a nonlinear effect on yogurt purchases: the effect first increases with the NuVal score but peaks at a threshold NuVal score. The exact value of the threshold score depends on household demographics. Consistent with expectations, I found consumers who may have been less likely to use Nutrition Facts labels before availability of NuVal tend to respond more to NuVal information. They include households without young children or headed by persons without college degrees. Consequently, these consumers benefit more from NuVal. On average, I estimate the value of NuVal information to be 3-4% of total yogurt expenditures at the NuVal store. As of 2006, low- and higher-income households spent about $19 and $27 per year on yogurts, respectively (Zhen and Zheng, 2015). Assuming universal adoption of NuVal labels, our model implies annual increases of $0.57 and $0.81 per household in consumer welfare in the yogurt category alone for low- and higher-income households, respectively.

In lieu of proposed regulations on interpretive nutrition symbols, policymakers continue to modify the Nutrition Facts label with the intention to make it more effective in communicating nutrition facts to consumers. In May 2016, FDA published its final rule on the revision of the Nutrition Facts label (FDA, 2016a). Prominent changes include requiring increased type size and placing in bold type the number of calories, and mandatory declaration of added sugars. By making calorie information more prominent, users of the Nutrition Facts label who did not pay attention to calories before may be more likely to notice this information in the revised label and react. The rationale for mandating provision of added sugar information is to benefit consumers who are already aware of the adverse link between health and overconsumption of added sugars. However, it may be reasonable to expect these changes to have limited incremental effect on healthy eating at the population level because the consumer segments standing to benefit most from these revisions may be relatively small.

Under Executive Orders 12866 and 13563, FDA is directed to calculate the costs and benefits of all regulatory options for all economically significant regulatory actions. In its regulatory impact analysis (RIA) of the 2016 final rule, FDA economists predicted the benefit to range from $0.2 billion to $5.2 billion (in 2014 dollars) per year assuming a discount rate of 3 percent (FDA, 2016a). The significance of this RIA is that FDA used a revealed preference approach to quantify the value of revised Nutrition Facts information,[11] while it used the cost of illness approach to estimate the benefits associated with the original NLEA of 1990 (RTI International, 1991).[12] In this respect, our approach for calculating labeling benefits is closer to

[11]FDAs numbers are obtained by scaling willingness-to-pay (WTP) for the original Nutrition Facts label estimated by Abaluck (2011) in a working paper where the author estimated the WTP by revealed preference. FDA assumed the revision to have a smaller impact on food purchases than the original NLEA (FDA, 2016a).

[12]The cost of illness approach to benefit calculation counts medical costs and lost wages averted due to the policy being evaluated. It does not generally equal the willingness-to-pay estimate more accepted by economists. Note that the revealed preference approach implicitly accounts for cost of illness although the degree to which it is

the current FDA approach than to its previous one.

Under the (bold) assumption that our 3% value of information estimate extends to all retail food-at-home categories regulated by FDA, a back of the envelope calculation suggests that NuVal may provide as much as $10.3 billion (in 2014 dollars) per year in value of information to U.S. consumers.[13] As such, a mandated adoption of NuVal or other similar multiple-level interpretive shelf or FOP nutrition symbol has the potential to create larger benefits to consumers than revisions to the Nutrition Facts label. Of course, the value of interpretive nutrition labels likely varies across product categories. Yogurt is a relatively homogenous group in terms of ingredients. Even without NuVal, consumers may be able to determine the healthfulness of a particular yogurt product using simple heuristics by looking for keywords such as fat-free and plain on the package. This suggests that value of NuVal-type labels may be higher in categories such as frozen meals that are more heterogeneous in recipe and more difficult for some consumers to select healthier options in the absence of a summary nutrition symbol. I leave empirical investigation of these possibilities to future research.

accounted for is affected by myopia, the discount factor, time inconsistency, and lack of knowledge on diet-health links.

[13] This is calculated by multiplying 3% by $342 billion, which was 2014 U.S. aggregate food-at-home expenditure reported by the Consumer Expenditure Survey excluding meats, and fresh fruits and vegetables that are either regulated by USDA or not required to have a Nutrition Facts label.

Table 1.1: Summary Statistics of Time-Invariant Product Characteristics Variables

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Danone	0.31	0.46	0	1
Mills	0.47	0.50	0	1
Type	0.96	0.18	0	1
Vol	0.77	0.72	0.25	4
Score	0.52	0.27	0.23	1
Calories	0.65	0.22	0.38	1.25
Fat	0.14	0.27	0	1.72
Sfat	0.09	0.18	0	1.35
Chol	0.11	0.17	0	1.30
Sodium	0.89	0.18	0.22	1.58
Carbo	0.76	0.26	0.17	1.25
Fiber	0.10	0.28	0	1.50
Sugars	0.60	0.25	0.17	1.10
Protein	0.63	0.25	0.20	1.80
Calcium	0.51	0.14	0	1.10

Notes: Number of products included: 199. Variable definitions: *Danone*: =1 if the product is produced by Groupe Danone and 0 otherwise; *Mill*: =1 if the product is produced by General Mills Inc. and 0 otherwise; *Type*: =1 if the product is yogurt or soy yogurt and 0 otherwise (e.g. cultured dairy drink, yogurt drink or yogurt smoothie); *Vol*: package size of the product in pts (1 pt=16 ounces); *Score*: the original NuVal score/100; *Calories*: total calories in kcal per 0.85 grams of serving; *Fat*: total fat in grams per 17 grams of serving; *Sfat*: saturated fat in grams per 17 grams of serving; *Chol*: cholesterol in milligrams per 3.4 grams of serving; *Sodium*: sodium in milligrams per 1.7 grams of serving; *Carbo*: carbohydrate in grams per 5.67 grams of serving; *Fiber*: fiber in grams per 34 grams of serving; *Sugars*: sugars in grams per 5.67 grams of serving; *Protein*: protein in grams per 17 grams of serving; *Calcium*: calcium in daily percentage points per 4.25 grams of serving. Deciles of the original NuVal scores: 10^{th}: 24; 20^{th}: 27; 30^{th}: 28; 40^{th}: 32; 50^{th}: 39; 60^{th}: 58; 70^{th}: 61; 80^{th}: 81 and 90^{th}: 91.

Table 1.2: Regression Results of NuVal Score on Nutrient Variables

Dependent Variable: NuVal Score	
Variable	OLS
Constant	0.72***
	(0.06)
Calories	0.43
	(0.32)
Fat	-0.28
	(0.26)
Sfat	-0.34
	(0.28)
Chol	0.19*
	(0.11)
Sodium	0.21***
	(0.05)
Carbo	0.35
	(0.25)
Fiber	0.03
	(0.24)
Sugars	-1.52***
	(0.14)
Protein	-0.08
	(0.08)
Calcium	0.15**
	(0.07)
N	199
R^2	0.8547

Standard errors in parentheses. Two-tailed test.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.3: Summary Statistics of Household Demographic Variables

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Midage	0.61	0.49	0	1
Older	0.37	0.48	0	1
Educ	0.17	0.38	0	1
Kid	0.07	0.25	0	1
Income	0.50	0.33	0.05	1.22
Family	0.23	0.12	0.1	0.8

Notes: Number of households: 1,666. Variable definitions: *Midage*: =1 if the age of the household head is between 35 and 64 and 0 otherwise; *Older*: =1 if the age of the household head is greater than or equal to 65 and 0 otherwise; *EduC*: =1 if the household head has at least a college degree and 0 otherwise; *Kid*: =1 if the household has a child less than 12 years old and 0 otherwise; *Income*: annual household income in $100,000s; *Family*: number of people in the household (in 10 persons).

Table 1.4: Summary Statistics of Variables Used in Estimation

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Price	0.65	0.84	0	5.23
Danone	0.06	0.23	0	1
Mills	0.29	0.45	0	1
Type	0.43	0.50	0	1
Vol	0.18	0.27	0	4
Calories	0.25	0.31	0	1.25
Fat	0.02	0.10	0	1.72
Sfat	0.02	0.07	0	1.35
Chol	0.02	0.08	0	1.3
Sodium	0.38	0.44	0	1.58
Carbo	0.31	0.38	0	1.25
Fiber	0.05	0.16	0	1.50
Sugars	0.23	0.31	0	1.10
Protein	0.24	0.29	0	1.8
Calcium	0.20	0.24	0	1.10
Adopt	0.04	0.20	0	1
Adopt*Score	0.03	0.13	0	1
Adopt* Score2	0.02	0.09	0	1
D	0.10	0.30	0	1
F	0.15	0.35	0	1
Pr	0.28	0.45	0	1
Adopt*Midage	0.03	0.17	0	1
Adopt*Older	0.01	0.12	0	1
Adopt*Educ	0.01	0.09	0	1
Adopt*Kid	0.00	0.05	0	1
Vol*Family	0.04	0.08	0	2
Pr*Income	0.15	0.30	0	1.22

Notes: The summary statistics are based on 10,960,538 product-trip observations (the unit of observation is one product on one trip) from 63,120 trips as on average, a consumer faced about 174 UPCs on each trip. Variable definitions: for *Danone, Mills, Type, Vol, Calories, Fat, Sfat, Chol, Sodium, Fiber, Sugars, Protein, Calcium* and *Score*, see the notes in Table 1.1; for *Midage, Older, Educ, Kid, Family* and *Income*, see the notes in Table 1.2; *Price*: price of the product per pint (16 ounces); *Adopt*: =1 if the product was sold in the NuVal store after August 2010 and the product had already been scored at least one month earlier; *D*: =1 if the product was on display and 0 otherwise; *F*: =1 if the product was featured and 0 otherwise; *Pr*: =1 if the temporary price reduction for the product is 5% or greater of the regular price and 0 otherwise.

Table 1.5: Mixed Logit Estimation Results

Variable Name	**Parameter**	**Estimate**	**Variable**	**Parameter**	**Estimate**
Income-Price	$\bar{\gamma}$	0.61***	Calories	$\bar{\beta}_{Calories}$	4.99***
		(0.02)			(0.54)
	σ^{γ}	0.47***		$\sigma_{Calories}$	2.70***
		(0.02)			(0.11)
Danone	$\bar{\beta}_{Danone}$	0.19***	Fat	$\bar{\beta}_{Fat}$	-2.19***
		(0.04)			(0.56)
	σ_{Danone}	0.11		σ_{Fat}	-0.07
		(0.22)			(0.11)
Mill	$\bar{\beta}_{Mill}$	1.20***	Sfat	$\bar{\beta}_{Sfat}$	5.45***
		(0.03)			(0.56)
	σ_{Mill}	0.00		σ_{Sfat}	0.10
		(0.08)			(0.14)
Type	$\bar{\beta}_{Type}$	-0.60***	Chol	$\bar{\beta}_{Chol}$	-5.75***
		(0.09)			(0.20)
	σ_{Type}	-0.02		σ_{Chol}	-0.57
		(0.09)			(0.47)
Vol	$\bar{\beta}_{Vol}$	-2.09***	Sodium	$\bar{\beta}_{Sodium}$	-0.60***
		(0.08)			(0.07)
	σ_{Vol}	-0.47***		σ_{Sodium}	-0.01
		(0.06)			(0.08)
Carbo	$\bar{\beta}_{Carbo}$	-6.66***	Fiber	$\bar{\beta}_{Fiber}$	0.85***
		(0.34)			(0.07)
	σ_{Carbo}	-0.03		σ_{Fiber}	-0.01
		(0.10)			(0.07)
Sugar	$\bar{\beta}_{Sugar}$	1.99***	Protein	$\bar{\beta}_{Protein}$	-0.66***
		(0.26)			(0.14)
	σ_{Sugar}	0.02		$\sigma_{Protein}$	-0.04
		(0.14)			(0.11)
D	$\bar{\beta}_d$	0.54***	Calcium	$\bar{\beta}_{Calcium}$	-1.52***
		(0.04)			(0.12)

Table 1.5 – Mixed Logit Estimation Results, Continued

Variable Name	Parameter	Estimate	Variable	Parameter	Estimate
	σ_d	0.95***		$\sigma_{Calcium}$	-0.09
		(0.08)			(0.13)
F	$\bar{\beta}_f$	0.49***	Pr	$\bar{\beta}_{Pr}$	0.07**
		(0.03)			(0.03)
	σ_f	0.06		σ_{Pr}	0.04
		(0.09)			(0.06)
Adopt	$\bar{\beta}_{Adopt}$	-0.40	Pr*Income	θ_{Pr_Income}	0.36***
		(0.31)			(0.04)
	σ_{Adopt}	-0.08	Vol*Family	θ_{Vol_Family}	1.39***
		(0.19)			(0.14)
Adopt*Score	θ_{Adopt_Score}	3.12***	Store 1	α_1	-1.91***
		(0.65)			(0.12)
Adopt*Score2	$\theta_{Adopt_Score^2}$	-2.02***	Store 2	α_2	0.52***
		(0.54)			(0.04)
Adopt*Midage	θ_{Adopt_Midage}	-0.14	Store 3	α_3	0.10**
		(0.25)			(0.05)
Adopt*Older	θ_{Adopt_Older}	-0.42*	Store 4	α_4	0.04
		(0.25)			(0.06)
Adopt*Educ	θ_{Adopt_Educ}	-0.11	Store 5	α_5	0.89***
		(0.08)			(0.04)
Adopt*Kid	θ_{Adopt_Kid}	-0.27*	W	α_w	2.36***
		(0.14)			(0.21)
			W^2	α_{w^2}	-2.37***
					(0.19)

N: 63,120

$Log - Likelihood$: 160,202.8

Standard errors in parentheses. Two-tailed test.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.6: Summary Statistics of Median Own-price Elasticities

	Mean	**Std. Dev.**	**Min**	**Max**
Own-price Elasticity	-3.01	0.61	-4.93	-1.43

Notes: summary statistics for the 199 median own-price elasticities.

Table 1.7: Median Cross-price Elasticities for Seven Representative UPCs

Elasticity	**51(26)**	**39(35)**	**196(40)**	**70(59)**	**28(65)**	**76(81)**	**132(99)**
51(26)	-2.943	0.002	0.001	0.020	0.006	0.021	0.011
39(35)	0.010	-3.786	0.001	0.018	0.006	0.018	0.010
196(40)	0.008	0.001	-4.194	0.015	0.005	0.015	0.010
70(59)	0.009	0.002	0.001	-2.734	0.006	0.019	0.010
28(65)	0.007	0.002	0.001	0.016	-2.550	0.017	0.010
76(81)	0.009	0.002	0.001	0.018	0.006	-2.706	0.010
132(99)	0.007	0.001	0.001	0.016	0.006	0.017	-2.195

Notes: The seven representative UPCs are all popular regular yogurt products in 6-ounce packages. NuVal scores of the UPCs are in parentheses. The values in the table represent the cross-price elasticities for the product in the row to a change in the price of the product in the column. For example, the value in third row and first column (0.008) indicates the demand for UPC 196 will increase by 0.08% when there is a 10% increase in the price of UPC 51. The values in diagonal are own-price elasticities.

Table 1.8: Informational Value of the NuVal Labels

Mean of Value of Information	\$0.014*** (0.003)
Mean of (Value of Information / Expenditure)	0.031*** (0.007)

Notes: The informational value of the NuVal labels was computed for each of the 3,477 trips consumers made to the NuVal store after the NuVal label was adopted and also where one of the 199 yogurt products was purchased. Standard errors are in parentheses. * denotes statistical significance at 10% level. ** denotes statistical significance at 5% level. *** denotes statistical significance at 1% level.

Table 1.9: Informational Value of the NuVal Labels by Demographic Groups

Demographic Group	**# of Trips**	**Mean of Value of Information**	**Mean of (Value of Information / Expenditure)**
Young	75	\$0.018 (\$0.017)	0.027 (0.026)
Midage	2299	\$0.018 (\$0.004)***	0.032 (0.007)***
Older	1103	\$0.007 (\$0.003)**	0.014 (0.007)**
Educ=0	2786	\$0.015 (\$0.003)***	0.027 (0.006)***
Educ=1	691	\$0.010 (\$0.004)***	0.017 (0.006)***
Kid=0	3240	\$0.014 (\$0.003)***	0.026 (0.006)***
Kid=1	237	\$0.007 (\$0.005)	0.012 (0.008)

Notes: The informational value of the NuVal labels was computed for each of the 3,477 trips consumers made to the NuVal store after the NuVal label was adopted and also where one of the 199 yogurt products was purchased. The means of these values of information by consumer demographic group are reported here. Standard errors are in parentheses. * denotes statistical significance at 10% level. ** denotes statistical significance at 5% level. *** denotes statistical significance at 1% level.

Table 1.10: Summary Statistics of Spillover Variables

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Spillover	0.13	0.34	0	1
Spillover*Score	0.07	0.20	0	1
Spillover*Score^2	0.04	0.13	0	1
Spillover*Midage	0.10	0.30	0	1
Spillover*Older	0.03	0.18	0	1
Spillover*Educ	0.02	0.14	0	1
Spillover*Kid	0.01	0.09	0	1

Notes: Number of products included: 199. Variable definitions: $Spillover$: =1 for UPCs in control stores if $Adopt_{jt}$for the corresponding UPCs equal 1 in the treatment store during the same week, and 0 otherwise.

Table 1.11: Mixed Logit Estimation Results with Spillover Variables

Variable Name	Parameter	Estimate	Variable	Parameter	Estimate
Income-Price	$\bar{\gamma}$	0.59***	Calories	$\bar{\beta}_{Calories}$	4.91***
		(0.02)			(0.54)
	σ^{γ}	0.45***		$\sigma_{Calories}$	2.68***
		(0.02)			(0.11)
Danone	$\bar{\beta}_{Danone}$	0.14***	Fat	$\bar{\beta}_{Fat}$	-2.53***
		(0.04)			(0.55)
	σ_{Danone}	0.10		σ_{Fat}	-0.07
		(0.19)			(0.11)
Mill	$\bar{\beta}_{Mill}$	1.07***	Sfat	$\bar{\beta}_{Sfat}$	5.67***
		(0.03)			(0.55)
	σ_{Mill}	-0.01		σ_{Sfat}	0.09
		(0.08)			(0.14)
Type	$\bar{\beta}_{Type}$	-0.55***	Chol	$\bar{\beta}_{Chol}$	-5.22***
		(0.09)			(0.20)
	σ_{Type}	-0.02		σ_{Chol}	-0.48
		(0.09)			(0.41)
Vol	$\bar{\beta}_{Vol}$	-2.25***	Sodium	$\bar{\beta}_{Sodium}$	-0.60***
		(0.08)			(0.07)
	σ_{Vol}	-0.47***		σ_{Sodium}	-0.01
		(0.06)			(0.08)
Carbo	$\bar{\beta}_{Carbo}$	-6.39***	Fiber	$\bar{\beta}_{Fiber}$	0.84***
		(0.34)			(0.07)
	σ_{Carbo}	-0.03		σ_{Fiber}	-0.02
		(0.08)			(0.10)
Sugar	$\bar{\beta}_{Sugar}$	1.75***	Protein	$\bar{\beta}_{Protein}$	-0.67***
		(0.27)			(0.14)
	σ_{Sugar}	0.01		$\sigma_{Protein}$	-0.04
		(0.15)			(0.12)
D	$\bar{\beta}_{d}$	0.58***	Calcium	$\bar{\beta}_{Calcium}$	-1.47***
		(0.04)			(0.12)

Table 1.11 – Mixed Logit Estimation Results, Continued

Variable Name	**Parameter**	**Estimate**	**Variable**	**Parameter**	**Estimate**
	σ_d	0.91***		$\sigma_{Calcium}$	-0.09
		(0.09)			(0.13)
F	$\bar{\beta}_f$	0.41***	Pr	$\bar{\beta}_{Pr}$	0.11**
		(0.03)			(0.03)
	σ_f	0.07		σ_{Pr}	0.04
		(0.09)			(0.06)
Adopt	$\bar{\beta}_{Adopt}$	-0.53*	Pr*Income	θ_{Pr_Income}	0.32***
		(0.32)			(0.04)
	σ_{Adopt}	-0.10	Vol*Family	θ_{Vol_Family}	1.30***
		(0.21)			(0.14)
Adopt*Score	θ_{Adopt_Score}	3.95***	Store 1	α_1	-1.88***
		(0.66)			(0.12)
Adopt*Score2	$\theta_{Adopt_Score^2}$	-2.76***	Store 2	α_2	0.47***
		(0.55)			(0.04)
Adopt*Midage	θ_{Adopt_Midage}	-0.15	Store 3	α_3	0.04
		(0.25)			(0.05)
Adopt*Older	θ_{Adopt_Older}	-0.43*	Store 4	α_4	-0.01
		(0.25)			(0.06)
Adopt*Educ	θ_{Adopt_Educ}	-0.12	Store 5	α_5	0.82***
		(0.08)			(0.04)
Adopt*Kid	θ_{Adopt_Kid}	-0.27*	W	α_w	2.20***
		(0.14)			(0.21)
			W^2	α_{w^2}	-2.37***
					(0.19)
Spill	$\bar{\beta}_{Spill}$	-0.39*	Spill*Score	θ_{Spill_Score}	3.08***
		(0.17)			(0.36)
	σ_{Spill}	0.16***	Spill*Score^2	$\theta_{Spill_Score^2}$	-3.04***
		(0.07)			(0.32)

Table 1.11 – Mixed Logit Estimation Results, Continued

Variable Name	**Parameter**	**Estimate**	**Variable**	**Parameter**	**Estimate**
Spill*Midage	θ_{Spill_Midage}	0.23*	Spill*Educ	θ_{Spill_Educ}	-0.21***
		(0.14)			(0.05)
Spill*Older	θ_{Spill_Older}	-0.36***	Spill*Kid	$\theta_{Spill*Kid}$	-0.25***
		(0.14)			(0.12)

N: 63,120

$Log - Likelihood$: 159,973.1

Standard errors in parentheses. Two-tailed test.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.12: Informational Value of the NuVal Labels with Spillover Effects

	Adoption	**Spillover**
Mean of Value of Information	\$0.019*** (0.005)	\$0.011*** (0.002)
Mean of (Value of Information/Expenditure)	0.042*** (0.011)	0.024*** (0.004)

Notes: The informational value of the NuVal labels was computed for each of the 3,477 trips consumers made to the NuVal store after the NuVal label was adopted, and for each of the 11,557 trips consumers made to other stores after the NuVal label was adopted in the NuVal store (spillover effect), and also where one of the 199 yogurt products was purchased. Standard errors are in parentheses. * denotes statistical significance at 10% level. ** denotes statistical significance at 5% level. *** denotes statistical significance at 1% level.

Table 1.13: Informational Value of the NuVal Labels with Spillover Effects by Demographic Groups

Demographic Group	Adoption			Spillover		
	# of Trips	Mean of VOI	Mean of VOI /Expenditure	# of Trips	Mean of VOI	Mean of VOI /Expenditure
Young	75	$0.023	0.035	177	$0.005***	0.009**
		(0.018)	(0.028)		(0.002)	(0.004)
Midage	2299	$0.024***	0.042***	8315	$0.013***	0.026***
		(0.006)	(0.010)		(0.002)	(0.003)
Older	1103	$0.009*	0.020**	3065	$0.004**	0.007**
		(0.005)	(0.010)		(0.002)	(0.003)
Educ=0	2786	$0.020***	0.037***	9811	$0.011***	0.021***
		(0.005)	(0.010)		(0.002)	(0.003)
Educ=1	691	$0.014**	0.023**	1746	$0.006***	0.012***
		(0.006)	(0.010)		(0.002)	(0.003)
Kid=0	3240	$0.019***	0.035***	10778	$0.010***	0.020***
		(0.005)	(0.010)		(0.002)	(0.003)
Kid=1	237	$0.010	0.018	779	$0.005***	0.009***
		(0.010)	(0.012)		(0.002)	(0.003)

Notes: The informational value of the NuVal labels was computed from each of the 3,477 trips consumers made to the NuVal store after the NuVal label was adopted, and from each of the 11.557 trips consumers made to other store after adoption (spillover effect), and also where one of the 199 yogurt products was purchased. The means of these values of information by consumer demographic groups are reported here. Standard errors are in parentheses. * denotes statistical significance at 10% level. ** denotes statistical significance at 5% level. *** denotes statistical significance at 1% level.

Figure 1.1: Examples of Price Tags with NuVal Scores
Note: rating from 1 (the least healthy) to 100 (the healthiest).

Chapter 2

Information Spillover in NuVal Shelf Nutrition Label

2.1 Introduction

Obesity has been increasingly considered as a major health issue in the U.S. The obesity rate for adults had continued grown from 13% in 1962, to 19.4% in 1997, 24.5% in 2004, 26.6% in 2007 and 36.5% in 2014 (CDC, 2007, 2015; Ogden et al., 2015). Obesity has become one of the biggest health concerns in communities across the country, with about 70 percent of county officials ranking it as a leading problem where they live (the State of Obesity, 2017). Obesity has also been cited as a contributing factor to approximately 100,000 to 400,000 deaths and results in $147 billion additional medical expenditure per year in the U.S. (CDC, 2017). Furthermore, obesity is expected to increase medical expenditure by $1.24 billion per year until 2030 (Antonelli et al., 2014).

Poor diet is the first to blame for the increasing prevalence of obesity. U.S. Department of Agriculture (USDA) and U.S. Department of Health and Human Services (DHHS) reported that per capita caloric intake of solid fat and added sugar, refined grains and sodium exceeded the recommended limits by 180%, 100% and 49%, respectively, in 2010 (USDA and DHHS, 2010). Various efforts had been made with the goal to improve Americans' diet. These include federal ban on sales of high-calorie drinks and snacks in elementary schools, tax imposition on sugary soda drinks in some places such as Philadelphia and Berkeley, and appropriate food labeling.

Food labeling is one of the most important ways to guide consumers to choose high-quality and nutritious food. The Nutrition Facts Panel is mandated for most food products under the provisions of the 1990 Nutrition Labeling and Education Act (NLEA). The law mandates certain information including name of the product, net quantity, serving size, number of servings per package, nutrition facts, ingredient list, and name of manufacturer or distributor to be listed on the label (Bye, 2013). However, studies have shown that the majority of the U.S. population could not fully understand the information provided by the Nutrition Facts Panel, because the information presented is too much and too complicated (Record, 2008; Rothman et al., 2006). Nutrition label numeracy is particularly low among individuals who are older, of black or Hispanic race/ethnicity, unemployed, born outside of the US, having lower English proficiency, less educated, having lower income, or living in the South (Nogueira et al., 2016). Therefore, the information provided by the Nutrition Facts Panel might fail to reach the individuals who need it the most.

Over the last decade, the U.S. food industry has introduced and expanded the use of various voluntary nutrition labels (VNL), because these labels help manufacturers and retailers better segment the market and reach targeted groups of consumers more easily (Teisl and Roe, 1998; Golan et al., 2001). VNLs include both front-of-package labels (FOP) and retail-shelf nutrition labeling systems (Hersey et al., 2013). FOP labels are words, pictures, or symbols added by the manufacturers on the front of food package that make nutrition or health claims, such as a label of low fat or organic. Three general formats of FOP labels are currently in use: nutrient specific, summary indicator, and food group information. Nutrient specific labels display information on a few key nutrients. Examples include the Facts Up Front label, introduced by the Grocery Manufacturers Association and Food Marketing Institute, which displays the amounts of calories, saturated fat, sodium, and sugar per serving (Grocery Manufacturers' Association and Food Marketing Institute, 2012).[1] Summary indicator labels are labels that provide an overall nutrition score or ranking. It is usually binary, like the Health Choices Program in Belgium, which displays a check mark on a food package if the food meets certain nutrition criteria. Food group information labels are labels that display the category or key features of the product, like whether the product is whole grains or gluten free. Another type of VNLs is retail-shelf nutrition labeling systems. They are labels added by the retailers on shelves or price tags, like Guiding Stars and NuVal. These labels reflect the interpretation of nutrition facts by nutrition and health experts based on scientific evidence on diet-health links. For example, NuVal scores products on a 1-100 scale with 1 indicates being least healthy and 100 the healthiest. These labels are different from FOP labels as they are labels added by retailers on the price tag or shelf and hence not on the products packages, while FOP labels are added by manufacturers and part of a product's package.

There is a growing number of empirical stydies of the impacts of VNLs on market sales. Most of the previous studies have focused on the sales effect of FOP labels, which measures

[1]The manufacturers or retailers also have the option to display up to two healthy nutrients that are key features of the product, such as fiber, potassium, protein, vitamin A, vitamin C, vitamin D, calcium, and iron. If the package has limited space, only the amount of calories needs to be displayed.

how the additional or simplified information provided by FOP labels changes consumers' purchase decisions. It is found that FOP labels increase the probability of consumers choosing products with FOP labels, and made consumers switch from unhealthy products to healthier ones (Drichoutis et al., 2006; Zhu et al., 2015; Hersey et al., 2013; Grunert and Wills, 2007; Kiesel and Villas-Boas, 2013).

Only a few researches have studied retail-shelf nutrition labels. Rahkovsky et al. (2013) investigated how Guiding Stars affected ready-to-eat cereals and showed that sales of low-ranked products decreased while sales of high-ranked ones increased. Zhen and Zheng (2018) applied difference-in-differences method to show that adoption of NuVal labels affected market sales. However, both studies focused on how retail-shelf nutrition labels affect consumers' demand within the stores that adopted the retail-shelf nutrition labels, without considering potential spillover effects on the sales of the same products in stores that did not adopt the same retail-shelf nutrition labels. Spillover effect occurs when shoppers at the non-adopting stores use information they learned from either their self previous trips to the adopting stores or other shoppers who shopped at the adopting stores to make their purchasing decisions at the non-adopting stores.[2,3]

In this article, I examine both the within-store and spillover effects of a retail-shelf nutrition label, the NuVal, on yogurt sales. One store in a small town in the Midwest adopted the NuVal label in August 2010, while other stores didn't adopt any retail-shelf nutrition labels. Below, I call the store that adopted the NuVal label "the NuVal store" and the others "non-NuVal stores." The NuVal label affects product sales within the NuVal store as the nutrition information conveyed by the NuVal label provides consumers a better idea on the healthfulness of yogurt products. There can also be spillover effects in non-NuVal stores. When products are labeled in the NuVal store, the information would diffuse to consumers who shop at the non-NuVal stores. Furthermore, I investigate how the within-store and spillover effect are different for consumers with different characteristics. Finally, I explore different channels through which the spillover effect occurs. For the households who have never been to the NuVal store after the labeled was adopted, they acquire the nutritional information through word-of-mouth, the indirect channel. For those who have been to the NuVal store after Nu-

[2]No such spillover effects exist for FOP labels because an FOP is part of a product's package and hence the labels have an effect in all stores where the products are sold. Zhu, Lopez, and Liu (2017) studied the effect of FOP labels when information spillover is taken into account. However, their definition of spillover is an effect on unlabeled products sold in the same stores where the labeled products are sold. This is different from the spillover effect I study in this paper.

[3]Researches have studied spillover effect similar to the one studied in this paper in other fields. Lyon and Maxwell (2007) and Zhou et al. (2016) found voluntary environmental programs affected not only the participants,but also non-paticipants. Rincke and Traxler (2011) showed that TV license inspection increased compliance among the households that were not inspected in Australia. Aitken et al. (1997), Greenaway et al. (2004), Greenaway and Kneller (2008) and Barrios et al. (2003) found that firms were more likely to export or export more when their neighbors were exporting.

Val labels was adopted, the spillover effect in the non-NuVal stores can occur through direct observation, the direct channel, or through the indirect channel, or through both.

The NuVal label is found to have an economically and statistically significant spillover effect on consumers' demand. The more products are labeled in the NuVal store, the greater the spillover effects are in the non-NuVal stores. The spillover effect varies across products with different NuVal scores as well as consumers with different characteristics. Finally, I found evidence that the spillover effect occurs through both the direct and indirect channels.

This research fills three gaps in the literature. First, no previous study has estimated the spillover effect from retail-shelf nutrition labels. If the spillover effect is ignored, the effectiveness of retail-shelf labels would be underestimated. Second, I also examine how the spillover effect varies for consumers with different characteristics. This allows us to assess whether retail-shelf nutrition labels have successfully reached the consumers who need them the most, which could have important policy implications. Finally, this is the first study on different informational channels in food labeling. It sheds light on how food labeling information is disseminated.

The remainder of this article is organized as follows. Section 2.2 provides the background of NuVal labeling. Section 2.3 discusses my empirical strategy. Section 2.4 describes data, followed by Section 2.5 that discusses the empirical results. The final section provides concluding remarks.

2.2 Background of NuVal Labeling

The NuVal labeling was introduced in 2008. It scores foods based on an algorithm known as ONQI that profiles 21 nutrients and the quality of four nutrition factors (Katz et al., 2010). Scientists developed the ONQI at the Yale-Griffin Prevention Research Center, which was independent of food industry interest. It penalizes nutrients (e.g., saturated fat, sodium, and sugar) as well as nutrition factors the larger community generally considers to have negative health effects, and rewards those (e.g., fiber, potassium) that are considered to be beneficial to health. In order to test the utility of ONQI, Chiuve, Sampson, and Willett (2011) applied the algorithm to evaluate the diet quality of over 100,000 health professionals for over 20 years. They found that the diets with a lower score of ONQI are associated with higher risks of cardiovascular disease, diabetes, chronic disease, and all-cause mortality. NuVal is the ONQI algorithm's commercial face.

NuVal LLC, NuVal's licensing company, is partially owned by Topco, a private organization that is co-owned by grocery store chains, many of which are implementing NuVal scores into their stores. NuVal scores and labels products on a 1-100 scale with 1 indicating the least healthy products and 100 the healthiest. This labeling design makes NuVal scores more visually accessible. It provides an easy cue for consumers to identify healthier products even when the differences may be small. However, small differences aggregated over repeat shopping trips could result in significant health effects. In addition, previous research has found that NuVal have an information provision effect and a publicity effect on food demand. The information provision effect promotes demand for healthier yogurts by offering information through the NuVal score that is new to consumers. The publicity effect increases demand for healthier and less healthy yogurts equally by making the labeled products more salient (Zhen and Zheng, 2018). As of August 2017, 16 retail chains had adopted NuVal shelf labels.

NuVal LLC scores products in batches over time. It released scores for the first batch of yogurt products in January 2009. By August 1 2010, it had scored 918 yogurt products and by October 25, 2013 (the end date for the data to which I have access), it had scored 2,372 yogurt products.

In this article, I investigate NuVal effects from scanner data for all yogurt products in a small town in the Midwest. I chose yogurt as the case study for two reasons. First, most consumers are familiar with yogurt, and likely some consumers perhaps have an understanding of the nutrition of different yogurt products even before NuVal is available to them. This allows me to study how the adoption of NuVal labels changes preferences and perceptions of nutrition. Second, there is a large variation in the nutrition ranking of individual products, as reflected by the NuVal scores. This variation could help identify the effects of NuVal scores on demand.

There are six grocery stores in the case study. One of the six stores is owned by a regional grocery chain, which started adopting the NuVal label in August 2010. Among the remaining five, two are owned by a local dependent grocer, two by a local food co-operation, and one by another regional grocery chain. None of these five stores adopted the NuVal label or any other shelf nutrition label during my sample period. NuVal LLC scores products and sends monthly files to retail partners. The NuVal store updates the labels on the shelves accordingly. I assume there is one-month lag between when NuVal LLC first scores the product and when the label appears on the shelves. So, I define September 2010 and onward as the adoption period in the NuVal store. Some yogurt products might not be labeled until sometime after September 2010 because they were not scored until later. In general, the NuVal store updates the labels by adding the NuVal scores which were most recently released, or by revising the scores in response to nutrient content changes.[4] The number of NuVal-labeled yogurt products on Universal Product Code (UPC) level in the NuVal store was 120 on September 6, 2010, and increased to 238 at the end of February 2011. The score shown on the shelves in the NuVal store ranges from 23 to 100.

[4]In the dataset I study, no NuVal scores have been revised because of nutrient content changes. Therefore the NuVal store only adds newly released scores on the yogurt products every month.

2.3 Empirical Strategy

2.3.1 Demand Model

To quantify the effect of the NuVal label, I estimate a structural discrete choice demand model for yogurt, using the method proposed by McFadden (1973) and Train (2009). In a discrete choice framework, consumers face a choice set of J differentiated products. On each shopping trip, the consumer is assumed to purchase one unit of the product that yields him the maximum utility. This is a conditional demand model that consumer must purchase at least one unit product. I allow the possibility that the consumer purchase a yogurt product that is not one of my selected choice set of UPCs whose demand I explicitly estimate in the mixed logit model; that is, the choice set includes a *numèraire* or outside good. The *numèraire* is a composite good, representing other excluded yogurt products. This setup is required to obtain correct measure of utility changes (LaFrance and Hanemann, 1989).

Formally, the utility consumer i obtains from purchasing the jth yogurt product on shopping trip t is specified as

$$U_{ijt} = \gamma_{it}(y_i - p_{ijt}) + \delta_{it} Adopt_{jt} + \lambda_{it} Spillover_{jt} + X_{jt}\beta_{it} + \sum_{s=1}^{5} \alpha_s d_s + \alpha_w w_t + \alpha_{w^2} w_t^2 + \epsilon_{ijt} \quad (2.1)$$

where $j = 1, ..., J_t$ and J_t is the number of yogurt products in my sample available to household i on shopping trip t, a combination of time and store; y_i is the income of household i; p_{ijt} represents the price per pint (16 liquid ounces) of product j on household i's trip t; $Adopt_{jt}$ is equal to 1 if product j is labeled with a NuVal score and trip t is to the NuVal store, and 0 otherwise; $Spillover_{jt}$ is equal to 1 if trip t is to one of the non-NuVals stores and product j is sold and labeled with a NuVal score at the NuVal store in the same week when trip t occurs, and 0 otherwise; X_{jt} is a $1 \times K$ vector of observable attributes of product j; d_s are store dummies; w_t is linear weekly trend; ϵ_{ijt} represents an independent and identically distributed error term; and $\gamma_{it}, \delta_{it}, \lambda_{it}, \beta_{it}, \alpha_s, \alpha_w, \alpha_{w^2}$ are parameters to be estimated.

My variables of interest are dummy variables for whether the product is NuVal-diffused, $Spillover_{jt}$. The observable product attributes include dummies for manufacturer, whether the product is a regular yogurt or yogurt drink, package size, whether the product is on display or featured, and whether the price reduction is larger than 5% of the regular price. I also include amount of calories, total fat, cholesterol, fiber, sugar, protein, calcium, and sodium as additional attributes. Including a rich set of product attributes, especially Nutrition Facts label information that is available to consumers at all times, is essential for controlling for omitted variables and avoiding spuriously attributing baseline taste differences as NuVal label effects.

Next, to complete the model and for identification purpose, the utility consumer i obtains from purchasing the *numèraire* good is specified as

$$U_{i0t} = \gamma_{it} y_i + \epsilon_{i0t}, \tag{2.2}$$

where subscript 0 denotes the outside good.[5]

γ_{it} represents household i's marginal utility of income on trip t. As marginal utility of income has to be positive, I assume γ_{it} follows a log normal distribution with log mean $\bar{\gamma}$ and log variance $(\sigma^{\gamma})^2$. δ_{it} captures the within-store effect of the NuVal label on consumer demand for yogurt in the NuVal store. λ_{it} captures the spillover effect of the NuVal label on consumer demand for yogurt product in the non-NuVal stores. I assume both δ_{it} and λ_{it} are random. δ_{it} follows a normal distribution with mean $\bar{\delta} + Z_i\theta^{\delta}$ and variance $(\sigma^{\delta})^2$. Z_i is a $1 \times D$ vector of NuVal score variables, NuVal up-to-date coverage level in the NuVal store, observed household's previous shopping history and household demographic variables, which include household size, income, the age and education level of the household head, and indicator for presence of children. θ^{δ} is a $D \times 1$ vector of corresponding parameters. λ_{it} follows a normal distribution with mean $\bar{\lambda} + Z_i\theta^{\lambda} + \sum_{s=1}^{4} \theta_s^{\lambda} d_s$ and variance $(\sigma^{\lambda})^2$. The $K \times 1$ parameter vector β_{it} describes household i's taste for observable product attributes and NuVal labels. Its kth element β_{it}^k is equal to $\beta^k + Z_i\theta^k$. As a result, (1) can be rewritten as

$$\begin{aligned} U_{ijt} = exp(\bar{\gamma} + \sigma^{\gamma}\mu_{it}^{\gamma})(y_i - p_{ijt}) &+ Adopt_{jt}(\bar{\delta} + Z_i\theta^{\delta} + \sigma^{\delta}\mu_{it}^{\delta}) \\ &+ Spillover_{jt}(\bar{\lambda} + Z_i\theta^{\lambda} + \sum_{s=1}^{4} \theta_s^{\lambda} d_s + \sigma^{\lambda}\mu_{it}^{\lambda}) \\ &+ \sum_{k=1}^{K} x_{jt}^k(\beta^k + Z_i\theta^k) + \sum_{s=1}^{5} \alpha_s d_s + \alpha_w w_t + \alpha_{w^2} w_t^2 + \epsilon_{ijt} \end{aligned} \tag{2.3}$$

where $\mu_{it}^{\gamma}, \mu_{it}^{\delta}, \mu_{it}^{\lambda}$ are i.i.d. standard normal random variables, and x_{jt}^k, $k = 1, ...K$, is the kth product attribute. This specification allows household's taste for product attributes to depend on observed household characteristics. In addition, it allows household's taste for the NuVal label to depend on both observed and unobserved household attributes, which is more general and realistic than other discrete choice models that do not allow random coefficients. In fact, as shown in McFadden and Train (2000), this mixed logit model can approximate arbitrarily close any discrete choice model.

Since I have 15 observed product attributes variables and six observed household demographic variables, potentially there could be 90 interaction variables $x_{jt}^k Z_i$, and more than six

[5] The price and the product characteristics of the *numèraire* are normalized to 0. One might concern that whether this setup could represent the price change in the outside goods. However, the unit prices of outside goods in my sample only have a minor change over time. We could assume that the price of outside good remains constant. See the discussion on Section 2.4.

interaction variables for both $Adopt_{jt}$ and $Spillover_{jt}$ in (2.3). This could lead to overfitting, poor identification and numerical issues in estimation. Therefore, I only include a select few of them, guided by economic intuition. First, I interact $Adopt_{jt}$ with $Score_j$ (product j's NuVal score) and its square, $Coverage_t$ (NuVal coverage level, percentage of yogurt products being labeled among available products in the NuVal store), $Previsit_{it}$ (household's previous shopping history, total number of trips by consumer i to shop at the NuVal store during the period from September 2010 to one week before trip t occurs) and household demographic variables, including the age and education level of the household head, and the indicator for presence of children. The interaction terms $Adopt_{jt} * Score_j$ and $Adopt_{jt} * Score_j^2$ give the model a triple-difference specification that accounts for the differential impact of the NuVal label on yogurts with varying nutrition profile. The square term $Score_j^2$ allows for the possibility of a nonlinear effect. The interaction term $Adopt_{jt} * Coverage_t$ captures household's degree of convenience to notice and capture the information conveyed by NuVal. The interaction term $Adopt_{jt} * Previsit_{it}$ captures household's degree of acquisition of the NuVal information. The interactions between $Adopt_{jt}$ and household demographics are intended to capture heterogeneity in the labeling effect across household types. Second, I interact the key variable, $Spillover_{jt}$, with the same variables that are interacted with $Adopt_{jt}$ to capture the heterogeneity in spillover effect in terms of NuVal score, NuVal coverage, household's previous shopping history and demographics. In addition, I interact $Spillover_{jt}$ with store dummies to capture the unobservable fixed effect on spillover in different non-NuVal stores.[6] Third, I interact the package size variable with the household size variable as households with more family members are likely to purchase products packaged in larger containers. Finally, I interact the dummy variable for whether the price reduction is larger than 5% of the regular price with the household income variable as households with higher income are less likely to respond to price reductions.

Assuming the error term ϵ_{ijt} is distributed i.i.d. with a Type I extreme value distribution, the probability for household to purchase product on trip can be written as (McFadden, 1973)

$$s_{ijt} = \int \frac{exp(V_{ijt})}{1 + \sum_{m=1}^{J_t} exp(V_{imt})} f(\mu_{it}) d\mu_{it} \tag{2.4}$$

where $V_ijt = -exp(\bar{\gamma} + \sigma^{\gamma}\mu_{it}^{\gamma})p_{ijt} + (\bar{\delta}Adopt_{jt} + \theta^{\delta}Adopt_{jt}Z_i + \sigma^{\delta}Adopt_{jt}\mu_{it}^{\delta}) + (\bar{\lambda}Spillover_{jt} + \theta^{\lambda}Spillover_{jt}Z_i + \sigma^{\lambda}Spillover_{jt}\mu_{it}^{\lambda}) + \sum_{k=1}^{K}(\beta^k x_{jt}^k + \theta^k x_{jt}^k Z_i) + \sum_{s=1}^{5}\alpha_s d_s + \alpha_w w + \alpha_{w^2}w^2$ and $f(\cdot)$ represents the joint density for $\mu_{it}^{\gamma}, \mu_{it}^{\delta}$ and μ_{it}^{λ}. As a result, I can write the log likelihood

[6] Spillover effect only occurs in one of the five non-NuVal stores. To avoid multicollinearity, I only interact $Spillover_{jt}$ with four store dummies.

function for the estimation problem as

$$LL = \sum_{i=1}^{N} \sum_{t=1}^{T_i} \sum_{j=1}^{J_t} d_{ijt} ln s_{ijt} \tag{2.5}$$

where $d_{ijt} = 1$ if household i purchases yogurt product j on trip t and 0 otherwise, T_i is the number of trips taken by household i, and N is the number of households in my sample. The log likelihood function (2.5) is not directly estimable because μ_{it}^{γ}, μ_{it}^{δ} and μ_{it}^{λ} are unobserved. I get around this problem by estimating the simulated version of (2.5), that is

$$SLL = \sum_{i=1}^{N} \sum_{t=1}^{T_i} \sum_{j=1}^{J_t} d_{ijt} ln \tilde{s}_{ijt} \tag{2.6}$$

where $\tilde{s}_{ijt} = \frac{1}{R} \sum_{r=1}^{R} s_{ijt}(\mu_{it}^{r})$ and R is the number of simulations, which I set to 50. The variable μ_{it}^{r}, $r = 1, ..., 50$ are random numbers drawn from standard normal distributions.[7] The parameter estimates are obtained by searching for the maximum of (2.6) using the Broyden-Fletcher-Goldfarb-Shanno (BFGS) Quasi-Newton method. The software used is MATLAB.

One potential concern with my specification and estimation procedure is whether the price variable as well as other advertising related variables, such as whether the products are on display or featured or have a price reduction larger than 5% of the regular price, are endogenous in the demand model. This is the classical example for endogeneity if aggregate level demand function is estimated, as stores and firms may base their pricing and advertising decisions on market demand conditions. This is less of a concern when the demand function is estimated at the household level as firms and stores are not likely to change their decisions in response to demand by a particular household. Therefore, when micro or household-level data are used for demand estimation, the price- and advertising-related variables are often treated as exogenous. Dubé, Hitsch, and Rossi (2010), Hendel and Nevo (2013), and Choi, Wohlgenant, and Zheng (2013) are some of the recent examples.

2.3.2 Information Channels

Households could acquire the nutritional information conveyed from the NuVal label, either through self-observation at the NuVal store, or through word-of-mouth. If a consumer has never been to the NuVal store after the NuVal label was adopted there, the only way for him

[7]To take a sequence of draws that provide a better approximation to the relevant integral and reduce the variance caused by simulation than a purely random sequence, I draw numbers from the Halton Sequences and then convert those numbers into random numbers from the standard normal distributions (Spanier and Maize, 1994).

to acquire the NuVal information is through word-of-mouth, the indirect channel.[8] On the other hand, if a consumer has been to the NuVal store after the NuVal label was adopted, he could learn the information either through self observation, direct channel, or through word-of-mouth, or through both. If the information spillover is driven by the households' own experience and observation, one might question the external validity of my results on spillover. If, however, NuVal shelf nutrition label spillover is also triggered by interpersonal communication, the evidence will carry strong implications for the optimal retail-shelf labeling design.

$Previsit_{it}$ captures the previous shopping history of household i up to the date when trip t occurs. It measures the total number of household i's visits to the NuVal store, where he would have a chance to observe the label directly. Only the transaction made by the households who have been to both the NuVal store and the non-NuVal stores could identify the spillover effect from both channels. Therefore, underlying the demand model on equation (2.3), the $Spillover_{jt} * Previsit_{it}$ variable captures spillover effect from both channels, while other $Spillover_{it}$ terms only capture the effect from the indirect channel.

2.4 Data

I analyze yogurt purchases by IRI BehaviorScan (Bronnenberg et al., 2008) panel data in a small town in the Midwest. The IRI BehaviorScan tracked not only household purchases but also weekly retail sales from the universe of grocery stores in this small town. By observing store sales, I know what products were available at what prices when a household visited the store even if the household did not purchase those products.[9] The benefit of possessing this extra piece of information is to reduce measurement error in the estimation of cross-price effects. I focus on trips to six grocery stores in the IRI data.[10] Of the six, one is owned by a regional grocery chain, which started adopting the NuVal label in August 2010. It is referred to Store No.6 in my sample data ($s1, ...s5 = 0$). Among the remaining five, two are each owned by a local independent grocer, two by a local food co-op, and one by another regional grocery chain. None of these five stores adopted the NuVal label or any other shelf nutrition labels during my sample period. The non-NuVal stores are referred to Stores No.1, 2, 3, 4 and 5 in my sample data.

My sample stores offered 640 yogurt UPCs. Estimating barcode-level demand for all yogurt

[8] In fact, for those consumers who have never been to a NuVal store, it is possible that they do not even notice the NuVal label, not even through word-of-mouth. In this case, the spillover related estimates through indirect channel would be insignificant.

[9] If there is no single transaction on a product being made in a store during a week, I would not know whether the product was available and its price. However, the bias created by this scenario is likely to be economically insignificant due to the zero market shares of such products.

[10] Two stores are dropped in my data because they sold very few yogurt products.

products is computationally burdensome, if not impossible even with a discrete-choice model. I use the following procedure to select a subset from the universe of UPCs into my demand model. For UPC j to be included in trip t of the demand model, it has to satisfy all of the following two criteria. First, UPC j had to be available for purchase at the store to which trip t was made as determined by the retail scanner data. Second, the UPC had a dollar share of at least 0.125% in yogurt category in this town during 2010 to 2011. Applying this selection procedure yields 250 yogurt UPCs, thus accounting for 85% of yogurt market in dollar sales in this town during these two years.

The outside choice (i.e. the *numèraire*) encompasses the purchase of a yogurt product that is not one of the 250 UPCs whose demand I explicitly estimate in the mixed logit model. It includes 390 UPCs which are indicated in the store-level scanner data but didn't satisfy the criteria above. I calculate the weekly average price per pint of the outside goods in each stores and report the summay statistics on Table 2.6. Compared to the 250 explicit UPCs in my demand model, the average prices of the outside goods had much fewer changes during the time period. It's reasonable to assume that the price of outside good remains almost constant and could be normalized to zero in the demand estimation.

Because the NuVal store adopted NuVal labels in August 2010 and estimation with many products and/or observations is computationally intensive, I focus the analysis on the two months before the adoption event (i.e. June and July 2010) and the six months after the event (i.e. from September 2010 to February 2011). A total of 1,709 households made 67,388 trips to the six stores during this sample period. On 63,686 of these trips, yogurt was purchased. As NuVal scores are specific to UPC, I model yogurt demand at the barcode level.[11] I observe, on each shopping trip from the household scanner data, the UPC of the yogurt purchased (if any) and the price paid. I have household demographic data including household income, household size, presence of and age group of children, and the age and education level of the household head.

The store retail scanner data in BehaviorScan gives us the households choice set for each trip and the prices for products the household did not purchase on each trip. For each UPC in the retail scanner data, I have information on weekly dollar and unit sales, whether the price mark-down is larger than 5%, and advertising and promotion activities in the store. The IRI data also provides product-specific information on the following time-invariant product characteristics for each UPC: the manufacturer, the package size and whether the product is regular yogurt, a yogurt drink, or a smoothie.

The IRI scanner data, however, does not indicate whether a UPC was labeled with a NuVal score at the NuVal store. To construct the variables of interest, $Adopt_{it}$ and $Spillover_{it}$, I lever-

[11] Throughout discussion below, I use the terms product and UPC interchangeably.

age a variable in the NuVal score dataset provided by NuVals licensing company, NuVal LLC, that records the date on which a product was first scored by the company. In my conversion with staff at NuVal LLC, I learned that the company sends NuVal scores of newly rated UPCs to its retail partners on a monthly basis. In light of this, I assume a 30-day lag between when NuVal first scores the product and when the label appears on store shelves.[12] Some UPCs may not be labeled in the demand model until sometime after September 1 2010, when the adoption period starts. $Coverage_t$, percentage of yogurt products being labeled among available products in the NuVal store, is a necessary inclusion in the model, because it demonstrates the updating process of NuVal adoption in the NuVal store.

Table 2.1 reports the summary statistics of the time-invariant product characteristics variables including nutrient information for the 250 UPCs. Product nutrient information is from the Nutrition Facts label and provided to us by NuVal LLC. Note all variables have been scaled such that mean of the scaled variable ranges between 0 and 1. This was done to avoid numerical issues in nonlinear estimation caused by variables measured on different scales. 25% of the products are produced by Danone, while 48% of the products by General Mills. 97% of the products are regular or soy-based yogurt, while the rest are yogurt drinks or smoothies. The average package size is 0.91 pint, or 14.56 ounces. Finally, I can see that the NuVal scores of the 250 UPCs range from 23 to 100, with an average score of 51. This wide variation in product healthfulness will help with the identification of the NuVal effect. Table 2.2 reports the results from a regression of the NuVal score on the nutrient variables. As expected, the R squared is 0.84, indicating that the variation in NuVal scores is largely determined by the differences in nutrients. Also, yogurt products with higher calories, fiber, calcium, and sodium but less fat, sugar, and protein, receive higher scores.

Table 2.3 reports the summary statistics of household characteristics variables for the 1,709 households in my estimation sample. 64% of the households have a head aged between 35 and 64 and 33% of the households have a head aged 65 or above, while the rest are headed by a person younger than 35 years old. 20% of the household heads have a college or higher degree. The average income for the households is about $52,000 and the average household size is 2.4.

Table 2.4 reports the summary statistics for all variables used in estimation. These are calculated based on 13,847,329 product-trip observations (the unit of observation is one UPC on one trip) from 67,388 trips. On average, there are about 205 UPCs in a consumers choice set on each trip. The average price over all products in the consumers choice set per trip was $1.47 per pint (16 ounces). There are several advertising and promotion activities in the stores; about

[12] This might not be an impeccable assumption. However, to the extent that it introduces measurement error in $Adopt_{it}$ and $Spillover_{it}$, my estimate of the label effect will be biased toward zero. Therefore, the estimates may be interpreted as lower bounds of the true values.

20% and 31% of the product-trip observations are associated with display or feature ads, respectively. In addition, about 61% of the product-trip observations are those where the price reduction was 5% or greater of the regular price. The percentage of label yogurt products in the NuVal store increases from 48% to 80% from September 2010 to February 2011. Among the trips to the NuVal store, consumers had visited the same store up to 100 times before. And among the trips to the non-NuVal store, consumers had visited the NuVal store up to 78 times. The previous shopping histories can not be ignored when studying the effect of NuVal labels.

2.5 Empirical results

Table 2.5 presents the parameter estimates from my mixed logit demand model. Several results are worth discussing. First, since the marginal utility of income parameter γ_{it} is assumed to follow a lognormal distribution with log mean $\bar{\gamma}$ and log standard deviation σ^{γ}, the mean and median of γ_{it} take the form of $exp[\bar{\gamma} + \frac{(\sigma^{\gamma})^2}{2}]$ and $exp(\bar{\gamma})$, respectively. Plugging the estimates into these formulas, I obtain the mean and median marginal utility of income to be 1.90 and 1.34, respectively.

Second, most of the estimated efficients on product characteristics $(\beta^k s)$ and their interactions with household characteristics $(\theta^k s)$ have expected signs. Consumers have higher demand for products produced by General Mills, compared to Danone or other manufacturers. They have lower demand for products in larger packages. Larger households, however, have higher demand for products in larger packages. When products are displayed or featured, demand increases. Consumers have higher demand for products with price reduction greater than 5%, but this effect is smaller for households with higher income. In terms of nutrients, consumers prefer yogurt products with less cholesterol, less sugar, less sodium, more protein, and more calcium, as expected. Interestingly, consumers prefer more fat and less fiber in yogurts. Yogurts with less fat or more fiber may not be as tasty as other products.

Third, the posting of NuVal score is found to have a statistically significant within-store effect on consumer demand. This within-store effect increases with the NuVal score up to 71 and then decreases. It suggests that consumers regard ultra-healthful yogurts (e.g., nonfat or plain) as less tasty ones and therefore the effect is largest for yogurts with medium high score. The within-store effect also decreases with the NuVal coverage level (percentage of products being labeled among available products in the NuVal store). This is consistent with the conjecture that yogurt products with the NuVal label will be more prominent to consumers if only a small portion of products are labeled. When more yogurt products are labeled, this salience effect becomes smaller. In addition, the within-store effect varies across household demographics. The within-store effect is higher for households headed by adults older than 35, without college education level or without children. On the other hand, previous shopping history does not have a statistically significant within-store effect significantly. The within-store effect can also be measured in terms of dollars, using the formula $\frac{\beta_{adopt,ijt}}{\gamma_{mean}}$, where γ_{mean} represents the mean of marginal utility of income. For example, when the coverage level is 50% in the NuVal store, for those households headed by someone older than 65, without college education nor children and have been to the NuVal store seven times before ($previsit = 0.024$), the adoption (within-sotre) effect on a product with NuVal score of 70 is equivalent to a price reduction of $0.30. But at the same time when $coverage$ is equal to 50%, for those households who are headed by someone younger than 35, with college education and children, with the same $previsit$ equal to 0.024, the adoption effect on the same product is equivalent to a price reduction of $-0.25, which means a price increase of $0.25. The latter group of households are more likely to use nutrition facts and other food labels even before the adoption of NuVal labels. So NuVal has less effect on them.

Next, NuVal score is found to have a statistically significant spillover effect on consumer demand in the non-NuVal stores. The more products are labeled in the NuVal store, the greater the spillover effect in the non-NuVal stores is. This suggests that consumers could notice and gather the nutrient information more easily if more products are labeled in the NuVal store, therefore they are more likely to apply the knowledge from the NuVal label when they shop at other stores. Similar to the within-store effect, the spillover effect also increases with the NuVal score up to a point (37 in this case) and then decreases. The reason is similar to that of the within-store effect. The spillover effect also varies by households' previous shopping history. If a consumer has visited the NuVal store many times, the probability for him to purchase the NuVal adopted yogurts in the non-NuVal stores increases significantly. This is expected because those consumers who have visited the NuVal store many times could acquire the additional information more easily, and as a result the spillover effect is more likely to occur. In terms of consumer characteristics, the spillover effect is higher for consumers without children than those with children. On the other hand, households' age, education level and previous shopping history do not have a statistically significant effect on the spillover. Spillover effects in non-NuVal Stores No. 1 and No. 3 are significantly lower than that of Store No.5. The spillover effect could also be quantified using the formula $\frac{\beta_{spillover,ijt}}{\gamma_{mean}}$. For example, when the coverage level is 50% in the NuVal store, the spillover effect on a yogurt product with NuVal score of 70 in non-NuVal Store No.5 ($s_1, ...s_4 = 0$) is equivalent to a price reduction of $0.21 for a household without children nor college education, headed by someone younger than 35, and has been to the NuVal store seven times before ($previsit = 0.024$). With the same coverage level, the spillover effect on the same product in the same non-NuVal store is only equivalent to a price reduction of $0.09 for a household with children, without college education, headed by someone younger than 35, and has the same shopping history. The latter group probably have already paid more attention to the nutritional quality of the products so NuVal has less effect on them.

Finally, the estimation results also shed light on the channels through which the spillover effect occurs. If a consumer has never been to the NuVal store after the NuVal label was adopted there, the only way for him to acquire the additional nutritional information conveyed by NuVal is through word-of-mouth, the indirect channel. On the other hand, if a consumer has been to the NuVal store after the NuVal label was adopted, he could learn the information either through self observation, the direct channel, or through word-of-mouth, or through both. Therefore, the $spillover * previsit$ variable captures spillover effect from both channels, while other $spillover$ terms only capture the effect from the indirect channel. Take the same example provided above, when the coverage level is 50% in the NuVal store, the spillover effect on a yogurt product with NuVal score of 70 in non-NuVal Store No. 5 for a household without children nor college degree, headed by someone younger than 35, and $previsit = 0.024$, is equivalent to price reduction of $0.21. This is the total spillover effect. But if he hadn't been to the NuVal store before ($previsit = 0$), the spillover effect would only have occured through the indirect channel, and would have been equivalent to a price reduction of only $0.18. This example demonstrated that the indirect effect is less than the total effect and hence there is evidence that the spillover effect occurs through both channels.

2.6 Conclusion

In this article, I investigate both the within-store and spillover effects of a retail-shelf nutrition label, the NuVal label, on yogurt sales by estimating changes to purchase behavior due to the adoption or the spillover of NuVal labels under a mixed logit demand framework. As expected, the adoption of the NuVal label has a significant within-store effect in the adopting store. This effect provides evidence that consumers try to make a balance between palatability and level of healthfulness, as the within-store effect first increases and then decreases with NuVal score. It also suggests a salience effect, as the effect decreases as the NuVal coverage level increases. I also found that consumers who may have been less likely to use Nutrition Facts labels before availability of NuVal tend to respond more to NuVal information. They include households without young children and households headed by persons older than 35 or without college degrees. On average, the adoption of the NuVal label is equivalent to a price reduction of $0.02 in the NuVal store.

Empirical results also support the hypothesis that information spillovers affect consumer choices. I found that NuVal has an economically and statistically significant spillover effect on consumers' demand. Consumers' potential ways to learn NuVal information, including previous shopping history and label coverage level in the NuVal store, affect spillover effect in a positive direction. Similar to the adoption within-store effect, the spillover effect first increases with the NuVal score but peaks at a threshold NuVal score. The exact value of the threshold score depends on household demographics. Consistent with expectations, I found consumers who may have been less likely to use Nutrition Facts labels before the availability of NuVal tend to respond more to NuVal information in the non-NuVal stores. They are the households without young children. Consequently, these consumers benefit more from NuVal. On average, the spillover effect of the NuVal label is equivalent to a price reduction of $0.10 on the yogurt product, which is approximately 6.8% off the yogurt price. Ignoring food labeling spillover effect in empirical analysis leads to an underestimation of the effectiveness of the retail-shelf nutrition label.

In addition, I found evidence that the spillover effect occurs through both the direct and indirect channels. The households who had never been to the NuVal store before could only learn the additional NuVal information through word-of-mouth, the indirect channel. For those who had visited the NuVal store, the spillover effect could occur through the direct channel, or through the indirect channel, or through both. Significant evidence is found that the indirect effect is less than the total effect, and spillover effect occurs through both channels. Therefore, word-of-mouth also plays an important role in disseminating the nutrition information conveyed by NuVal.

Under Executive Orders 12866 and 13563, the U.S. Food and Drug Administration (FDA) is directed to calculate the costs and benefits of all regulatory options for all economically significant regulatory actions. In its regulatory impact analysis (RIA) of the 2016 final rule, FDA economists predicted the benefit to range from 0.2 billion to 5.2 billion (in 2014 dollars) per year, assuming a discount rate of 3% (FDA, 2016a,b). The significance of this RIA is that the FDA used a revealed preference approach to quantify the value of revised Nutrition Facts information,[13] while it used the cost of illness approach to estimate the benefits associated with the original NLEA of 1990 (RTI International, 1991). With presence of information spillover, my calculation of labeling benefits is greater than the current FDA approach. As such, a mandated adoption of NuVal or other similar multiple-level interpretive shelf or FOP nutrition symbol has the potential to create larger benefits to consumers than expected.

Some of the limitations of my analysis suggest spaces for further research. First, I assume price, advertising promotion, and discount activities to be exogenous in this article. It is reasonable to claim that those variables cause endogeneity issue in the demand estimation. Second, in stead of creating week dummies, I create week trend variables to capture the fixed effect along with time. They might not capture the holiday effect on sales very well. Lastly, this article studies the effects of NuVal label in terms of consumer demand; it is also perti-

[13]FDAs numbers are obtained by scaling willingness-to-pay (WTP) for the original Nutrition Facts label estimated by Abaluck (2011) where the author estimated the WTP by revealed preference. FDA assumed the revision to have a smaller impact on food purchases than the original NLEA (FDA, 2016a,b).

nent to investigate the effects in terms of health concerns, which reveal whether NuVal rollout leads to consumers' healthier diet choice. I leave empirical investigation of these possibilities to future research.

Table 2.1: Summary Statistics of Time-Invariant Product Characteristics Variables

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Danone	0.25	0.44	0	1
Mill	0.48	0.50	0	1
Vol	0.91	0.81	0.25	4
Type	0.97	0.17	0	1
Score	0.51	0.26	0.23	1
Calories	0.66	0.21	0.38	1.25
Fat	0.13	0.25	0	1.72
Cholesterol	0.11	0.17	0	1.3
Fiber	0.06	0.18	0	1.07
Sugar	0.61	0.24	0.17	1.10
Protein	0.68	0.30	0.20	1.8
Calcium	0.43	0.14	0	1
Sodium	0.89	0.20	0.22	1.58

Notes: Number of products included: 250. Variable definitions: *Danone*: =1 if the product is produced by Groupe Danone and 0 otherwise; *Mill*: =1 if the product is produced by General Mills Inc. and 0 otherwise; *Vol*: package size of the product in pts (1 pt=16 ounces); *Type*: =1 if the product is yogurt or soy yogurt and 0 otherwise (e.g. cultured dairy drink, yogurt drink or yogurt smoothie); *Score*: the original NuVal score/100; *Calories*: total calories in kcal per 0.85 grams of serving; *Fat*: total fat in grams per 17 grams of serving; *Cholesterol*: cholesterol in milligrams per 3.4 grams of serving; *Fiber*: fiber in grams per 34 grams of serving; *Sugars*: sugars in grams per 5.67 grams of serving; *Protein*: protein in grams per 17 grams of serving; *Calcium*: calcium in daily percentage points per 4.25 grams of serving; *Sodium*: sodium in milligrams per 1.7 grams of serving; Deciles of the original NuVal scores: 10^{th}: 24; 20^{th}: 27; 30^{th}: 28; 40^{th}: 32; 50^{th}: 39; 60^{th}: 58; 70^{th}: 61; 80^{th}: 81 and 90^{th}: 91.

Table 2.2: Regression Results of NuVal Score on Nutrient Variables

Dependent variable: NuVal Score	
Variables	OLS
Calories	0.63***
	(0.14)
Fat	-0.56***
	(0.09)
Cholesterol	0.10
	(0.10)
Fiber	0.14***
	(0.04)
Sugar	-1.26***
	(0.10)
Protein	-0.20***
	(0.03)
Calcium	0.10*
	(0.06)
Sodium	0.21***
	(0.04)
Constant	0.82***
	(0.04)
N	250
R^2	0.8400

Standard errors in parentheses. Two-tailed test.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.3: Summary Statistics of Household Demographic Variables

Variable	Mean	Std. Dev.	Min	Max
Midage	0.64	0.48	0	1
Elder	0.33	0.47	0	1
Edu	0.20	0.40	0	1
Kid	0.12	0.33	0	1
Income	0.52	0.33	0.05	1.22
Familysize	2.42	1.21	1	8

Notes: Number of households: 1,709. Variable definitions: *Midage*: =1 if the age of the household head is between 35 and 64 and 0 otherwise; *Elder*: =1 if the age of the household head is greater than or equal to 65 and 0 otherwise; *Edu*: =1 if the household head has at least a college degree and 0 otherwise; *Kid*: =1 if the household has a child less than 12 years old and 0 otherwise; *Income*: annual household income in $100,000s; *Familysize*: number of people in the household (in 10 persons).

Table 2.4: Summary Statistics of Variables Used in Estimation

Variable	Mean	Std. Dev.	Min	Max
Price	1.47	0.69	0	5.23
Danone	0.15	0.35	0	1
Mill	0.64	0.48	0	1
Type	0.94	0.23	0	1
Vol	0.42	0.33	0	4
Vol*Familysize	1.09	1.18	0	24
D	0.20	0.40	0	1
F	0.31	0.46	0	1
Pr	0.61	0.49	0	1
Pr*Income	0.34	0.38	0	1.22
Calories	0.55	0.23	0	1.25
Fat	0.06	0.14	0	1.72
Cholesterol	0.06	0.11	0	1.30
Fiber	0.05	0.15	0	1.07
Sugar	0.52	0.26	0	1.10
Protein	0.53	0.18	0	1.8
Calcium	0.38	0.14	0	1
Sodium	0.83	0.24	0	1.58
Adopt	0.11	0.32	0	1
Adopt*Score	0.07	0.20	0	1
Adopt*Score2	0.04	0.14	0	1
Adopt*Coverage	0.07	0.20	0	0.80
Adopt*Midage	0.08	0.27	0	1
Adopt*Elder	0.03	0.18	0	1
Adopt*Edu	0.03	0.16	0	1
Adopt*Kid	0.01	0.11	0	1
Adopt*Previsit	0.00	0.02	0	0.36
Spillover	0.43	0.50	0	1
Spillover*score	0.24	0.31	0	1
Spillover*score2	0.15	0.23	0	1
Spillover*Coverage	0.28	0.33	0	0.80
Spillover*Midage	0.31	0.46	0	1
Spillover*Elder	0.11	0.31	0	1

Table 2.4 – Summary Statistics of Variables Used in Estimation, Continued

Variable	Mean	Std. Dev.	Min	Max
Spillover*Edu	0.08	0.27	0	1
Spillover*Kid	0.07	0.25	0	1
Spillover*Previsit	0.00	0.02	0	0.28
Spillover*S1	0.01	0.08	0	1
Spillover*S2	0.15	0.35	0	1
Spillover*S3	0.06	0.23	0	1
Spillover*S4	0.05	0.22	0	1
S1	0.02	0.12	0	1
S2	0.28	0.45	0	1
S3	0.11	0.31	0	1
S4	0.09	0.28	0	1
S5	0.32	0.47	0	1
W	0.42	0.11	0.24	0.61
W2	0.19	0.09	0.06	0.37

Notes: The summary statistics are based on 13,847,329 product-trip observations (the unit of observation is one product on one trip) from 67388 trips as on average, a consumer faced about 205 UPCs on each trip. Variable definitions: for *Danone, Mills, Type, Vol, Calories, Fat, Cholesterol, Fiber, Sugars, Protein, Calcium, Sodium* and *Score*, see the notes in Table 1; for *Midage, Elder, Edu, Kid, Familysize* and *Income*, see the notes in Table 2; *Price*: price of the product per pint (16 ounces); *D*: =1 if the product was on display and 0 otherwise; *F*: =1 if the product was featured and 0 otherwise; *Pr*: =1 if the temporary price reduction for the product is 5% or greater of the regular price and 0 otherwise; *S1-S5*: dummy variable indicating the store of the trip; *W*: time trend/100; *Adopt*: =1 if the product was sold in the NuVal store after August 2010 and the product had already been scored at least one month earlier; *Coverage*: percentage of yogurt products being labeled among available products in the NuVal store; *Previsit*: total number of trips by consumer i to shop at the NuVal store during the period from September 2010 to one week before trip t occurs, divided by 280 to scale it from 0 to 1; *Spillover*: = 1 if trip t is to one of the non-NuVals stores and product j is sold and labeled with a NuVal score at the NuVal store in the same week trip t occurs.

Table 2.5: Mixed Logit Estimation Results

Variable Name	Estimate	Variable Name	Estimate
Price	0.29***	Adopt	-0.25
	(0.02)		(0.27)
Sigma_Price	0.84***	Adopt*Score	3.66***
	(0.02)		(0.34)
Danone	-0.08***	Adopt*Score^2	-2.56***
	(0.02)		(0.28)
Mill	0.69***	Adopt*Coverage	-2.11***
	(0.02)		(0.27)
Type	-0.09	Adopt*Midage	0.56***
	(0.09)		(0.19)
Vol	-1.63***	Adopt*Elder	0.56***
	(0.03)		(0.20)
Vol*Familysize	0.10***	Adopt*Edu	-0.24***
	(0.01)		(0.06)
D	0.74***	Adopt*Kid	-0.24***
	(0.01)		(0.08)
F	0.53***	Adopt*Previsit	0.05
	(0.02)		(0.76)
Pr	0.69***	Sigma_Adopt	-0.03
	(0.02)		(0.16)
Pr*Income	-0.36***	Spillover	-0.07
	(0.03)		(0.16)
Calories	-0.22	Spillover*Score	0.40**
	(0.21)		(0.19)
Fat	3.11***	Spillover*Score^2	-0.54***
	(0.12)		(0.16)
Cholesterol	-3.78***	Spillover*Coverage	0.77***
	(0.11)		(0.26)
Fiber	-0.36***	Spillover*Midage	0.10

Table 2.5 – Mixed Logit Estimation Results, Continued

Variable Name	Estimate	Variable Name	Estimate
	(0.05)		(0.10)
Sugar	-0.52***	Spillover*Elder	-0.05
	(0.14)		(0.10)
Protein	0.65***	Spillover*Edu	-0.01
	(0.05)		(0.04)
Calcium	0.14***	Spillover*Kid	-0.24***
	(0.05)		(0.04)
Sodium	-0.49***	Spillover*Previsit	3.19***
	(0.04)		(0.97)
S1	-1.01***	Spillover*S1	-1.02***
	(0.21)		(0.12)
S2	1.76***	Spillover*S2	-0.02
	(0.11)		(0.04)
S3	0.40***	Spillover*S3	-0.09*
	(0.12)		(0.05)
S4	0.87***	Spillover*S4	0.03
	(0.14)		(0.03)
S5	1.41***	Sigma_Spillover	-1.08***
	(0.11)		(0.13)
W	9.07***	W^2	-7.74***
	(0.81)		(1.14)
$Log - Likelihood$: 304,041			

Notes: Number of trips used in estimation: 67,388. The Value of log-likelihood is 303,993.8. W denotes weekly trend variable. S1-S5 denote dummies for stores 1-5.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.6: The Summary Statistics of Price Changes in Outside Goods

Store No.	Mean	Std. Dev.	Min	Max
s_1	1.59	0.14	1.27	1.89
s_2	2.24	0.16	1.84	2.51
s_3	2.25	0.14	1.98	2.53
s_4	2.25	0.15	1.98	2.59
s_5	2.14	0.13	1.89	2.36
NuVal-Store	2.16	0.04	2.08	2.23

The price represents the unit price per pint (16oz), unit is dollar. $s_1, ...,_5$ denote the non-NuVal stores.

Chapter 3

Estimating the Effects of NuVal Label on Food Purchase

3.1 Introduction

Over the past century, deficiencies of essential nutrients have dramatically decreased. Many infectious diseases have been conquered, and the majority of the U.S. population can now anticipate a long and productive life (Murphy et al., 2017; Arias et al., 2017; Dwyer-Lindgren et al., 2017). At the same time, rates of chronic diseases, many of which are related to poor quality diets and physical inactivities, have increased (Picavet et al., 2017; Donovan, 2018). About half of all American adults have one or more preventable, diet-related chronic diseases, including cardiovascular disease, type 2 diabetes, overweight, and obesity (Fardet et al., 2015).

The US Department of Health and Human Services (2017) provides quantitative key recommomdations for several components of the diet that should be limited in *Dietary Guidelines for Americans*. These components are of particular public health concern in the United States, and the specified limits can help individuals achieve healthy eating patterns within calorie limits. The *Dietary Guidelines for Americans* suggests that households should consume less than 10% of calories, 10% of calories and 2,300 milligrams (mg) per day from added sugar, saturated fats and sodium, respectively, from 2015 to 2020. Various efforts have been made with the goal to improve Americans diet. These include the federal ban on sales of high-calorie drinks and snacks in elementary schools, tax imposition on sugary soda drinks in some places such as Philadelphia and Berkeley, and appropriate food labeling.

Food labeling is considered as one of the most important ways to guide consumers to choose high-quality and nutritious food. The Nutrition Facts Panel is mandated for most food products under the provisions of the 1990 Nutrition Labeling and Education Act (NLEA). The law mandates certain information including the name of the product, net quantity, serving size, number of servings per package, nutrition facts, ingredient list, and the name of manufacturer or distributor to be listed on the label (Longe, 2008). However, consumers often report difficulty in interpreting quantitative information contained in Nutrition Facts Panel, because the information presented is too much and too complicated (Rothman et al., 2006). Nutrition label literacy is particularly low among individuals who are older, of black or Hispanic race/ethnicity, unemployed, born outside of the US, having lower English proficiency, less educated, having lower income, or living in the South (Nogueira et al., 2016). Therefore, the information provided by the Nutrition Facts Panel might fail to reach the individuals who need it the most.

Over the last decade, the U.S. food industry has introduced and expanded the use of various voluntary nutrition labels (VNL), because these labels help manufacturers and retailers better seg- ment the market and reach targeted groups of consumers more easily (Teisl and Roe, 1998; Golan et al., 2001). VNLs include both front-of-package labels (FOP) and retail-shelf nutrition labeling systems (Hersey et al., 2013). FOP labels are words, pictures, or symbols added by the manufac- turers on the front of food package that make nutrition or health claims, such as a label of low fat or organic. Three general formats of FOP labels are currently in use: nutrient specific, summary indicator, and food group information. Nutrient specific labels display information on a few key nutrients. Examples include the Facts Up Front label, introduced by the Grocery Manufacturers Association and Food Marketing Institute, which displays the amounts of calories, saturated fat, sodium, and sugar per serving (Grocery Manufacturers Association and Food Marketing Institute, 2010).[1] Summary indicator labels are labels that provide an overall nutrition score or ranking. It is usually binary, such as the Health Choices Program in Belgium, which displays a check mark on a food package if the food meets certain nutrition criteria. Food group information labels are labels that display the category or key features of the product, like whether a product is whole grains or gluten free. Another type of VNLs is retail-shelf nutrition labeling systems. They are labels added by retailers on shelves or price tags, like Guiding Stars and NuVal. These labels reflect the interpretation of nutrition facts by nutrition and health experts based on scientific evidence on diet-health links. For example, NuVal scores products on a 1-100 scale with 1 indicating being least healthy and 100 the healthiest. These labels are different from FOP labels as they are labels added by retailers on the price tag or shelf and hence not on the products packages, while FOP labels are added by manufacturers and part of a products package.

There is a growing amount of empirical research on the impacts of VNLs on market sales. Most of the previous studies have focused on the sales effects of FOP labels, which measures

[1]The manufacturers or retailers also have the option to display up to two healthy nutrients that are key features of the product, such as fiber, potassium, protein, vitamin A, vitamin C, vitamin D, calcium, and iron. If the package has limited space, only the amount of calories needs to be displayed.

how the additional or simplified information provided by FOP labels changes consumers purchase decisions. It is found that FOP labels increase the probability of consumers choosing products with FOP labels, and made consumers to switch from unhealthy products to healthy ones (Drichoutis et al., 2006; Zhu et al., 2015; Hersey et al., 2013; Grunert and Wills, 2007; Kiesel and Villas-Boas, 2013). A few researchers have studied retail-shelf nutrition labels. Rahkovsky et al. (2013) investigated how Guiding Stars affected ready-to-eat cereals and showed that sales of low-ranked products decreased while sales of high-ranked ones increased. Zhen and Zheng (2018) applied difference-in-differences method to show that the adoption of NuVal labels affected market sales. However, both studies focused on how retail-shelf nutrition labels affect consumers demand within the stores that adopted the retail-shelf nutrition labels. My previous two chapters also show that the adoption of the NuVal label increased the sales of labeled products, including both the within-store direct effect as well as the spillover effects in other stores.

Even though previous research has shown that the nutrition labels affect consumers' purchase behavior, whether the labels make consumers diets healthier is uncertain. On one hand, VNL provides additional information on products' nutrition facts, serving as a supplementary tool for Nutrition Facts Panel, without changing the true level of healthiness. Consumers might switch from the unlabeled products to labeled ones; while some of the unlabeled products consumers switch away from are unhealthier, others are in fact healthier than the labeled products. On the other hand, even though consumers are actually switching to healthier products, this psychological suggestion tends to make consumers overeat (Finkelstein and Fishbach, 2010). It raises a possible concern that nutrition labels will also cause uncertainty on consumers' total calories intake.

In this article, I apply the synthetic control method to study whether the adoption of retail-shelf nutrition label, NuVal, has a significant effect on consumers calories intake and the healthfulness of their shopping baskets. The shopping basket in this study includes yogurt, frozen dinner, cereal and salty snacks. I study the case in a small town in the Midwest. One store in this town adopted the NuVal label in August 2010, while other stores didn't adopt any retail-shelf nutrition labels. Below, I call the store that adopted the NuVal label "the NuVal store" and the others "non-NuVal stores." The NuVal label affects consumers' diet choice in the NuVal store by providing consumers a better idea on the healthiness of products. For the consumers who had visited the NuVal store, the treated households, there is an effect on total calories purchase and healthiness of the products. For the consumers who never visited the NuVal store during the same period, the control households, there is no such effect on their diet choices. The difference between total calories purchase and healthiness of the products from the treatment group and control group is the treatment effect on diet from NuVal label. To implement a comparative case study, there are two assumptions that needed to be satisfied:

first, the intervention or the event has no effect on the outcomes before the implementation period; second, the outcomes of the untreated units are not affected by the intervention implemented for the treated units. The first assumption is likely to be satisfied. The second one will be problematic since chapter 2 of this dissertation has shown that there is a significant information spillover effect through both the direct and indirect channels. Spillover effect occurs when consumers learned information in the adopting store to make their purchasing decisions at the non-adopting stores. Households could learn the nutrition information by either directly observing the NuVal label, or hearing from others who had observed the NuVal label at the adopting store. For the households who have never been to the NuVal store after the labeled was adopted, they acquire the nutritional information through word-of-mouth, the indirect channel, only. For those who have been to the NuVal store after the NuVal label was adopted, the spillover effect in the non-NuVal stores can occur through either direct observation, the direct channel, or through the indirect channel, or through both. In my study, I select consumers who only visited the non-NuVal stores during the treatment period as my control group, and the consumers who ever visited the NuVal store during the treatment period as my treatment group. Because of the direct and indirect spillover effects, the estimated effects of NuVal label on consumers diet, which is the difference of outcome variables of interest between the two groups, would be a lower bound of the true effects. The NuVal label is found to have a statistically significant effect on consumers dietary healthfulness. On average, the adoption of NuVal label makes households reduce their calories intake and purchase food products with a higher score. The effects vary by different demographic groups of households.

A wide range of studies have examined the association between label use and health practices. Turrini et al. (2018) provide a conceptual framework to suggest how collect food products for healthy diet. Individuals with healthier eating habits report greater use of nutrition labels, either as a result of personal preference (Satia et al., 2005; Jackey et al., 2017), or because of the requirements of a health-related diet (McArthur et al., 2001; Gorton et al., 2009; Lin and Yen, 2008; Krystallis and Ness, 2004). The evidence on the effectiveness of nutrition label use is mixed. Some research has shown that introducing nutrition labels can positively influence food selection (Kelly et al., 2013; Hammond et al., 2015). Conversely, other research has found posting labels has little influence on food choice or dietary behavior in young adults (Freedman and Connors, 2010; Hoefkens et al., 2011). However, only a few research studies the effect of nutrition labels on nutrients intake. Zhang et al. (2017) found frequent use of nutrition labels was associated with lower consumption of sodium and high-sodium foods in the U.S. Neuhouser et al. (1999) found that label use was significantly associated with lower fat intake and explained 6% of the variance in fat intake. Aron et al. (1995) found that the nutrition labels in a student cafeteria increased college students' calories, fat and carbohydrate intake, but decreased protein intake. And Schwartz et al. (2012) designed three experiments and found that the calorie labeling in fast-food restaurants caused customers to reduce calories intake by taking a smaller portion of their chosen order. These research relied on self-reported data. Christoph and Ellison (2017) combined survey and meal photographic data to compare food selection, servings, and consumption, and found that label users behaved differently compared with nonusers. These differences appeared more in qualitative in selecting different food than selecting more or less food.

This research fills two gaps in the literature. First, I use true scanner data to study the effect on consumers' purchase in terms of healthfulness, while previously related researches were based on self-reported survey data. And second, this is the first study to apply synthetic control method on effects from food nutrition labels use.

The remainder of this article is organized as follows. Section 2 provides the background of NuVal labeling. Section 3 discusses my empirical strategy. Section 4 describes data, followed by Section 5 which discusses the empirical results. Section 6 explore whether there is a change in stores' offering of food products. The final section provides concluding remarks.

3.2 Background of NuVal label

NuVal labeling was first introduced in 2008. It scores foods based on an algorithm known as Overall Nutritional Quality Index (ONQI) that profiles 21 nutrients and the quality of four nutrition factors (Katz et al., 2010). Scientists developed the ONQI at the Yale-Griffin Prevention Research Center, which was independent of food industry interest. It penalizes nutrients (e.g., saturated fat, sodium, and sugar) as well as nutrition factors generally considered to have negative health effects, and rewards those (e.g., fiber, potassium) that are considered to be beneficial to health. In order to test the utility of ONQI, Chiuve, Sampson, and Willett (2011) applied the algorithm to evaluate the diet quality of over 100,000 health professionals for over 20 years. They found that the diets with a lower score of ONQI are associated with higher risks of cardiovascular disease, diabetes, chronic disease, and all-cause mortality. NuVal is the ONQI algorithms commercial use.

NuVal LLC, NuVals licensing company, is partially owned by Topco, a private organization that is co-owned by grocery store chains, many of which are implementing NuVal scores into their stores. NuVal scores and labels products on a 1-100 scale with 1 indicating the least healthy prod- ucts and 100 the healthiest. This labeling design makes NuVal scores more visually accessible. It provides an easy clue for consumers to identify healthier products even when the differences may be small. However, small differences accumulated over repeat shopping trips could result in significant health effects. Reduced formed researches have found that shares of healthier prod- uct purchases increase following rollout of NuVal (Nikolova and Inman, 2015; Zhen and Zheng, 2018). As of August 2017, 16 retail chains had adopted NuVal shelf labels.

In this article, I investigate NuVal effects on dietary healthfulness from scanner data for the basket products in a small town in the Midwest. The basket includes yogurt, salty snacks, frozen dinner and cold cereal. I chose these four categories as the case study for three reasons. First, they represent the households' choice of food at home, covering from breakfast, main dinner, dessert and snacks. In this way, the basket could be a good representative to estimate household's diet. Second, the NuVal scores for these four categories are available, so that I could design outcome variables to represent the healthfulness level of the food. Lastly, there is a large variation in the nutrition ranking of individual products, as reflected by the NuVal scores from 1 to 100.

3.3 Empirical Strategy

The traditional model for case comparative study is difference-in-differences. However, I apply the synthetic control method for the study. The synthetic control method is more appropriate in this study for two reasons. First, comparative studies require random selection so that the control units can credibly proxy for treated units' counterfactual outcomes. A synthetic control unit is a weighted average of available control units that approximates the most relevant characteristics of the treated unit prior to the treatment, which provides a better fit for the treated units. Second, DID allows for the presence of unobserved factors but restricts the effect of those factors to be constant over time (Bertrand, Duflo, and Mullainathan, 2004; Abadie, Diamond, and Hainmueller, 2010). Thats why DID could eliminate the unobserved effect by taking time differences. But the synthetic method allows the unobserved characteristics to vary with time.

The outcome variables of interest are consumer i's calories intake and calories-weighted average NuVal score at time t. Each variable of interest can be represented as below:

$$Y_{it} = Y_{it}^0 + \alpha_{it} D_{it} \tag{3.1}$$

where Y_{it}^0 represents the outcome for consumer i at time t in the absence of the NuVal adoption event, for $i = 1, ..., J+1$ and time period $t = 1, ..., T$. Let T_0 be the number of pretreatment periods, with $1 \leq T_0 \leq T$. Assume only the first consumer ($i = 1$) is in the treatment group. And

$$D_{it} = \begin{cases} 1, & \text{if } i = 1 \text{ and } t > T_0 \\ 0, & \text{otherwise} \end{cases} \tag{3.2}$$

Therefore α_{it} is the effect of NuVal label on consumer is calories intake or calories-weighted average NuVal score. Since only the first consumer is in the treatment group, we only need to estimate α_{1t}.

Suppose Y_{it}^0 is written by a factor model:

$$Y_{it}^0 = \delta_t + \theta_t Z_i + \lambda_t \mu_{it} + \epsilon_{it}, \tag{3.3}$$

where δ_t is an unknown fixed time effect for all consumers, Z_i is a $(r \times 1)$ vector of observed covariates, θ_t is a $(1 \times r)$ vector of parameters, μ_{it} is an $(F \times 1)$ vector of unobserved factors varying over time, λ_t is a $(1 \times F)$ vector of parameters, and the ϵ_{it} are error terms with zero means. Notice that $\lambda_t \mu_{it}$ are heterogeneous responses to multiple unobserved factors.

Suppose there is a $(J \times 1)$ vector of weights $W = (w_2, ..., w_{J+1})$ such that $w_j \geq 0$ for $j = 2, ..., J+1$ and $w_2 + ... + w_{J+1} = 1$. Each particular value of the vector W represents a potential synthetic control consumer in the control group. The value of the outcome variable for each synthetic control indexed by W is

$$\sum_{j=2}^{J+1} w_j Y_{jt} = \delta_t + \theta_t \sum_{j=2}^{J+1} w_j Z_j + \lambda_t \sum_{j=2}^{J+1} w_j \mu_{jt} + \sum_{j=2}^{J+1} w_j \epsilon_{jt} \tag{3.4}$$

My goal is to find a $W = (w_2, ..., w_{J+1})$ that make the synthetic control group and treatment group identical to (or closest to) each other at any time when $t \leq T_0$, written as

$$\sum_{j=2}^{J+1} w_j Z_j = Z_1, \text{ and } \sum_{j=2}^{J+1} w_j \mu_{j1} = \mu_{11}, \sum_{j=2}^{J+1} w_j \mu_{j2} = \mu_{12}, ... \sum_{j=2}^{J+1} w_j \mu_{jT_0} = \mu_{1T_0},$$

In this case, such a W means that a synthetic control provides an unbiased estimator of Y_{1t}^0. Choosing a synthetic control in this manner is not feasible because μ_{jt} are unobserved. If we assume that (i) the terms ϵ_{it} are independent across units and in time, (ii) ϵ_{it} are mean-independent of $\{Z_i, \mu_{it}\}_{i=1}^{J+1}$, (iii) $\sum_{t=1}^{T_0} \lambda_t' \lambda_t$ is nonsingular, and (iv) the number of pre-intervention periods is greater than the number of unobserved factors (Abadie, Diamond, and Hainmueller, 2010; Abadie and Gardeazabal, 2003), a synthetic control indexed by $W^* = (w_2^*, ..., w_{J+1}^*)$, which can fit Z_1 and long enough set of pre-intervention outcomes, $Y_{11}, ..., Y_{1T_0}$, could make Equation (4) hold approximately.

$$\sum_{j=2}^{J+1} w_j^* Y_{j1} = Y_{11}, \sum_{j=2}^{J+1} w_j^* Y_{j2} = Y_{12}, \text{ ..., } \sum_{j=2}^{J+1} w_j^* Y_{jT_0} = Y_{1T_0}, \text{ and } \sum_{j=2}^{J+1} w_j^* Z_j = Z_1 \tag{3.5}$$

Therefore the estimator of α_{1t} is obtained by:

$$\hat{\alpha}_{1t} = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt} \tag{3.6}$$

So Z_i and all pre-intervention outcomes variables are implemented to choose W^*. To make sure the unobserved factors are matched by W^*, we need a long enough sequence of pre-intervention outcomes combining with Z_i. Let a $(T_0 \times 1)$ vector $K = (k_1, ...k_{T_0})$ defines a linear combination of pre-intervention outcome: $\bar{Y}_i^K = \sum_{s=1}^{T_0} k_s Y_{is}$.[2] Consider M of such linear combinations $(M > F)$ defined by the vectors $K_1, ..., K_M$. Let $X_1 = (Z_1', \bar{Y}_1^{K_1}, \bar{Y}_1^{K_2}, ...\bar{Y}_1^{K_M})$ be a $(k \times 1)$ vector of pre-intervention characteristics for the treatment unit, with $k = r + M$. Similarly, X_0 is a $(k \times J)$ matrix that contains the same variables for the control units. W^* is chosen to minimize the some distance, $||X_1 - X_0 W||$, conditional on $w_2 \geq 0, ...w_{J+1} \geq 0, w_2 + ...w_{J+1} = 1$. In practice, the computation of W^* can be simplified by considering only a few linear combination of pre-intervention outcomes, as long as $M > F$. In my dataset, the pre-intervention period, when the NuVal label is not adopted, is long enough, I simply choose the values of the outcome variable for all available pre-intervention periods, that is, $\bar{Y}_i^{K_1} = Y_{i1}, \bar{Y}_i^{K_2} = Y_{i2}, ...\bar{Y}_i^{K_M} = Y_{iT_0}$. Z_i includes household annual income, education level, age level, whether have children, the number of family size and marital status. So $k = 7 + T_0$.

To measure the distance between X_1 and $X_0 W$, following the strategy from Abadie et al. (2010), I will find a W^* to minimize $\sqrt{(X_1 - X_0 W)' V (X_1 - X_0 W)}$, where V is a $k \times k$ diagonal matrix with nonnegative components, representing the relative importance of the predictors. Following Abadie and Gardeazabal (2003), I select V that the outcome variable for the treatment group before T_0 is best reproduced by the synthetic control defined by $W^*(V)$. Let Y_1^0 be a $(T_0 \times 1)$ vector containing the outcome variable for the treatment consumer, Y_0^0 be a $(T_0 \times J)$ matrix containing the value fo the same variables for the J potential control consumers. Then

$$V^* = argmin(Y_1^0 - Y_0^0 W^*(V))'(Y_1^0 - Y_0^0 W^*(V)) \tag{3.7}$$

The process above is the effect of NuVal label on only one consumer in the treatment group. For each treated household, the control period and treatment periods need to be redefined, and the control group needs to be recreated accordingly as well. Each household in the control group is assigned with a non-zero weight, with the sum of 1, to represent the potential synthetic control household. The treatment effects in interest are calculated as the difference of the outcome variables between the treated household and synthetic household during the treatment period. To obtain the average effect and the entire distribution of the effect, replicate

[2] For example, if $k_1 = k_2 = ... = k_{T_0 - 1} = 0$ and $k_{T_0} = 1$, then $\bar{Y}_i^K = Y_{iT_0}$. If $k_1 = k_2 = ... = k_{T_0} = 1/T_0$, then $\bar{Y}_i^K = \frac{1}{T_0} \sum_{s=1}^{T_0} Y_{is}$.

the process for all the consumers in the treatment group and report the results.

3.4 Data

I analyze the purchases of yogurt, salty snacks, frozen dinner and cold cereals by IRI BehaviorScan (Bronnenberg et al., 2008) households from a small town in the year of 2010. I focus on the data from April to December with August omitted.[3] The NuVal score and product nutrients data are from NuVals licensing company, NuVal LLC.

The original weekly scanner data is aggregated into monthly data. Therefore a month is considered as a period in the estimation. The treatment store adopted NuVal label in August 2010. I use the following procedure to classify households into the treatment and control groups. For a household to be included in the treatment group, he had to visit one of the stores before August, and visited the NuVal store at least once since September 2010. The treatment period for this household is from the first month since September that he visited the NuVal store to Decemeber, removing the months he didn't visit any of the stores in the small town; the control period is from April to the month before the treatment period, removing the months he didn't visit any of the stores. Applying this procedure yields 817 households in the treatment group. For each treated household, I create a control group using the following two criteria: first, the household only visited the non-NuVal stores since August 2010; second, the household had transaction history during the defined treatment and control periods. For example, one household in the treatment group visited the stores from April to June and then from September to December, and his first visit to the NuVal store since September is October. Therefore for this treated household, the control period is from April to September (July and August are omitted), and the treatment period is from October to December. The control group for this treated household then consists of all households who visited the stores during both the control and treatment periods but never visited the NuVal store between August and December. This yields 343 households in the control group for this household. Column (1) in Table 3.1 shows the demographic characteristics (predictor variables) of the treated household. Column (2) shows the summary statistics of the 343 households in the corresponding control group. This specific treated household has an annual income of $69,760, two members, is headed by a non-married person aged above 65 without a college degree and has no children present. In the corresponding control group, 67% of the households have a head aged between 35 and 64 and 29% of the households have a head aged 65 or above, while the rest are headed by a person younger than 35 years old. 6% of the household heads have a college or higher degree. The average income for the households is about $51,990 and the average household

[3]Data from August is not used because I only know the NuVal label was adopted in August 2010, but not the exact date.

size is 2.55. The summary statistics indicate that the treatment household and the households in the corresponding control group are not similar as their characteristics differ a lot.

For each treated household, the control and treatment periods need to be redefined. And the control group for the treated household needs to be recreated accordingly as well. By doing so, there are a total of 890 households being selected into the control groups. The summary statistics of the demographic characteristics of the households in treatment and control groups are shown in Table 3.2. The information on the treatment effective dates are reported in Table 3.3. In the treatment group, 62% of the households have a head aged between 35 and 64 and 36% of the households have a head aged 65 or above, while the rest are headed by a person younger than 35 years old. 7% of the household heads have a college or higher degree. The average annual income for the households is about $54,700 and the average household size is 2.39. In the control groups, 60% of the households have a head aged between 35 and 64, and 36% of the households have a head aged 65 or above, while the rest are headed by a person younger than 35 years old. 7% of the household heads have a college or higher degree. The average annual income for the households is about $45,800 and the average household size is 2.32.

I focus on two outcome variables: household's monthly calories purchase and monthly calories-weighted average NuVal score. A household's monthly calories purchase is calculated as the sum of total calories from his purchases of yogurt, salty snacks, frozen dinner and cold cereals. The monthly calories-weighted average NuVal score is calculated as the average NuVal score from all products in the four categories purchased in the month, weighted by the total calories of each product. The summary statistics of outcome variables are shown in Table 3.4. On average, the treatment group consumes more calories every month. But there is no a clear pattern of difference in calories-weighted average NuVal scores between the two groups.

3.5 Results

3.5.1 Results for the treated household in our example

For the treated household in our example above, the control period is from April to September, and the treatment period is from October to December. 343 households are selected into the corresponding control group. Applying the method in Section 3.3, 33 households from the control group are assigned a weight greater than zero to construct the synthetic control household for the calories purchase and 59 households are assigned a weight greater than zero for the calories-weighted average NuVal score. Table 3.1 shows the stastistics of the preditor variables for the treated household, households in the corresponding control group and the synthetic control household. Columns (3) and (4) of Table 3.1 present the demographic characteristics of the synthetic control household for calories purchase and calories-weighted average NuVal score, respectively. Tables 3.5 and 3.6 and Figures 3.1 and 3.2 show the summary statistics of the outcome variables for the treated household, households in the corresponding control group and the synthetic household. According to Columns (3) and (4) of Tables 3.1, 3.5, 3.6 and Figures 3.1 and 3.2, the synthetic control household is almost identical to the treated household in terms of the value of the demographic characteristics and outcome variables during the control period. Therefore, the differences in the values of the outcome variables between the treated and the synthetic control households in the treatment period can be taken as the treatment effects.

The treatment effects on calories purchase are -7,165.4, -4,056.3 and -2,809.4 kcal in October, November and December, respectively. The NuVal label caused the treated household to decrease the total calories purchase by 7,165.4, 4,056.3 and 2,809.4 kcal in October, November and December, respectively. On average, the NuVal label caused the treated household to decrease the total calories purchase by 4,677 kcal per month during the treatment period, which is equivalent to about 73.4% of what the treated household would have consumed during the same period if NuVal label had not been introduced. The treatment effect for calories purchase reached its greateset level in the first month of the treatment period, and then decreased afterward.

The treatment effects on calories-weighted average NuVal scores are 8.531, -8.173, -1.072 points in October, November and December, respectively. The label caused the treated household to purchase healthier food products in October, but less healthy ones in November and December. On average, the treatment effect on calories-weighted average NuVal scores for this treated household is 7.01 points during the treatment period, which is a 16.2% increase compared to the case if the NuVal label had not been introduced.

Combining both results together, the NuVal label caused this treated household to purchase healthier products and consumed fewer calories. In addition, the treatment effects decreased over time, meaning that the NuVal label had more significant effect on the treated household at the beginning, and then the effects faded afterward.

3.5.2 Results for total calories purchase

I repeated the same procedure for all households in the treatment group and Table 3.7 shows the treatment effects on calories purchase for all the treated households from September to December. In September, when at the beginning of the adoption of NuVal label, the treated households dramatically reduced the calories purchase on average, with the average treatment effect of -1,727.4 kcal. In October, on the contrary, the NuVal label caused the treated households to increase the calories purchase on average, with the average treatment effect of

849.3 kcal. When it comes to November and December, the treatment effects are again negative but very small in terms of magnitude. Compared to what they would have purchased if the NuVal label had not been introduced, the NuVal label caused the treated households to decrease calories purchase by 21.05%, 2.68% and 2.39% in September, November and December, respectively; and to increase calories purchase by 16.94% in October.

The average treatment effect on calories purchase for the treatment group is reported in Table 3.8. For each treated household it is calculated as the mean of monthly treatment effects during his own treatment period. On average, the treated households reduced their total calories purchase by 220.26 kcal per month during their treatment periods, which is equivalent to a 4.36% reduction compared to what they would have purchased if the NuVal label had not been introduced. Overall, the NuVal label caused the treated households to reduce the amount of calories purchase. This is consistent with Kim et al. (2000) that food label use decreases individuals' average calories intake.

Table 3.9 futher reports the average treatment effects on calories purchase for different demographic groups. The treatment effects from the NuVal label on calories purchase for the households with a head aged less than 35, between 35 and 64, and above 65 are 98.23, -227.52 and -219.62 kcal per month during the treatment period, respectively. Therefore, the NuVal label has a negative effect on the households with a head older than 35, but a positive effect on younger households, in terms of calories purchase. Compared to the middle-age and old people, young people care more about the evaluation of the nutrient composition rather than the seperate nutritional values (Viola et al., 2016). The value of nutrient composition, which means the values for energy and nutrients combining protein, carbohydrates, fat, vitamins and minerals and other important food components such as fiber (Gebhardt et al., 2008), is different than the seperate nutritional values, which means intake of a single nutrient, like caloric intake or fat content. The NuVal score could be considered as an example to show the value of nutrient composition of food products. According to Viola et al. (2016), younger people are more likely to increase the total calories intake as the overall diet quality (NuVal score in this case, see the results in Section 3.5.3) increases, due to the rebound effect (Greening et al., 2000), which in our case means the misleading psychological thought of eating healthier would lead to overintake of calories. Second, the average treatment effects on calories purchase for all households with or without children, headed by a person with or without a college degree, married or unmarried, are all negative. The treatment effect for households with children is greater than those without children in magnitude. The treatment effect for households headed by a person with a college degree is much greater than those without a college degree. It is because households with chidren or headed by a person with higher education are more aware of healthy diet and nutrients intake (Hiza et al., 2013). Therefore the NuVal label had a greater effect on them rather than those households without chidren or headed by a person without college degree. It is also consistent with the results from food consumption surveys in Netherland and the U.S. (Hulshof et al., 2003; Davis, 1982). Third, the treatment effects also varied by treatment effective date. For those households who were exposed to the NuVal score earlier (in September), the treatment effect on calories purchase is positive, while the treatment effects for the households who were exposed to the NuVal label later are negative. The effect of the NuVal label on the consumers is largest at the beginning due to NuVal's salience effect (Zhen and Zheng, 2018), and then fade over time and even becomes positive after some period of the time that consumers actully purchased more due to the rebound effect (Greening et al., 2000) as well. So the average treatment effects per month are positive to those households who were exposed to NuVal label with a long time frame, but negative to those with a short time frame. Finally, the treatment effects on calories purchase also varied by income level. Based on the 2018 Federal Tax Rate Table (IRS, 2018), the treated households were classified into three classes: the households with annul income lower than \$19,050, between \$19,050 and \$77,400, and above \$77,400. For households with the highest level of income, the treatment effect is 448.68 kcal per month, while for other households the effects are negative. For households with the lowest level of income, the treatment effect is the largest in magnitude, as -1,206.31 kcal per month. It's because households headed by a person with higher level of income, are more likely to use nutrition facts and other food labels even before the adoption of NuVal labels (Hiza et al., 2013; Kim et al., 2000). Therefore the appearance of the NuVal label will make a bigger change in the calories purchase on the poor rather than the rich.

3.5.3 Results for calories-weighted average NuVal score

The same procedure is applied to all the households in the treatment group on the calories-weighted NuVal score. Table 3.10 shows the treatment effect on calories-weighted average NuVal score for all the treated households from September to December. In September, at the beginning of the adoption of NuVal label, the treated households purchase healthier products, with the treatment effect of 3.73 points, which is equivalent to a 15.80% increase compared to what they would have purchased if the NuVal label had not been introduced. In October, on the contrary, the treated households' average NuVal score decreased by 0.46 points, which is a 1.77% reduction compared to what they would have consumed if the NuVal had not been introduced. During the following two months, the average treatment effects on NuVal scores are 0.18 points (a 0.70% increase) and -0.96 points (a 3.93% reduction) in November and December, respectively. A possible explanation to the changes in treatment effects is that the effect of the NuVal label on consumers fades over time, as we discussed above.

The average treatment effect on NuVal score is reported in Table 3.11. The average treatment effect for each household is calculated as the calories-weighted average of monthly treatment effect on NuVal score during his own treatment period. On average, the treated households purchase the food with a higher NuVal score, with a treatment effect of 0.67 points, which is equivalent to a 2.69% increase compared to what they would have purchased without the introduction of NuVal label. It indicates that consumers are eating healthier after the availability of the NuVal label.

Table 3.12 reports the average treatment effects on NuVal scores within different demographic groups. First, the treatment effects for all households with a head aged in different groups are all positive. The treatment effect for the households with a head aged less than 35 is greater than other age groups in magnitude. This group of household is more likely to recognize the change in food labels, and they are more willing to switch to healthier food products (Viola et al., 2016). Another possible explanation is that the general quality of diet increases as consumers become older, even before the availability of NuVal label (Hiza et al., 2013). Second, the treatment effects for all households with or without chidren are all positive. The magnitude is greater for the households without children than those with children. Hiza et al. (2013) found that households with chidren usually pay more attention to the healthfulness of their diet than those withou chidren, therefore they are more likely to use nutrition facts and other food labels even before NuVal. Third, the treatment effects for all the households are positive regardless of the effective dates. It is greater for the households who were exposed to the treatment in September and November than those in October and December. Finally, the treatment effects have different signs for those households headed by a person with or without a college degree, married or unmarried, and with different income level. The NuVal label caused negative treatment effects for households with a head with a college degree or married, or with income greater than $77,400, and positive effects for households with a head without a college degree or unmarried, or with income lower than $77,400. This is because households headed by a person with higher education or married, or with higher level of income, are more likely to use nutrition facts and other food labels even before the adoption of NuVal labels (Hiza et al., 2013; Kim et al., 2000). The results are consistent with previous research (Madden and Yoder, 1972; Liang, Zhen, and Zheng, 2017; Liang, 2017).

3.6 The changes in retailers' offering

It is also worthy to explore whether there is a change in the health composition of the products being offered at the NuVal store. During the control period, there were a total of 1,287 and 1,089 UPCs being sold in the non-NuVal stores and the NuVal store, respectively. During the treatment period, there were a total of 1,224 and 1,035 UPCs being sold in the non-NuVal stores and the NuVal store.[4] The difference-in-differences (DID) approach allows us to examine the effects of NuVal label on the retailers' offereing in terms of healthfulness of the products. We use the following DID regression to examine the effect of the NuVal label on the average NuVal score for the products offered in the four categories:

$$log(Score_{st}) = \beta_0 + \beta_1 D_s + \beta_2 D_t + \beta_3 D_s * D_t + \gamma_s + \eta_t + \sum_{m=1}^{3} \rho_m D_m + \varepsilon_{st}, \tag{3.8}$$

where $Score_{st}$ is either the sales-weighted average NuVal score or the simple average NuVal score of the products in the four categories sold in Store s during week t. D_s is a dummy variable indicating the treatment store (the NuVal store), D_t is a dummy variable indicating the treatment period. γ_s is the store fixed effect controlling for the time-invariant store-specific factors, η_t is the week fixed effect controlling for store-invariant time-specific factors, $D_m(m = 1, 2, 3)$ are the dummy variables indicating the category of the products[5] and ε_{st} is the error term. The coefficient of interest is β_3, which can be interpreted as the average treatment effect on the treated. Note that in (3.8), the term $\beta_1 D_s$ is subsumed in the store fixed effects γ_s and the term $\beta_2 D_t$ is subsumed in the time fixed effects η_t. Hence, coefficient estimates for β_1 and β_2 will not be reported.

The results for equation (3.8) are shown in Table 3.13. If we focus on sales-weighted average NuVal score, the estimated average treatment effect on the treated is 2.91% and statistically significant, meaning that on average, posting NuVal label increased the sales-weighted average NuVal score of the UPCs in the four categories offered at the treatment store by 2.91% relative to that of the non-NuVal stores. For the simple average NuVal score, the estimated average treatment effect on the treated is 1.30% and also statistically significant, meaning that on average, posting the NuVal label increased the average score of UPCs in the four categories offered at the treatment store by 1.30% relative to that of the control stores. Both results show that there was no big change in the nutritional quality of the products offered because of the introduction of the NuVal label. A potential explanation is that the time frame is too short for the retailers to change the product offering, considering that the contracts between retailers and manufacturers are usually set up annually (Tsay, Nahmias, and Agrawal, 1999).

3.7 Conclusion

In this article, I investigate how the adoption of NuVal label changes households' diet choice. Applying the synthetic control method, I focus on how the NuVal score affected two outcome

[4]The counts are based on the sales data at the store level. The UPCs without NuVal scores are omitted.

[5]D_1, D_2 and D_3 indicate dummy of yogurt, frozen dinner and salty snacks, respectively. D_4 is omitted because of collinearity.

variables, total calories purchase and calories-weighted average NuVal score, in the treated group compared to what they would have purchased in absence of NuVal. On average, the adoption of NuVal label made treated households reduce their calories purchase and increase the calories-weighted average scores of food products per month during the treatment period. It indicates that NuVal score makes household alter their diet habit in a positive way. The results provide evidences of the effectiveness of NuVal score on households' dietary healthfulness.

The treatment effects vary by households' demographic characteristics. First, Consistent with expectations and previous results in Hiza et al. (2013); Kim, Nayga Jr, and Capps Jr (2000); Madden and Yoder (1972); Liang (2017); Liang, Zhen, and Zheng (2017), I found consumers who may have been less likely to use Nutrition Facts labels before availability of NuVal tend to respond more to purchase of food products in terms of NuVal score. They include households without children, headed by persons without college degrees, or with a lower level of income. Consequently, these increased more calories-weighted average NuVal score by more points. Second, I found that the NuVal label would cause a greater effect on the calories purchase from the consumers who have been more likely to use nutrition labels before. They reduced more calories purchase after the introduction of the NuVal label. Third, the households with a head aged less than 35 would increase the calories-weighted average NuVal score by the most kcal and also increase the calories purchase by the most points, compared to other age group. It reveals that different groups of households in age have different opinion on healthy diet, while the younger people care more about the overall quality of nutritiong composition and older people care more about seperate nutrition intakes. And last, I also confirm the rebound effect in the relationship between calories purchase and nutrition label. The psychological thought of eating healthier would misleadingly cause overeating.

Some limitations of my analysis suggest spaces for further research. First, I only include the transaction data from yogurt, frozen dinner, salty snacks and cold cereal due to the data availability. It represents an approximation of households' overall diet choice at home. Second, I consider the effectiveness of NuVal label in terms of health concern, by investigating comparative studies on the total calories intake and calories-weighted average NuVal score, ignoring other essential nutrients intake from the food. I leave the empirical investigation of these possibilities to future research.

Table 3.1: Demographic Characteristics of Example Treatment, Control and Synthetic Households

Variable	**Treatment (1)**	**Control (2)** Mean	Std. Dev.	Min	Max	**Synthetic (3)**	**Synthetic (4)**
Income	6.976	5.199	3.324	0.504	11.989	6.888	7.346
Family Size	2	2.55	1.21	1	6	1.87	2.22
Midage	0	0.67	0.47	0	1	0.00	0.00
Elder	1	0.29	0.45	0	1	0.95	1.11
Kid	0	0.14	0.35	0	1	0.00	0.00
Edu	0	0.06	0.24	0	1	0.00	0.00
Marital Status	0	0.09	0.29	0	1	0.00	0.00
Obs	1	343				—	—

Notes: Variable definitions: *Income*: annual household income in 10,000 dollar; *Family Size*: number of people in the household; *Midage*: =1 if the age of the household head is between 35 and 64 and 0 otherwise; *Elder*: =1 if the age of the household head is greater than or equal to 65 and 0 otherwise; *Edu*: =1 if the household head has at least a college degree and 0 otherwise; *Kid*: =1 if the household has a child less than 12 years old and 0 otherwise; *Maritial Status*: =1 if the household head is married, 0 if he/she is single, divorced, separated or widowed.

Table 3.2: Summary Statistics of Observed Consumer Characteristics

	Treatment Goup		**Control Group**	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Income	5.47	3.41	4.58	3.12
Family Size	2.39	1.20	2.32	1.19
Midage	0.62	0.48	0.60	0.49
Elder	0.36	0.48	0.36	0.48
Kid	0.10	0.30	0.11	0.32
Edu	0.07	0.26	0.07	0.25
Marital Status	0.11	0.31	0.13	0.33
Obs	817		890	

Notes: The variables are defined as Table 1.

Table 3.3: Treatment Effective Dates for Households in the Treatment Group

Treatment Effective on	**Number of Household**
September	354
October	253
November	123
December	87
Total	817

Table 3.4: Summary Statistics of the Outcome Variables

Month	Treatment Goup			Control Group		
	Obs	Calories Purchase	NuVal Score	Obs	Calories Purchase	NuVal Score
Apr	725	7561	24.0	771	6140	25.0
May	701	6764	24.9	732	5239	24.4
Jun	734	8565	26.3	773	7265	26.0
Jul	661	5855	27.1	721	4874	28.5
Sep	719	7119	27.3	768	7064	25.7
Oct	732	6145	25.3	711	4160	26.5
Nov	606	4205	26.1	624	3946	26.5
Dec	647	4745	23.5	651	4114	24.6

Table 3.5: Summary Statistics of Calories Purchase (Kcal)

Month	**Treatment**	**Control (2)**				**Synthetic**
	(1)	Mean	Std. Dev.	Min	Max	**(3)**
April	8310	7736	6805	100	36140	7922.7
May	4980	6634	5131	140	34330	4604.1
Jun	6480	9567	7727	110	55530	5922.4
September	5090	9586	8091	250	47840	4355.9
Octorber	1840	5514	5031	100	36130	9005.4
November	1620	4772	4448	110	33910	5676.3
December	1620	4911	4179	110	32040	4429.4
Obs	1	343				—

Table 3.6: Summary Statistics of Weighted Average NuVal Scores

Month	**Treatment**	**Control (2)**				**Synthetic**
	(1)	Mean	Std. Dev.	Min	Max	**(3)**
April	35.370	25.6	12.8	1	99	38.079
May	24.952	24.3	13.6	2	99	27.646
Jun	29	25.7	13.6	5.3	99	31.548
September	41.252	25.1	12.9	2	100	43.572
Octorber	62.402	26.9	15.3	4	100	53.871
November	29	27.1	16.9	4.1	100	37.173
December	29	24.5	14.4	2	99	30.072
Obs	1	343				—

Table 3.7: Summary Statistics of Treatment Effects on Calories Purchase (Kcal) Over Time

Variable	Obs	Mean	Std. Dev.	Min	Max
September	354	-1727.4	6501.9	-27996.8	19886.4
October	574	849.3	5786.1	-26617.6	42594.5
November	556	-116.4	4802.4	-19099.9	44175.4
December	647	-116.1	4675.9	-18728.8	25956.0

Table 3.8: Summary Statistics of Average Treatment Effect on Calories Purchase (Kcal)

Variable	Obs	Mean	Std. Dev.	Min	Max
ATE on calories intake	817	-220.26	3618.03	-26617.6	14044.65

Table 3.9: Summary Statistics of Average Treatment Effects on Calories Purchase (Kcal) for Different Demographic Groups

Demographic Group	Obs	Mean	Std. Dev.	Min	Max
Midage=0 & Elder==0	11	98.23	3184.20	-3537.18	6229.30
Midage=1	509	-227.52	3894.12	-16998.13	14044.65
Elder==1	297	-219.62	3116.88	-26617.60	12334.40
Kid=0	735	-203.07	3522.43	-26617.60	13218.27
Kid=1	82	-374.41	4405.75	-15598.17	14044.65
Edu=0	758	-109.35	3585.88	-26617.60	14044.65
Edu=1	59	-1645.27	3756.56	-16998.13	5162.20
Marital Status=0	731	-219.97	3567.26	-16998.13	14044.65
Marital Status=1	86	-222.73	4046.87	-26617.60	13218.27
Effective on September	354	17.97	3625.90	-15598.17	14044.65
Effective on October	253	-146.86	3627.64	-26617.60	13218.27
Effective on November	123	-905.73	3219.02	-13525.95	9669.55
Effective on December	87	-434.00	4001.39	-9389.90	11066.70
Income<1.905	139	-1206.31	3972.11	-26617.60	8072.77
1.905<Income<7.74	446	-260.93	3216.48	-11651.83	13218.27
Income>7.74	232	448.68	3980.84	-13525.95	14044.65

Table 3.10: Summary Statistics of Treatment Effects on Calories-Weighted Average NuVal Scores Over Time

Variable	Obs	Mean	Std. Dev.	Min	Max
September	354	3.73	16.56	-49.03	82.98
October	574	-0.46	18.18	-73.42	84.36
November	556	0.18	18.68	-62.14	84.65
December	647	-0.96	16.93	-84.97	87.50

Table 3.11: Summary Statistics of Average Treatment Effect on Calories-Weighted Average NuVal Scores

Variable	Obs	Mean	Std. Dev.	Min	Max
ATE on NuVal Score	817	0.67	9.34	-55.19	51.15

Table 3.12: Summary Statistics of Average Treatment Effects on Calories-Weighted Average NuVal Scores for Different Demographic Groups

Demographic Group	Obs	Mean	Std. Dev.	Min	Max
Midage=0 & Elder=0	11	1.15	4.39	-5.17	10.52
Midage=1	509	0.59	9.02	-55.19	51.15
Elder=1	297	0.79	10.02	-42.99	45.20
Kid=0	735	0.74	9.65	-55.19	51.15
Kid=1	82	0.04	5.92	-25.84	13.65
Edu=0	758	0.84	9.39	-55.19	51.15
Edu=1	59	-1.44	8.55	-16.37	42.87
Marital Status=0	731	0.84	9.28	-55.19	51.15
Marital Status=1	86	-0.73	9.79	-23.49	45.20
Effective on September	354	1.13	9.27	-53.11	49.60
Effective on October	253	0.01	9.90	-55.19	45.20
Effective on November	123	1.19	11.43	-20.22	51.15
Effective on December	87	0.00	0.05	-0.09	0.15
Income<1.905	139	1.13	9.90	-23.10	45.20
1.905<Income<7.74	446	0.98	9.15	-42.99	51.15
Income>7.74	232	-0.20	9.35	-55.19	37.18

Table 3.13: DID Estimation Results for Changes in Retailer's NuVal Score

	Sales-weighted Ave. NuVal Score		**Average NuVal Score**	
	Estimate	Std. Err.	Estimate	Std. Err.
$D_s * D_t$	0.0291**	0.011	0.0130***	0.002
Category Fixed Effects	Included		Included	
Store Fixed Effects	Included		Included	
Time Fixed Effects	Included		Included	
Adjusted R-squared	0.45		0.63	

Note: The estimate method is OLS. ** denotes statistical significance at 5% level. *** denotes statistical significance at 1%.

Figure 3.1: Calories Purchase (Kcal) by the Household in the Example, the Corresponding Control Group and the Corresponding Synthetic Control Household

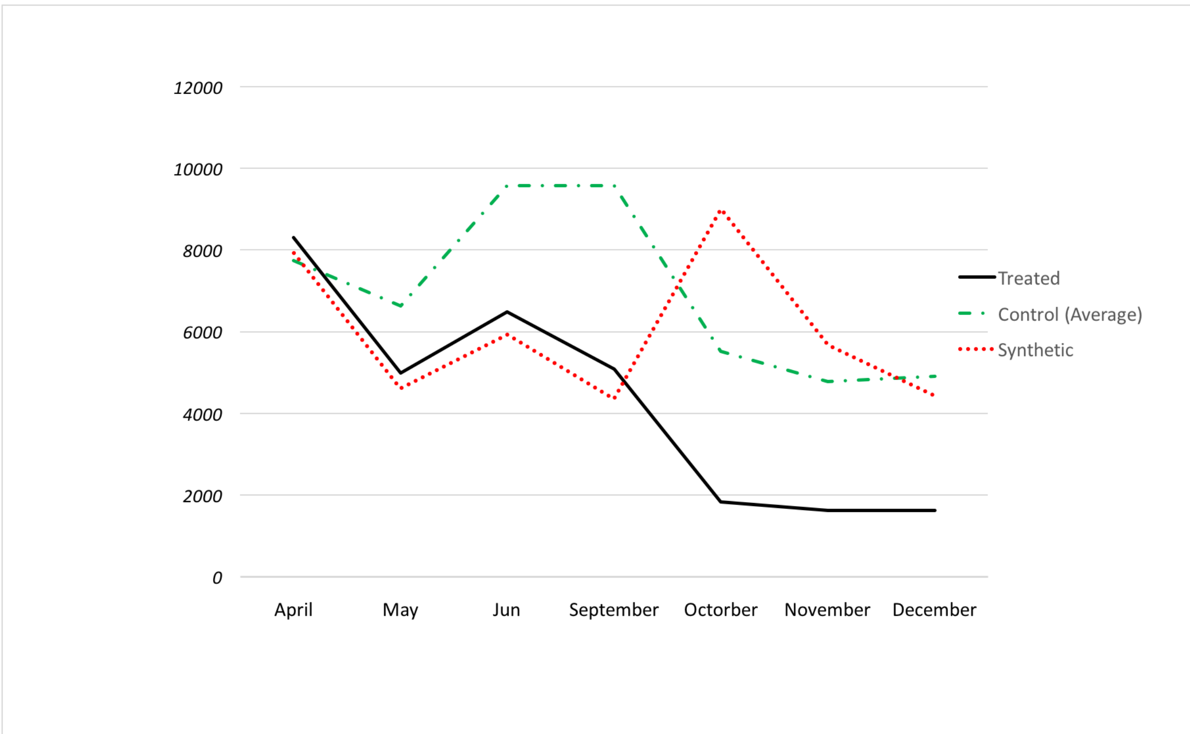
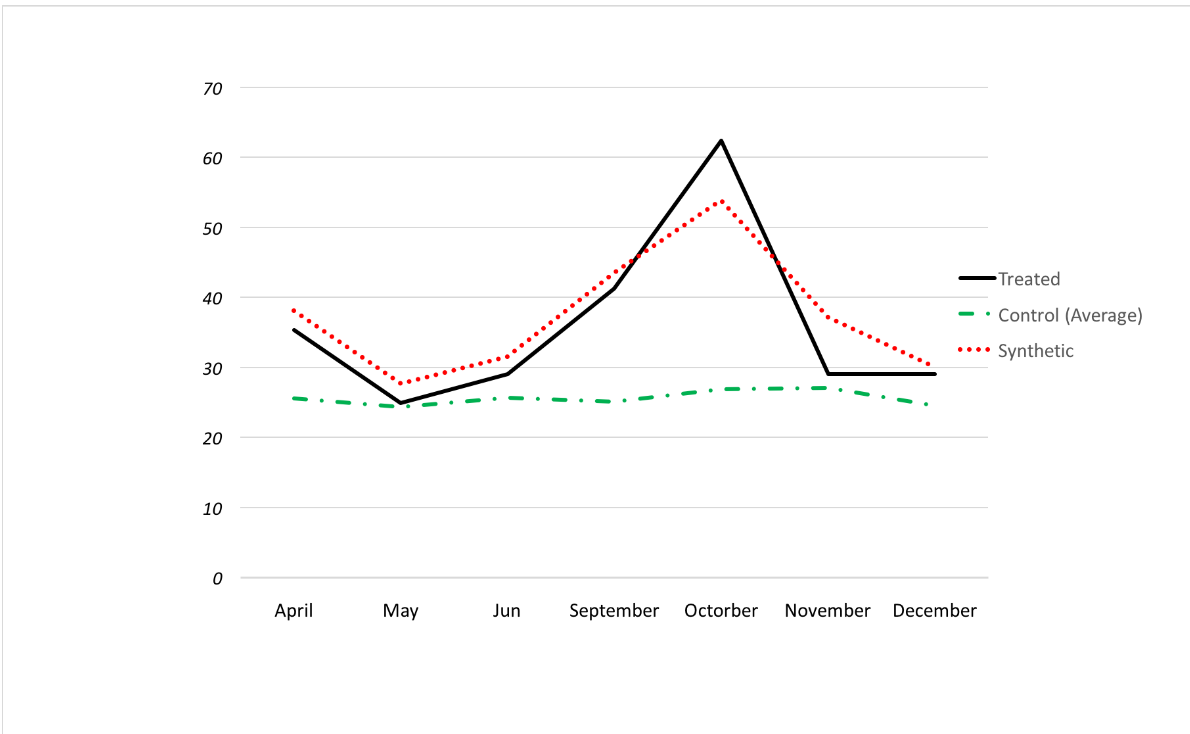


Figure 3.2: Calories-Weighted Average NuVal Scores by the Household in the Example, the Corresponding Control Group and the Corresponding Synthetic Control Household



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